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How do marijuana state laws affect crime?

Autor: Marcos J. Mercado[1]
36990275

Mentor: Martín Rossi

Buenos Aires, Argentina

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[1] Marcos J. Mercado, Universidad de San Andrés, Vito Dumas 284, Victoria, Provincia de Buenos Aires, Argentina, mercadom@udesa.edu.ar. I would like to thank my mentor, Martin Rossi, for his valuable comments and guidance. I am also thankful to my family who helps through thick and thin.

Tesis de Maestría en Economía de

Marcos J. Mercado

""¿Cuál es el impacto de las leyes estatales de marihuana sobre el crimen?"

Abstract

El propósito de este trabajo es el de analizar el efecto de las leyes de marihuana sobre los niveles de criminalidad en Estados Unidos. Tratamos a la descriminalización, la legalización de la marihuana medicinal y legalización de la marihuana recreacional como un tratamiento único. Nuestro objetivo es entender los posibles vínculos entre crimen y leyes de marihuana adentrándonos en los mecanismos. Encontramos que relajar las leyes de marihuana impactan negativamente los crímenes de propiedad. La distribución de recursos policiales podría ser el mecanismo detrás de la caída en crimen. Encontramos que la población penal cae rápidamente alrededor del tratamiento, la distribución de recursos hacia crímenes de drogas cae al mismo tiempo que el crimen cae, aproximadamente 10 años después del tratamiento. Esto puede darse por un mejor procesamiento de la política pública por parte del sistema judicial. La caída en las tasas de convicción de los crímenes de drogas podría estar agregando a la señal que recibe la policía de por sí por la política pública. Apoyamos la creencia que los crímenes siguen un comportamiento económico a la hora de cometer crímenes. Con una distribución más eficientes de recursos policiales crecen los riesgos de cometer crímenes, de esta manera reduciendo los crímenes. Encontramos que la descriminalización podría tener un impacto positivo sobre los crímenes violentos, pero no los crímenes de propiedad. Llevamos adelante un análisis de datos de panel controlando por varias variables que pueden confundir la identificación.

Palabras clave: Crimen, Microeconomía, Evaluación de Impacto, Abuso de Drogas, Leyes de Drogas, Marihuana, Econometría, Distribución de Recursos.

"How do marijuana state laws affect crime?"

Abstract

The purpose of this paper is to assess the effect of marijuana laws on crime rates in the United States. We treat decriminalization, medical marijuana legalization and recreational marijuana legalization as a sole treatment. Our objective is to understand possible links between crime and marijuana law and delve deeper into possible mechanisms at work. We find that relaxation of marijuana laws impacts negatively on property crimes. We find evidence that police resource allocation could be the mechanism explaining this fall in crime. We find that penal system population falls rapidly around the treatment, resource allocation towards drugs declines at the same time crime falls, around 10 years after the treatment. This could be explained by a better processing of public policy of the judicial system. Reduced conviction rates of drug criminals could be adding to the signal police already receive from public policy. We argue that criminals follow an economic model of crime. With more efficient police resource allocation brought by the treatment, higher risks are associated to committing crime, therefore reducing crime. We also find some evidence that decriminalization could have a positive impact on violent crime but not property crimes. We carry out a panel data analysis controlling for several variables which could confound the identification.

Keywords: Crime, Microeconomics, Impact Evaluation, Drug Use, Drug Laws, Marijuana, , Econometrics, Resource Allocation.

Códigos JEL: C01 Econometrics ; D04 Microeconomic Policy: Formulation, Implementation, and Evaluation; A14 Sociology of Economics; J18 Public Policy.

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1. Introduction

Recently several states have legalized marijuana for recreational purposes. This is especially interesting since marijuana is classified as a Schedule 1 drug. Schedule 1 drugs are defined by the Drug Enforcement Agency (DEA) “as drugs with no currently accepted medical use and a high potential for abuse”[2] Other examples of Schedule 1 drugs are heroin, LSD and ecstasy.

Since the compassionate use act of 1996, a California law permitting the use of medical cannabis, 30 states and the federal district have legalized marijuana for medical use. Since 1973, 22 state legislatures have enacted marijuana decriminalization. Marijuana use is no longer considered a crime when decriminalization laws are enacted. Marijuana users do not face jail time for the possession or use of small amounts of marijuana. In some states, users might have to attend court or pay a small fine. The political dichotomy generated by marijuana laws leads us to believe that this seems to be more of a political than a scientific matter. This is because public policy has not been justified by scientific data. Goode (1969) reinforces this affirmation by stating that this topic has turned into one of the bastions in the establishment of a moral hegemony.

The motivation for this paper comes from already enacted and impending marijuana laws in the US. The lack of a consensus regarding consequences of more permissive marijuana laws across the literature might very well be because of the influence that politics and emotion play over research.

The connection between drugs and crime is one of the main reasons used to block more permissive marijuana laws. This is why the purpose of this paper is to assess the effect that marijuana laws (MLs) have on crime rates.

The arguments against legalizing marijuana have to do with the impact increased drug use or through the illegality of drug itself. Users commit crime because of an economic compulsive behavior to sustain drug use or through the psychoactive effects of drug themselves. The illegality of drugs themselves has to do with the black market behind drug use. Gangs that generate money by incurring in illegal activities generate crime. Pro restrictive drug policies contenders will argue this means there has to be a tougher policy against drugs, pro liberalization of drug policies contenders will argue that if drugs are legalized these black markets would disappear and with them crime. We will delve deeper into these mechanisms throughout this paper.

We aim to understand the causal effects behind marijuana laws and to understand how this public policy really works.

The paper is organized as follows. The first section will be centered on the treatment. The first part is an in-depth analysis of marijuana laws, their history and different mechanisms linking them to crime. The second section will explain the data available to carry out a study, the Dif-in-Dif approach to panel data, the possibility of identifying a causal effect between marijuana law and crime, the model specified and the identification strategy. The fourth section will present the results and analyze empirically the mechanism of resource allocation as a causal of a fall in certain types of crime. Finally, we conclude summarizing our primary results.

[2] Drug Scheduling. (2020). Retrieved 14 March 2020, from https://www.dea.gov/drug-scheduling

2. The Treatment: Marijuana Law

A) *Marijuana Law History*

Prohibition is a law forbidding the manufacture and sale of a product[3]. Past prohibitions include the unsuccessful alcohol prohibition in the 1920s and early 1930s in the US. This prohibition brought upon the United States a crime wave that has been unmatched since. The illegality of alcohol, and the voracious demand for it, generated a market where opportunist criminals could greatly benefit, causing the surge of organized crime.

Marijuana laws date back to 1913, when California passed the first prohibition law aimed at recreational use of marijuana (Gieringer 1999). In 1937, the Federal Bureau of Narcotics (FBN) led a campaign portraying marijuana users as violent and criminal. With the support of the FBN and its assistant prohibition commissioner Harry Anslinger, the marihuana tax act terminated legal use of marijuana. In order to posess and use marijuana a tax stamp had to be paid. These tax stamps were difficult to obtain, making marijuana pretty much illegal. This referred to any kind of marijuana even that used for treating medical impairments (Bilz 1992)[4].

In 1944 Fiorello La Guardia, mayor of New York City at the time, commissioned a special committee of 31 scientists to study the effects of marijuana. This report was referred to as "The marijuana problem in the city of New York". Fiorello's idea was to abolish a law that can't be enforced. The common perception that laws legislate morality is interesting. If marijuana use had no effect on "bystanders" or would solely be carried out in the private property of a given person this would mean this activity would be a part of private morality. Though this report disproved all negative effects attributed to marijuana, it did not have any impact on the federal government's view on marijuana use[5].

In 1956, the Narcotic Control Act was passed as a result of a nationwide investigation on drug use and crime. This act imposed some of the most extreme penalties on drug users to date. In Missouri, a 2nd possession charge could be grounds for a life sentence. The Single Convention on Narcotics drugs (1961) was an international treaty that aimed to prohibit the sale and production of certain drugs[6]. If the Federal Drugs Administration (FDA) finds a drug to be addictive; then, under the authority of the Controlled Substances Act, it petitions the Drug Enforcement Administration (DEA) to place the drug on the list of controlled substances[7]. By 1970, the Controlled Substances Act classified marijuana as a schedule 1 drug. No significant change in federal law has happened since.

Contradictory to what federal law would lead us to believe, people have used marijuana historically for lots of different medical reasons, ranging from treating malaria to relieving headaches[8]. From 1850 to 1942, marijuana had been included in the "United States Pharmacopeia" with all recognized medicinal drugs (Bilz 1992)[9].

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[3] As defined by the Oxford Dictionary, 13/04 http://www.oxforddictionaries.com/es/definicion/ingles_americano/prohibition

[4] As seen in Anderson et. al (2013), page 335.

[5] "The La Guardia Committee Report." La Guardia Committee Report. http://www.druglibrary.org/schaffer/library/studies/lag/lagmenu.htm (accessed May 28, 2014).

[6] Wikimedia Foundation. "Single Convention on Narcotic Drugs." Wikipedia. http://en.wikipedia.org/wiki/Single_Convention_on_Narcotic_Drugs (accessed May 26, 2014).

[7] (The Controlled Substances Act, 2020)

[8] Examples of other drugs derived from botanicals: "Digitalis leaf, derived from Digitalis purpurea (the foxglove plant), is the source of drugs commonly used to treat congestive heart failure.48 Papaversomniferum (the opium poppy) provides opium49 from which morphine used to treat pain is derived.50 Donnatal™, a medication used to treat irritable bowel syndrome, contains belladonna alkaloids—originally found in Atropa belladonna, the deadly nightshade plant—as one of its active ingredients…" (Cohen,2009), page 46.

[9] As seen in Anderson et. al (2013), page 335.

"Marijuana is widely considered to be an extremely effective medicine to assist with those common side effects associated with cancer, chemotherapy, and AIDS. Marijuana also helps ease some of the suffering associated with ailments such as glaucoma, epilepsy, multiple sclerosis, paraplegia, quadriplegia, and chronic pain….There is a legitimate health interest in smoking marijuana that must be recognized for persons suffering from AIDS, cancer, multiple sclerosis, glaucoma, and other serious illnesses, who need to use the substance to help alleviate some of their ailments. Accordingly, there should be a distinction made between those in need of the medication, and those solely using it for recreational purposes, as there is for other controlled substances. (Hussein, 2000)[10]"

[10] Hussein (2001), page 2.

B) Types of Marijuana Laws

Marijuana Laws fall into one of three categories, decriminalization, medical marijuana legalization and recreational marijuana legalization. As we can appreciate in Table 1, starting in the 70s, several states have defied federal law by enacting state laws which are more permissive towards marijuana use for medical or recreational reasons.

Table 1 - Medical Marijuana Law Treatment Specifics

State	Decriminalization	Medical Marijuana	Recreational Marijuana
CALIFORNIA	1975	1996	2016
ALASKA	1975*	1999	2014
OREGON	1973	1998	2014
WASHINGTON		1998	2012
MAINE	1975	1999	2016
COLORADO	1975	2001	2012
HAWAII	2019	2000	
NEVADA		2001	2016
MONTANA		2004	
VERMONT	2012	2004	2018
RHODEISLAND		2006	
NEWMEXICO	2019	2007	
MICHIGAN	2018	2008	
ARIZONA		2011	
NEWJERSEY		2010	
DC		2010	
DELAWARE	2015	2011	
CONNECTICUT		2012	
MASSACHUSETTS		2013	2016
ILLINOIS	2016	2014	2019
MARYLAND	2014	2013	
NEWHAMPSHIRE	2017	2015	
ILLINOIS		2013	
PENNSYLVANIA		2016	
OHIO	1975	2016	
MINNESOTA	1976	2014	
MISSISSIPPI	1977		
NEW YORK	1977	2014	
NORTH CAROLINA	1977		
SOUTH DAKOTA	1977		
NEBRASKA	1978		
MISSOURI	2014	2018	
WEST VIRGINIA		2017	
OKLAHOMA		2018	
UTAH		2018	
NORTH DAKOTA	2019		

Source: Timeline of cannabis laws in the United States. (2020). Retrieved 21 March 2020, from https://en.wikipedia.org/wiki/Timeline_of_cannabis_laws_in_the_United_States
*Alaska recriminalized marijuana in 1990 to further decriminalize in 2003, recriminalize in 2004 and decriminalize in 2014.

Decriminalization

Decriminalization is a policy that intends to remove the drug user from the criminal system. This imposes civil penalties for cannabis related offenses such as possession or use (instead of criminal penalties) while maintaining penalties against drug sellers and traffickers[11] During the 1970s 11 states decriminalized marijuana. This was in great part catalyzed by the "Shafer Report" [12] which stated that "while public sentiment tended to view marijuana users as dangerous, they actually found users to be more timid, drowsy and passive. It concluded that cannabis did not cause widespread danger to society. It recommended using social measures other than criminalization to discourage use. It compared the situation of cannabis to that of alcohol"[13].

Medical Marijuana Legalization

Because of the possible advantages of providing medical marijuana, several states have decided to enact medical marijuana laws. The federal government can only prohibit marijuana from travelling to other states. The cultivation and its use within a state fall outside the scope of federal law. In 2009 the Attorney General has adopted a policy of not prosecuting users who are complying with state laws. This means individual states enjoy almost complete liberty in this matter with very limited federal interference.

Medical marijuana laws remove penalties for using, possessing, and, in some cases, cultivating marijuana plants. The patients are required to receive approval from a certified physician. The doctors and patients are not prosecuted as long as the drug is intended for medical purposes. Medical marijuana laws might even allow a caregiver to obtain marijuana for the aforementioned patient.

In 1996 California passed the Compassionate Use Act to allow sick residents the use of marijuana for its medicinal properties. A caretaker could even cultivate the plant for the patient. California Proposition 215 distinguishes between recreational and medical uses of marijuana[14]. Since California legalized medical marijuana, 28 other states and Washington D.C. have followed its path.

Recreational Marijuana Legalization

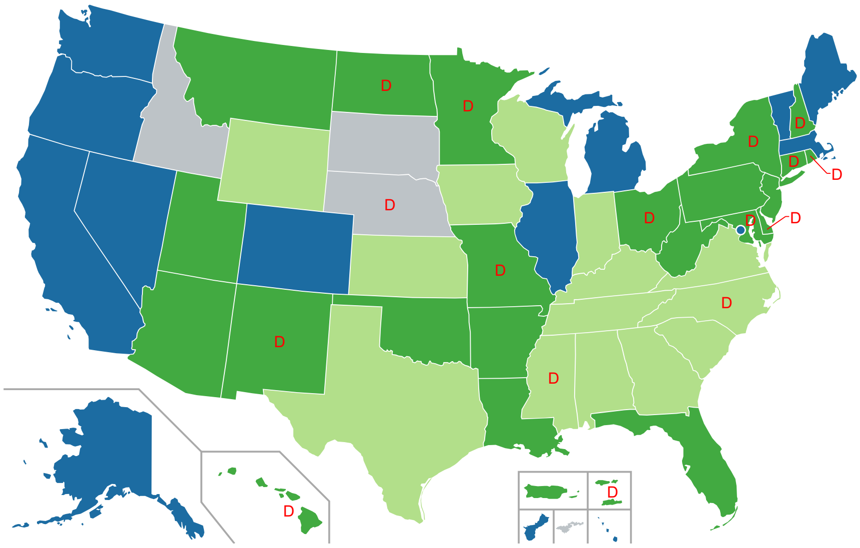
The main difference between decriminalization and recreational marijuana legalization is that, in recreational marijuana legalization, production and sale is regulated by the state. In decriminalization production and sale remain illegal. Marijuana provision is an economic activity which is taxed. In both, decriminalization and recreational marijuana legalization, marijuana users are not prosecuted.

To better understand the treatment, it is interesting to see the different combinations of treatments that have appeared throughout the United States. Not all states have all 3 levels of marijuana law relaxation and not all states pass treatments in the same order. This can be further noted in table 2. We can see that there is a majority of states that have decriminalized and legalized medical marijuana vs other combinations.

There was decriminalization wave in the 70s and a big part of these states ended up starting to legalize medical marijuana in the end of the 90s and all through the 00s. Another wave has commenced in 2012 with recreational marijuana legalizations.

[11] About Marijuana. (2020). Retrieved 21 March 2020, from https://norml.org/aboutmarijuana/decriminalization-2
[12] About Marijuana. (2020). Retrieved 21 March 2020, from https://norml.org/aboutmarijuana/decriminalization-2
[13] Drugs And Social Responsibility(2011) Retrieved April 20, 2011, from Druglibrary.org.
[14] All this information is in California Health & Safety Code 11362.5 Hussein (2001).

Figure 1 – Map of the United States showing Marijuana law Status March 2020[15]



Legal
Legal for medical use
Legal for medical use, limited THC content
Prohibited for any use
D Decriminalized Map includes laws which have not yet gone into effect. Data obtained from National Conference of State Legislatures.

We can assume that every state that legalizes recreational marijuana by default has legalized medical marijuana and decriminalized possession through this same law. Therefore, a condition to pass recreational marijuana laws seems to be to have some sort of experience with other type of marijuana law relaxations. All states that legalize recreational marijuana have some other type of marijuana law relaxation beforehand, also if a state legalizes recreational marijuana a more relaxed treatment is the legalization of medical marijuana. There is no state that has only passed recreational marijuana laws, no state has passed recreational marijuana laws before decriminalization or medical marijuana laws. It seems intuitive that law makers would take a gradual approach towards marijuana law relaxation, especially when there is no information on recreational marijuana law impacts.

Table 2 - Descriptive Statistics Treatments

	Total States
Decriminalized, Legalized Medical Marijuana and Legalized Recreational Marijuana	**7**
All 3 Levels but decriminalized first	5
All 3 levels but Medical Marijuana First	2
All 3 Levels but Legalized Recreational Marijuana First	0
Decriminalized and Legalized Medical Marijuana	**10**
All 2 Levels but decriminalized first	5
All 2 Levels but Legalized Medical Marijuana First	5
Legalized Medical Marijuana and Legalized Recreational Marijuana	**3**
All 2 Levels but legalized Medical Marijuana First	3
All 2 Levels but legalized Recreational Marijuana First	0
Only Decriminalized	**5**
Only Medical Marijuana	**11**

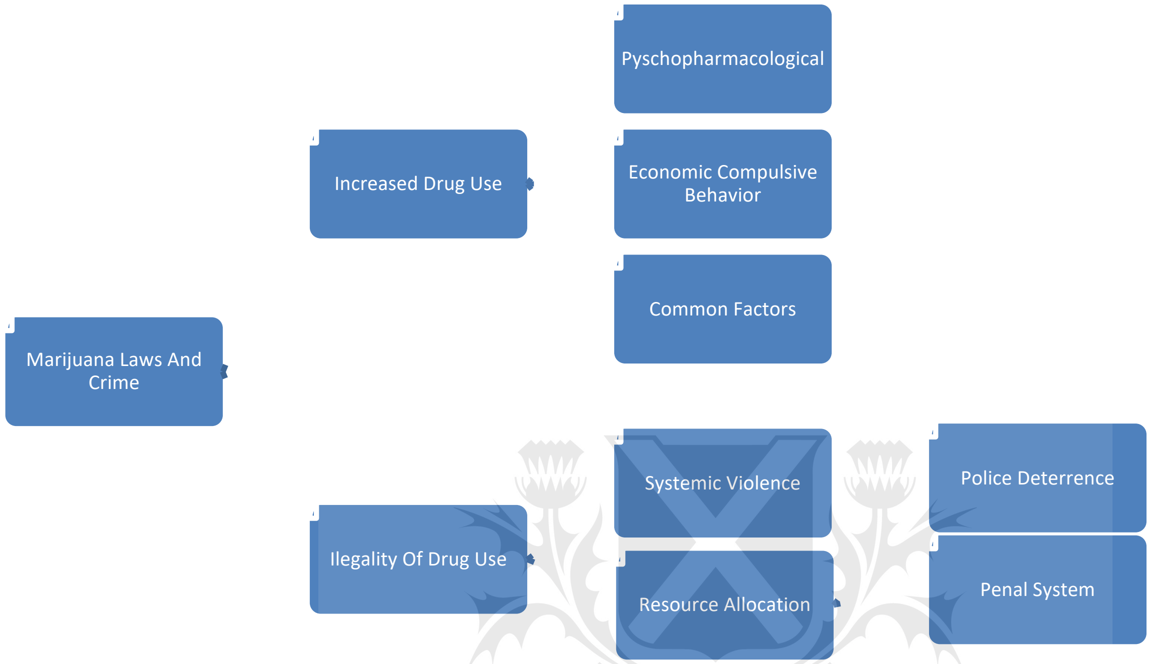
Source: Timeline of cannabis laws in the United States. (2020). Retrieved 21 March 2020, from https://en.wikipedia.org/wiki/Timeline_of_cannabis_laws_in_the_United_States
*Alaska recriminalized marijuana in 1990 to further decriminalize in 2003, recriminalize in 2004 and decriminalize in 2014

[15] User:Lokal_Profil - Wikimedia Commons. (2020). Retrieved 23 March 2020, from https://commons.wikimedia.org/wiki/User:Lokal_Profil

C) Possible Mechanisms linking Marijuana Laws and crime

We have constructed Figure 2 to visually identify 2 main groups of mechanisms linking marijuana and crime; increased drug use and the illegality of drug use itself.

Figure 2 – Linking Marijuana Laws and Crime



From Pacula and Kilmer (2003) we discern four main mechanisms to associate crime and the legality of marijuana. The link could be psychopharmacological, economic-compulsive, systemic violence or common factors. These four have either to do mainly with drug use itself.

The psychopharmacological explanation argues that the person who smokes marijuana becomes an offender because of the acute psychoactive effects of marijuana.

The second explanation would relate to the crime as a means to finance addiction. This would be an economic-compulsive behavior. Listed by Benson et al., taken from Kaplan (1983). It is the illegality of drug use itself that causes non drug related criminal activity. When drug use is made illegal, several consequences occur: Prices go up, forcing users to acquire more resources in order to fuel their consumption. Steady employment is difficult because of the time spent finding a safe supply source and because of the arrests and harassment by police forces. Finally, tagging them as criminals makes them forcibly have to deal with criminals.

The "common factor" hypothesis suggests that there are exogenous characteristics that make an individual more prone to commit crime, and, at the same time, more likely to try drugs. This theory is supported with evidence by Gottfredson and Hirschi (1990). This is an example of a spurious correlation in the way that factors associated with drug use are, at the same time, associated to criminal activity. From Benson et al (1992) we can say that drug crime and drug enforcement are linked to other types of crime in two major ways. The first is explained by the large amount of predatory crime committed by people who are drug users. Since a large percentage of the people arrested use drugs, this leads people to understand that drug use must cause crime. It is a common argument that this is how they finance their habit.

The systemic violence has to do with the black market behind marijuana. Cartels, dealers and gangs generate crime to resolve turf conflicts. Profits fuel competition, which in turns generates a hostile market environment with no government regulation.

Not included in Pacula and Kilmer's four mechanisms a potential linkage Benson et al. posit is through the allocation of resources. Since resources are scarce, legislation decides how these will be distributed. An increase in resources allocated to deter drug crime will, undoubtedly, reduce the amount of resources available to stop other types of crime. In an economic model of crime, an increased amount of resources destined to stop one type of crime turns other types of crime more attractive.

2. The Data

A) *The Empirical Model*

The purpose of this paper is to assess the effect of marijuana laws on crime rates. The data consists of a panel of observations from the 50 US states and Washington D.C.,[16] with information relating to crime reported during 1960-2018. The data on reported crime by state was obtained from the Uniform Crime Reports (UCR) program online data tool[17]. The data obtained from UCR is composed of two main groups of crime: property and violent crime. Property crimes are larceny theft, vehicle theft and burglary. Violent crimes are robbery, aggravated assault, forcible rape and murder[18]. We have constructed an index of crime which groups both types of crime. These can be seen in Table 2.

Table 3 - Descriptive Statistics Crime

Variable	Description	Obs	Mean	Std. Dev.	Min	Max	Years
Crime Variables							
index	Total violent and property crimes reported	3004	3959	1633	651	12174	1960-2018
violent	Violent crimes are defined in the UCR Program as those offenses that involve force or threat of force.	3003	396	291	10	2922	1960-2018
property	The object of the theft-type offenses is the taking of money or property, but there is no force or threat of force against the victims.	3002	3563	1422	573	9512	1960-2018
murder - violent	the willful (nonnegligent) killing of one human being by another.	3004	6	6	0	81	1960-2018
forcible rape - violent	The revised UCR definition of rape is: penetration, no matter how slight, of the vagina or anus with any body part or object, or oral penetration by a sex organ of another person, without the consent of the victim.	3004	29	16	1	162	1960-2018
robbery - violent	the taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.	3004	124	145	2	1635	1960-2018
aggravated assault - violent	an unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury	3004	236	161	4	1558	1960-2018
burglary - property	the unlawful entry of a structure to commit a felony or theft.	3004	884	446	136	2907	1960-2018
larceny theft - property	the unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another.	2996	2334	903	293	5834	1960-2018
vehicle theft - property	the theft or attempted theft of a motor vehicle.	3004	344	224	28	1840	1960-2018

All data on crime and police personnel was taken from the "Crime in the US publications" by the FBI CJIS.

[16] Robustness was checked not including Washington D.C. and results do not change significantly.
[17] CJIS - Criminal Justice Information Services. "Welcome to a new way to access UCR statistics." Uniform Crime Reporting Statistics. http://www.ucrdatatool.gov/ (accessed May 21, 2014).
[18] Specific definitions for UCR offenses will be found in the appendix.

The treatment that will be studied is the passing of Marijuana Laws (MLs). More policy changes over the studied period would increase the statistical power to detect a causal effect, as suggested by Harper et al. (2012). An increase in the time period observed with more pre- and post- treatment years available will also help isolate the causal effect. Information on marijuana laws was taken from the "National Organization For The Reform Of Marijuana Laws" (NORML) webpage (norml.org/)

Different state-related characteristics might potentially confound the identification; this is because states that approve MLs (marijuana laws) might be primarily different to those who do not, rendering comparisons amongst these states inaccurate. A cross-sectional analysis assesses the "between units" variability. This type of analysis would not be able to differentiate these effects from the impact of MMLs. These are time-invariant characteristics and can be controlled by using a differences-in-differences model.

The differences-in-differences estimator also includes year fixed effects. This means that shocks to crime rates that would have affected all states in the same way are accounted for. Time series analysis would have to assume that no shock has impacted the dependent variable aside from the treatment. The "within units" variability cannot differentiate exogenous shocks. All possible shocks would have to be accounted for as controls, in order to "earn" causality.

The treated group includes the states that have passed the law, while the control group includes the states that have not passed the law. The main assumption we have to make is that the control group's trend would be a good estimate of the counterfactual trend that treated states would have undergone, if no treatment had been administered. This is a more reasonable assumption than that of independent time-series or cross-sectional analysis. Under this specification, we are comparing within-state changes in crime before and after MLs with the same information for states without MLs.

The model we are going to estimate can be represented by equation (1) and (2).

(1) $Number\ of\ Crime\ Offenses\ Reported_{it} = \beta_{-15}MLE_{it-15} + \beta_{-14}MLE_{it-14} + \beta_{-13}MLE_{it-13} + \beta_{-12}MLE_{it-12} + \beta_{-11}\beta MLE_{it-11} + \beta_{-10}MLE_{it-10} + \beta_{-9}MLE_{it-09} + \beta_{-8}MLE_{it-08} + \beta_{-7}MLE_{it-07} + \beta_{-6}MLE_{it-06} + \beta_{-5}MLE_{it-05} + \beta_{-4}MLE_{it-04} + \beta_{-3}MLE_{it-03} + \beta_{-2}MLE_{it-02} + \beta_{-1}MLE_{it-01} + \beta_{0}MLE_{it} + \beta_{+1}MLE_{it+1} + \beta_{+2}MLE_{it+2} + \beta_{+3}MLE_{it+3} + \beta_{+4}MLE_{it+4} + \beta_{+5}MLE_{it+5} + \beta_{+6}MLE_{it+6} + \beta_{+7}MLE_{it+7} + \beta_{+8}MLE_{it+8} + \beta_{+9}MLE_{it+9} + \beta_{+10}MLE_{it+10} + \beta_{+11}MLE_{it+11} + \beta_{+12}MLE_{it+12} + \beta_{+13}MLE_{it+13} + \beta_{+14}MLE_{it+14}15 + MLE_{it+15+} + \theta X_{it} + \mu_t + \gamma_i + \varepsilon_{it}$

$Number\ of\ Crime\ Offenses\ Reported_{it}$ can be any of the UCR data available for state i in year t(these variables are per 100.000 people). In equation (1) MLE_{it-15} takes value one for each state that has passed the treatment 15 years before the treatment. This replicates with all the other coefficients for 15 years before, the year of treatment and 14 years after. The last coefficient, MLE_{it+15+} is to be interpreted differently, it takes value 1 for 15 years after treatment and every year after. β_n is the coefficient of interest which represents the average treatment effect for each n years before or after the treatment depending on the dummy assigned to it;X_{it} is a set of control variables that vary across state and time; μ_t represents a fixed effect for each year; γ_i is a fixed effect for each state, and ε_{it} is a state, year specific error term which is assumed to be independent across time and space.

2) $Number\ of\ Crime\ Offenses\ Reported_{it} = \beta MLE_{it} + \theta X_{it} + \mu_t + \gamma_i + \varepsilon_{it}$

In equation number 2 MLE_{it} is a dummy variable that takes the value one if the state i has some form of legalized marijuana on year t and zero if not. This means that the dummy variable will be zero for every year before the treatment and one for every year after the treatment, except if the treatment is no longer in effect. β is the coefficient of interest which represents the average treatment effect;X_{it} is a set of control variables that vary across state and time; μ_t represents a fixed effect for each year; γ_i is a fixed effect for each state, and ε_{it} is a state, year specific error term which is assumed to be independent across time and space. Having this in mind, as panel data is used, the possibility of error terms being correlated across time in the same state exists. When a positive correlation exists, the standard errors would be smaller than they really are, which would cause an over rejection of the null hypothesis. To avoid this type of bias in the estimation of coefficients, standard errors are clustered by state; this allows for an arbitrary covariance structure within states over time (Bertrand et. al:2004). If state error terms are highly correlated, clustering at the state level might reduce the statistical power of our regressions[19].

We have used the natural logarithm of the dependent variable. This lets us linearize the trend for our dependent variable and avoid outliers' effects. For dummy variables we can use the exponential of the β coefficient and subtract one.

Equation 1 helps us compare the effect of the treatment 15 years before, on the year, 15 years after the treatment and all subsequent years from year 15 onwards. With this information we can better understand how mechanisms are working. For example if gateway theory and psychopharmacological reasons are a mechanism connecting crime and marijuana use. Young adults who fall prey of drug use because of starting with marijuana will need to fuel their drug use by committing crime; this effect will be gradual and not instantaneous.

[19] In the case that no significant relation is found, nothing can be done because the amount of states can't be increased and the amount of groups already matches the amount of states. A N=51 might not be enough to achieve causality.

B) *The identification strategy*

The purpose of this paper is to identify the effect of any level of marijuana legalization on crime and how this treatment relates to crime. This relies on comparing trends in states which have legalized marijuana in some form and those who have not. Since MLs are not passed as an experiment we cannot assume that MLs have been passed at random in the different states.

Treatment exogeneity would certainly give our study a more robust causal interpretation but we can't asume exogeneity. Laws are dictated by representatives who look to benefit their electorate. This means that laws have some relation with public opinion[20]. Representatives who do not follow public opinion will be removed from their charges because of the nature of the democratic game. There is significant literature regarding how public opinion and the policymaking process influences policy[21]. Nonetheless, the democratic system will probably have a distorting effect on how public opinion is reflected in policies. This distortion happens through the canalization of public opinion through representatives. Examples of distortion are paternalism and the self-interest of representatives.

If something unobservable by our model relates to MLs then we can be confounding the effect of our treatment. The most appropriate confounding effect can be that of marijuana use, and marijuana approval. For this we can refer to results in Cerda, Wall, Keyes, Galea and Hasin (2012). The authors find that states which pass medical marijuana laws have a higher prevalence of past year marijuana use compared to states which never pass medical marijuana laws (7.1% vs 3.5%). A study by Harper et al. carried out a replication using information on drug use from 2002-2009 (Cerda et al. only used information until 2004) found similar results. States with medical marijuana laws have a higher prevalence of marijuana use (8.9%) than states which had not passed medical marijuana laws (6.9%). States that eventually passed marijuana laws by 2011 had a similar prevalence to states with marijuana laws (8.6%). The effects of medical marijuana laws might not be the same for states with higher and lower prevalence of marijuana use. Harper et al. (2012), on the other hand, find that medical marijuana laws have no effect on marijuana use once unmeasured state characteristics are accounted for.

For decriminalization, Thies & Register [22] find that there is no significant impact for drug use from decriminalizing small amounts of possession. Demand for drugs tends to be inelastic to this kind of incremental law changes. Single (1989) also backs up this finding, there is no evidence of a higher prevalence of marijuana use after decriminalization and it is also argued that there is no perceived crime justice savings.

The critical assumption that the control groups' post-treatment trend would be a good counterfactual of the treated groups' would not be true if prevalence of past year marijuana use dictated medical marijuana laws enactment and crime at the same time. This is certainly a weakness of our study as we can't control for marijuana use.

In order to make our model more robust we control for several variables that might influence the probability of a state passing a ML and crime in order to gain robustness and a better specification. We want to purge the error term of any omitted variables in order to avoid biased estimators.

The controls, represented by x_{it} are three main groups, economic, criminal justice and socio demographic. The economic controls include: employment per 100.000 people[23] and gross domestic product per capita[24].

[20] Another argument to be made relates to "The nature of belief systems…" (Converse, 1964) the author states the irrationality of public opinion.
[21] (Page and Shapiro 1983)
[22] Thies, C., & Register, C. (1993). Decriminalization of marijuana and the demand for alcohol, marijuana and cocaine. The Social Science Journal, 30(4), 385-399. doi: 10.1016/0362-3319(93)90016-o
[23] taken from the Bureau of Labor Statistics website, http://www.bls.gov/
[24] taken from the Bureau of Economic Analysis website, http://www.bea.gov/

These variables represent the macroeconomic conditions; states with high poverty and low employment tend to suffer greater crime rates. At the same time, these variables might be related to the passing, or not, of MLs. States with better macroeconomic conditions might be more proficient institutionally, meaning congress will be willing to pass riskier laws because their institutions can manage the change properly. Macroeconomic conditions might relate to education, which might mean more open minded-ness, and a higher rate of approval of MMLs or, terrible macroeconomic conditions might cause a desperate government to recur to extraordinary measures, in order to combat crime. The possibility of a relationship forces us to create the control in order to expunge any possible connection between our dependent and independent variables that would end up in the error term.

Socio-Demographic controls include yearly population growth and population density. Population growth was bult with data from the Bureau of Economic Analysis website[25]. Information on state surface area was taken from About.com[26] and helped construct the population density. Several papers link population, population growth and population density, to crime. An interesting idea comes from population density: in a more densely populated area, there is a bigger chance that someone observes crimes being carried out, and reports them. Population growth can also affect crime because this means that criminals are less likely to stand out because a lot of people are new, this was argued at the county level. It would be difficult to translate this argument to the state level growth, but we can see how population variables can affect crime. The idea that these variables might relate to Marijuana Laws passing comes from the relationship that might exist between population density and institutional capabilities or public opinion. The notion that the amount of people in a state, population density or population growth, might affect public opinion in that state, is not irrational. For example, states with higher population growth might feel that legislation regarding birth control is a must, in the same way as states with higher population density might want legislation regarding public use of marijuana. This generates the need to control these variables. Gallons of ethanol consumed in alcoholic beverages was obtained from the National Institute on Alcohol Abuse And Alcoholism [27] and is also included because we have found this variable to be closely linked to crime throughout crime literature.

Criminal justice variables include number of adults on probation per capita, adults on parole per capita, and average prisoners in custody of federal and state prisons. These variables were obtained from the Bureau of Justice Statistics website[28] specifically from the Annual Probation survey, the Annual Parole survey and the survey of Inmates in State and Federal Correctional Facilities. Combined with these variables are variables such as total sworn police officers per capita and total law enforcement employees' per capita constructed by using the FBI's crime in the US publications that are available annually from 1995 to 2018 and are part of the UCR program. All these variables relate by construction to crime, states with higher crime rates tend to have more prisoners and more police. The relationship with MML can be through resource availability, states with a high number of police officers per capita might feel more confident to pass MML and deal with the possible outcomes. States with very high numbers of prisoners might be more willing to pass MML in order to empty their prisons and leave some space for other kinds of criminals. This might in turn affect crime through more severe penalties for criminals since prison overcrowding might reduce penalties[29] the reverse effect might occur.

Anderson et al. and Morris et al. support our choice of controls. These are common in panel data analysis of law impact in the US. We have added tables analyzing main results to different control allocations in table 3A and 4A of the appendix.

[25] http://www.bea.gov/

[26] http://geofigurey.about.com/od/usmaps/a/states-area.htm

[27] APPARENT PER CAPITA ALCOHOL CONSUMPTION: NATIONAL, STATE, AND REGIONAL TRENDS, 1977–2014 . (2020). Retrieved 24 March 2020, from https://pubs.niaaa.nih.gov/publications/surveillance104/CONS14.htm

[28] http://www.bjs.gov/

[29] As suggested by Benson et al (1992).

Table 4 - Descriptive Statistics Control Variables							
Variable	Description	Obs.	Mean	Std. Dev.	Min	Max	Years
Economic Controls							
Employment per capita	Measures the nation's number of full- and part-time workers, as well as the self-employed	2.550	0,6	0,1	0,4	1,4	1969-2018
Gross Domestic Product Per Capita	GDP is the value of the goods and services produced in the United States. Measured in current USD	2.856	26.000	21.400	1.970	200.242	1963-2018
Penal System Controls							
Adults On Parole Per Capita	Parole refers to criminal offenders who are conditionally released from prison to serve the remaining portion of their sentence in the community	2109	0,00159	0,00167	0,00002	0,01367	1977-2016
Adults On Probation Per Capita	Probation refers to adult offenders whom courts place on supervision in the community through a probation agency, generally in lieu of incarceration	2009	0,00968	0,00648	0,00025	0,05159	1977-2016
Average Persons In Custody Per Capita*	Number of persons in custody of state or federal prisons.	2023	0,00337	0,00208	0,00029	0,01858	1978-2017
Policing Controls							
Number Of Police Desk Employees Per Capita	Number of police law enforcement employees working in administrative positions	1219	0,00088	0,00029	0,00027	0,00169	1995-2018
Number Of Sworn Police Officers Per Capita	Number of police officers	1219	0,00220	0,00081	0,00073	0,00768	1995-2018
Socio-Demographic Controls							
Yearly Population Growth	Number of population growth or decrease	2940	48885	85615	-273963	753915	1961-2018
Population/Square Kilometers	Population density	3009	145	580	0	5051	1960-2018
Gallons Of Ethanol Consumption Per Capita	Total gallons of ethanol consumed per capita	2448	2,0	0,6	0,9	5,2	1970-2017

Information on medical marijuana legality was taken from NORML. Information on employment, population and GDP was taken from the Bureau of economic analysis. Information on adults on probation, parole and people prison taken from the Bureau of Justice Statistics. All data on crime and police personnel was taken from the "Crime in the US publications" by the FBI CJIS.All regressions include year and state fixed effects.

C) Main Results

The treatment we evaluate is “Marijuana Law”. This treatment takes into consideration any level of marijuana legalization, be it decriminalization, medical marijuana legalization or recreational marijuana legalization. This means that if a state has any one of these treatments it will be considered as treated. Index 1 crimes are the sum of all crime and property crimes. In table 1 we can see the numerical values of coefficients for this regression. We can see the coefficients represented graphically in Figure 3 “Marijuana Law And Index 1 Crime” after year 0 of treatment the coefficient appears to be negative.

Figure 3

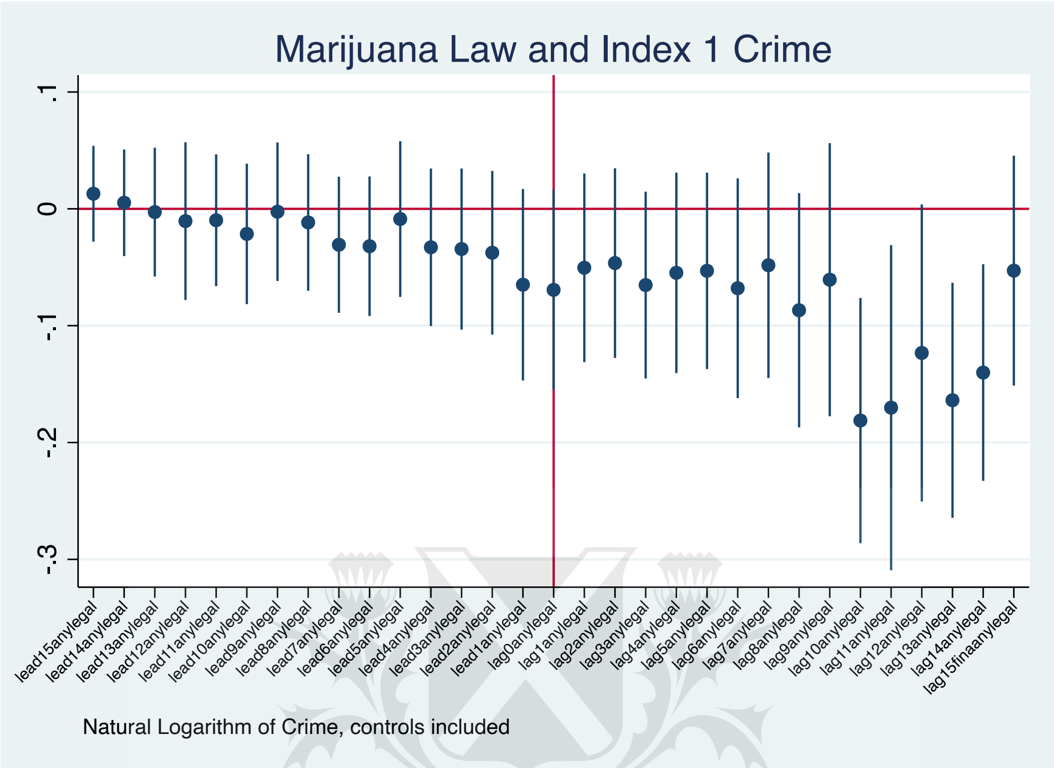


Table 4 shows that most significance happens from year 10 to 14, with significance statistically different from zero, mostly at the .01 level. The coefficient during these years averages -0,17. For dummy variables we can use the exponential of the β coefficient and subtract one, this gives us a result of -15,6%. This means that after the treatment passes from year 10 to 14 we see an average drop of index 1 crimes of around 15,6% relative to year 0 of treatment. The coefficient for year 15 and forward has a negative value but not significant. We might be lacking in power of treatment since controls are not available for all years for which crime is available. The amount of observations is cut in third approximately.

Table 5 - Marijuana Law and Crime Variables[ii]

VARIABLES	Index Crime	Property Crime	Violent Crime
lead15anylegal	0.0129	0.0144	0.0151
	(0.0204)	(0.0217)	(0.0306)
lead14anylegal	0.00517	0.00889	-0.00774
	(0.0227)	(0.0241)	(0.0350)
lead13anylegal	-0.00279	0.00141	-0.000601
	(0.0274)	(0.0282)	(0.0504)
lead12anylegal	-0.0105	-0.00886	0.00213
	(0.0336)	(0.0344)	(0.0644)
lead11anylegal	-0.00978	-0.00818	0.0331
	(0.0281)	(0.0299)	(0.0583)
lead10anylegal	-0.0215	-0.0226	0.0324

	(0.0299)	(0.0312)	(0.0582)
lead9anylegal	-0.00248	-0.00477	0.0263
	(0.0295)	(0.0298)	(0.0702)
lead8anylegal	-0.0117	-0.0178	0.00407
	(0.0291)	(0.0293)	(0.0633)
lead7anylegal	-0.0308	-0.0277	-0.0355
	(0.0290)	(0.0297)	(0.0677)
lead6anylegal	-0.0320	-0.0309	-0.0329
	(0.0297)	(0.0303)	(0.0688)
lead5anylegal	-0.00875	-0.0183	-0.000447
	(0.0332)	(0.0317)	(0.0700)
lead4anylegal	-0.0329	-0.0309	-0.0354
	(0.0335)	(0.0337)	(0.0703)
lead3anylegal	-0.0344	-0.0332	-0.0159
	(0.0343)	(0.0343)	(0.0777)
lead2anylegal	-0.0376	-0.0350	0.00110
	(0.0349)	(0.0348)	(0.0784)
lead1anylegal	-0.0650	-0.0600	-0.0221
	(0.0408)	(0.0409)	(0.0869)
lag0anylegal	-0.0694	-0.0651	-0.0467
	(0.0426)	(0.0420)	(0.0853)
lag1anylegal	-0.0505	-0.0499	-0.00270
	(0.0402)	(0.0401)	(0.0807)
lag2anylegal	-0.0465	-0.0460	-0.0212
	(0.0404)	(0.0405)	(0.0868)
lag3anylegal	-0.0653	-0.0694*	-0.0419
	(0.0398)	(0.0397)	(0.0870)
lag4anylegal	-0.0548	-0.0508	-0.0597
	(0.0427)	(0.0423)	(0.0961)
lag5anylegal	-0.0531	-0.0463	-0.0533
	(0.0418)	(0.0418)	(0.0910)
lag6anylegal	-0.0680	-0.0705	-0.0183
	(0.0468)	(0.0444)	(0.103)
lag7anylegal	-0.0483	-0.0543	0.0213
	(0.0480)	(0.0482)	(0.104)
lag8anylegal	-0.0868*	-0.0968*	0.0114
	(0.0499)	(0.0494)	(0.115)
lag9anylegal	-0.0607	-0.0716	0.0608
	(0.0582)	(0.0594)	(0.116)
lag10anylegal	-0.181***	-0.202***	0.0166
	(0.0522)	(0.0484)	(0.144)
lag11anylegal	-0.170**	-0.191***	0.0663
	(0.0693)	(0.0690)	(0.145)
lag12anylegal	-0.123*	-0.145**	0.116
	(0.0633)	(0.0618)	(0.139)
lag13anylegal	-0.164***	-0.192***	0.114
	(0.0501)	(0.0462)	(0.134)
lag14anylegal	-0.140***	-0.170***	0.128
	(0.0462)	(0.0436)	(0.137)
lag15finaanylegal	-0.0529	-0.0690	0.145
	(0.0490)	(0.0572)	(0.140)
gdppc	-3.358	-3.833	-1.271
	(3.174)	(3.123)	(5.175)
employmentpc	0.360	0.293	2.033
	(0.582)	(0.580)	(1.404)

swornpc	89.14**	86.53**	84.47
	(36.18)	(35.89)	(63.86)
policeofficeemployeespc	-69.84	-77.81	0.756
	(65.76)	(61.18)	(138.4)
probationpc	-0.00271	-0.520	3.415
	(1.887)	(1.844)	(3.207)
parolepc	21.95	20.80	11.60
	(15.20)	(15.68)	(20.55)
prisonerscustodypc	15.03	10.81	53.25*
	(16.11)	(15.98)	(31.73)
populationmain			
popdens	-0.000428	-8.74e-05	-0.00547
	(0.00198)	(0.00186)	(0.00425)
popgrowthh	1.56e-07	1.54e-07	1.74e-07
	(1.29e-07)	(1.39e-07)	(1.41e-07)
gallonspc	0.0925	0.0670	0.611***
	(0.109)	(0.109)	(0.191)
Constant	7.761***	7.765***	3.568***
	(0.350)	(0.314)	(1.152)
Observations	1,074	1,072	1,073
R-squared	0.943	0.940	0.924

Note.—All standard errors are in brackets clustered at the state level. * Statistically different from zero at the .1 level. ** Statistically different from zero at the .05 level*** Statistically different from zero at the .01 level. Regressions include controls for employment per capita, Gross Domestic Product per capita, number of police personnel per capita, number of adults on parole per capita, number of adults on probation per capita, estimated number of people in custody of federal or state prison per capita, population density per square kilometer, yearly population growth and estimated gallons of alcohol consumed per capita. Information on medical marijuana legality was taken from NORML. All regressions include year and state fixed effects. [i] Any Legal Law represents any change of legality, be it medical marijuana legalization, decriminalization or recreational marijuana legalization. [ii] All crime variables are natural logarithms of the actual crime rate per 100.000 people. All analysis was conducted with Stata (Version 13), and standard errors for the model were clustered at the state level.

What is also interesting is that for years before the treatment no significant effect is seen on crime. This means that the treatment has a direct impact on crime. It is useful as a robustness check to recreate these results with the model specified in equation 2. Where the average treatment effect is represented by a dummy variable which take value 0 before treatment and value 1 for every year after treatment. The results are shown in table 5.

Table 6 - Enacting Marijuana Law and its effect on main UCR crime categories[ii]

	Index Crime	Property Crime	Violent Crime
anylegallaw[i]	-0.0290*	-0.0315*	-0.00204
	(0.0154)	(0.0163)	(0.0348)
Observations	1,074	1,072	1,073
R-squared	0.940	0.936	0.922

Note.—All standard errors are in brackets clustered at the state level. * Statistically different from zero at the .1 level. ** Statistically different from zero at the .05 level*** Statistically different from zero at the .01 level. Regressions include controls for employment per capita, Gross Domestic Product per capita, number of police personnel per capita, number of adults on parole per capita, number of adults on probation per capita, estimated number of people in custody of federal or state prison per capita, population density per square kilometer, yearly population growth and estimated gallons of alcohol consumed per capita. Information on medical marijuana legality was taken from NORML. All regressions include year and state fixed effects. [i] Any Legal Law represents any change of legality, be it medical marijuana legalization, decriminalization or recreational marijuana legalization. [ii] All crime variables are natural logarithms of the actual crime rate per 100.000 people. All analysis was conducted with Stata (Version 13), and standard errors for the model were clustered at the state level. Coefficients rounded to 1 significant figure.

A coefficient of -0,03 indicates that marijuana law has an average treatment effect of -3% on index 1 crime, significant at the .05 level. This would mean that we can expect an average effect of -3% from that point onwards on crime when states pass some form of marijuana legalization.

Since Index 1 crimes are comprised of property crimes and violent crimes. It is interesting to delve deeper into how MLs affect these crimes which are considered to be significantly different. Violent Crimes are defined as offenses that involve force or threat of force by the Uniform Crime Reports published by the FBI. These are comprised of murders, rapes, robbery and aggravated assault. Property Crimes are those in which there is no use of force or threat of use of force (as defined by the FBI in UCRs). These are comprised of burglary, larceny theft and vehicle theft. Property crime has a mean of 3563 offenses yearly per 100.000 inhabitants. Violent crime is a less common offense (or at least less reported) with a mean of 396 offenses yearly per 100.000 inhabitants. We can gather from table 2 that most of the treatments effect on index crimes is through property crimes.

It is interesting to observe figure 4 and 5 to see the evolution of the treatments effect on property and violent crime separately.

Figure 4

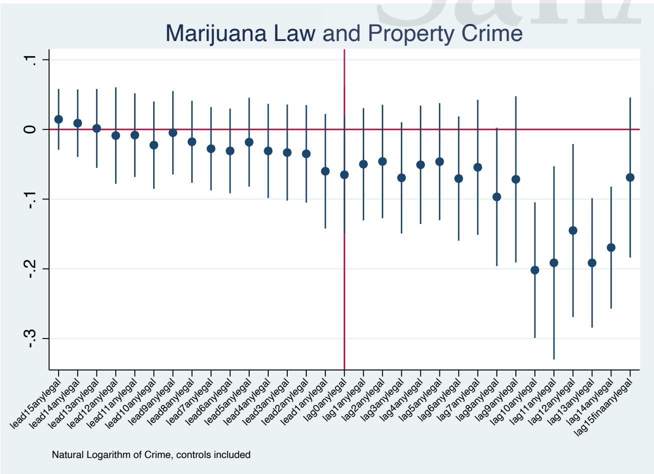
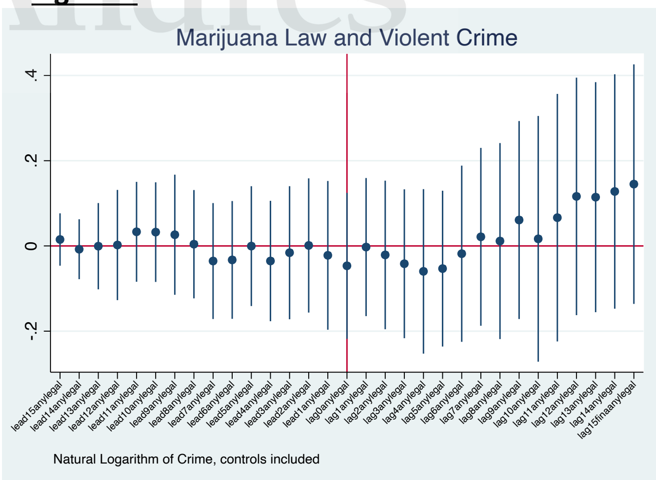


Figure 5



Property crimes seem to explain the relationship between the treatment and crime. Violent crime appears to only "dampen" the relationship. The treatment has no effect before year 0 on either type of crime. After the treatment, property crime sees a negative and significant effect of, in average, -0,18 which is interpreted as a fall of 16% in crime from year 10 to 14. This is the main explanation for the fall in index 1 crime. Violent crime sees no significant effect of MLs. We can observe in table 1A and 2A of the appendix the value and significance of each independent coefficient for all of crimes components.

4. Marijuana Laws And Crime – Studying Possible Mechanisms

A) *Possible Mechanisms*

As we have seen in section 2C there are different ways drug use and drug legality might be related to crime. Our results indicate our treatment reduces crime. Assuming Figure 3 has a correct identification of mechanisms at work, we can briefly hypothesize on how the mechanisms work and how these could be tested.

To start off in "Approaches to Decriminalizing Drug Use & Posession"[30] countries that have less punitive policies towards drug possession see no increments in drug use relative to countries with more punitive policies. Even if increased use is a consequence of more permissive marijuana laws, this in no way means an increased amount of crime.

In regard to the mechanisms at play, economic compulsive behavior has no relation to marijuana use. The notion that drug users have to finance their addictions is not very appropriate in marijuana use where addiction ranges 10%[31]. This incidence is below that of alcohol (15%), nicotine (32%) or Opioids (23%)[32]. We cannot find consistent evidence of a psychopharmacological mechanism linking marijuana use and crime throughout the literature. The common factor hypothesis is also dismissible, as Benson et al. (1992) question very diligently throughout their paper, the first relationship between drug crime and other types of crime is certainly a correlation but does not necessarily imply causation. Property criminals might use drugs but this does not mean that drug users are committing crimes because of their drug use/abuse. Implying this is as stating that, since criminals drink water, consumption of water might be a cause of crime. With this in mind increasing drug use wouldn't directly convert to increased crime.

We find the legality of drug use to be an area where more interesting mechanisms are at play. There are two links to be analyzed, systemic violence and resource allocation. When talking about systemic violence, we refer to crime generated by the black market in charge of drug provision. This has relation principally to gang and cartel activity. If we focus solely on supply side of illegal drugs. We could hypothesis that decriminalization would have a positive or null effect on systemic violence as it would reduce drug penalties for possession. These are intended to benefit drug users and not sellers but drug sellers will probably have it easier to evade police. This generates a positive incentive to take part of this illegal economic activity. This illegal economic activity is tied to increased crime because of the type of subjects it attracts and the unregulated competition which takes place between players. Medical Marijuana Legalization and Marijuana Legalization would have a negative or null effect on systemic violence. The main impact these laws have on the supply side is that new, more reliable and legal suppliers enter the market making it less attractive to sell drugs. This is a mechanism which we can't analyze deeper because of lack of data. This is a point which can be improved.

Resource allocation is the only mechanism left to analyze. There is a precedent for the connection between property crime and drug enforcement policy. Benson et al. (1992) make an interesting case for linking efforts to combat drug crime and the allocation of police resources. The argument is that, by reallocating police resources towards pursuing drug crime, there is a reduced deterrence towards property crime and, therefore, an increase in this type of crime.

Our results are consistent with those presented by Benson et al. (1992). The authors analyze drug enforcement policies and its effect on crime. Their results suggest that more severe drug enforcement policies

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[30] Drug Policy Alliance. (2015). Approaches to Decriminalizing Drug Use & Possession [Ebook] (1st ed.). New York. Retrieved from: https://www.drugpolicy.org/sites/default/files/DPA%20Fact%20Sheet_Approaches%20to%20Decriminalization_%28Feb.%202016%29_0.pdf

[31] Welch & Martin (1999). As seen in Cohen (2009).

[32] Anthony et al., supra note 104, at 254–55. As seen in Cohen (2009)

cause a surge in property crime. Benson et al. (1992) generate a model with different controls that would effect a criminal decision to commit crime or increase the supply of offenses, as Benson et al. refer to it in their model.

To understand both the systemic violence and resource allocation approach towards crime, we can observe what Gary Becker, Nobel laureate, says in his renowned paper, "Crime and Punishment: An Economic Approach".

> *"The approach taken here follows the economists´ usual analysis of choice and assumes that a person commits an offense if the expected utility to him exceeds the utility he could get by using his time and other resources at other activities. Some persons become "criminals," therefore, not because their basic motivation differs from that of other persons, but because their benefits and costs differ. I cannot pause to discuss the many general implications of this approach, except to remark that criminal behavior becomes part of much more general theory and does not require ad hoc concepts of differential association, anomie, and the like, nor does it assume perfect knowledge, lightning-fast calculation, or any of the other caricatures of economic theory.*
>
> *This approach implies that there is a function relating the number of offenses by any person to his probability of conviction, to his punishment if convicted, and to other variables, such as the income available to him in legal and other illegal activities, the frequency of nuisance arrests, and his willingness to commit and illegal act." From Becker's "Crime and Punishment…"*[33]

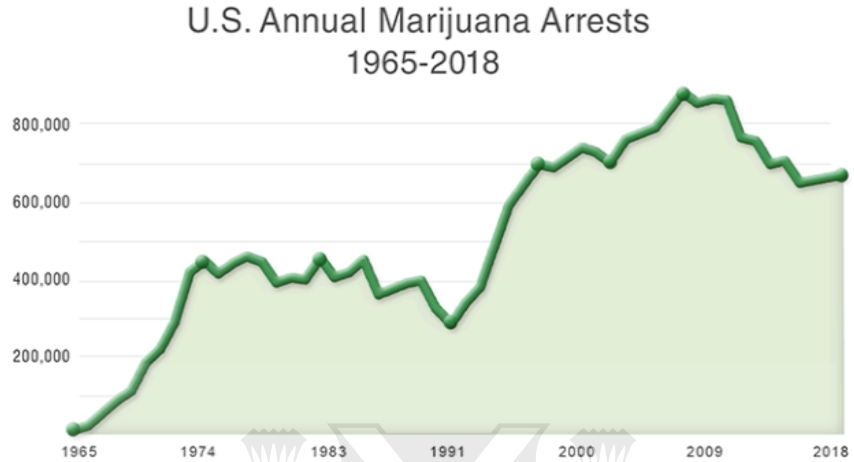
We have been able to find ways to test this hypothesis by retrieving different datasets and will be showing our results in sections 4B and 4C.

[33]BECKER, Gary S. Crime and punishment: An economic approach. En *Essays in the Economics of Crime and Punishment*.UMI, 1974. p. 1-54.

B) Arrests and resource allocation

Arrests are accountable for a large amount of the use of law enforcement resources. One arrest takes up to 9 hours of work, including paperwork. As we see in figure 6, these types of arrests are significant and have grown during the last 50 years.

Figure 6



Arrest Charts - NORML - Working to Reform Marijuana Laws. (2020). Retrieved 23 March 2020, from https://norml.org/webmasters/item/arrest-charts?category_id=822

Another mechanism taken from the conclusions of Benson et al. is that since drug arrests cause prison overcrowding, property criminals face less severe penalties. When drug arrests are reduced, the deterrence of property crime comes from more severe penalties associated to more readily available penal resources. Since property crime is a "logical"[34] type of crime, the analytical structured approach to criminal decision making put forward by these authors shows that the incentives can be shifted. This mechanism does not seem strong enough to cause an immediate reduction in crime, since criminals probably cannot perceive perfectly that penalties are less severe. This could be part of the explanation as to why property crime is reduced in the long run. Benson et al. (1992) conclude that drug enforcement is clearly not a positive-sum crime control policy.

We want to assess if the impact MLs has is through a change in law enforcement resource allocation. The first reaction is to observe the change in drug abuse violations per capita. We can see how MLs affect drug abuse violation arrests per capita. The controls used are the same as before but including index 1 crimes reported. We do this to control for the fact that a change in general crime level could be the explanation for a change in the level of drug arrests per capita.

Information on drug arrests was taken from table 69 of the different "Crime in the US" annual publications. This table gives us arrest data, disaggregated by type, state and two age groups (under 18 and total). This information is available from 1995-2018 year. This limits our analysis of long run pretreatment trends reducing the power of our analysis. We can appreciate descriptive statistic on these variables in table 7.

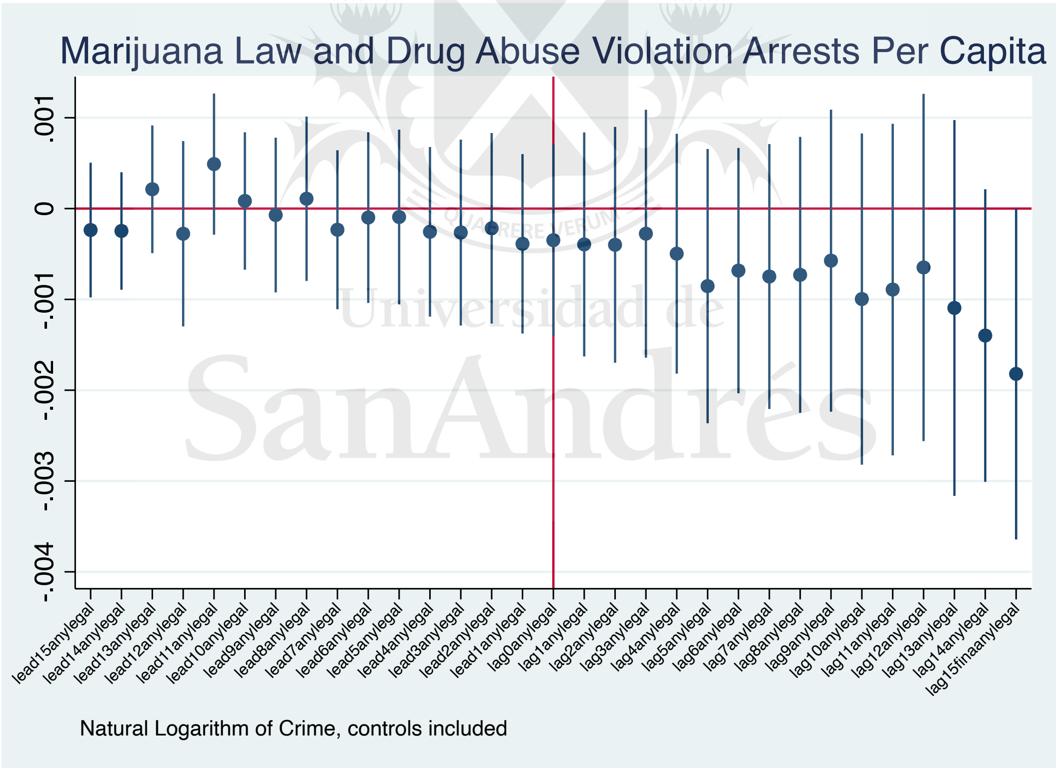
[34] Logical in the sense that it doesn't include emotional components such as violent crime might.

Table 7 - Descriptive Statistics Mechanisms						
Variable	Obs	Mean	Std. Dev.	Min	Max	Years Available
Drug Abuse Violation Arrests Per Capita	1165	0,0039	0,0017	0,0001	0,0102	1995-2018
Allocation Index	1162	0,6932	0,2794	0,0511	2,4094	1995-2018
Drug Arrests Per Police Office Employee	1160	4,8032	2,3729	0,1022	18,4545	1995-2018
Penal System Population Per Capita	1942	0,0147	0,0083	0,0016	0,0597	1978-2016

All data on crime and police personnel was taken from the "Crime in the US publications" by the FBI CJIS.

We would expect a fall in drug arrests per capita ceteris paribus. In figure 7 we appreciate a clearly negative coefficient for the change in drug arrests after the treatment. These coefficients become significant at the 0.1 for year 14 and 15 and every year after. For year 15 the impact would be of -0,18% for year 15 and every year.

Figure 7



These results give us further evidence that police are distributing less resources to drug related tasks. These can be verified in table 8 where each independent coefficient is shown.

The reduction in drug arrests could mean that the general level of arrests is falling. To isolate this possibility we construct a variable that represents the amount of resources that are destined to drug related policing activities. This approach towards resource allocation modelling was taken from Benson et al. (1992). The proxy to represent resource allocation in its most basic form will be

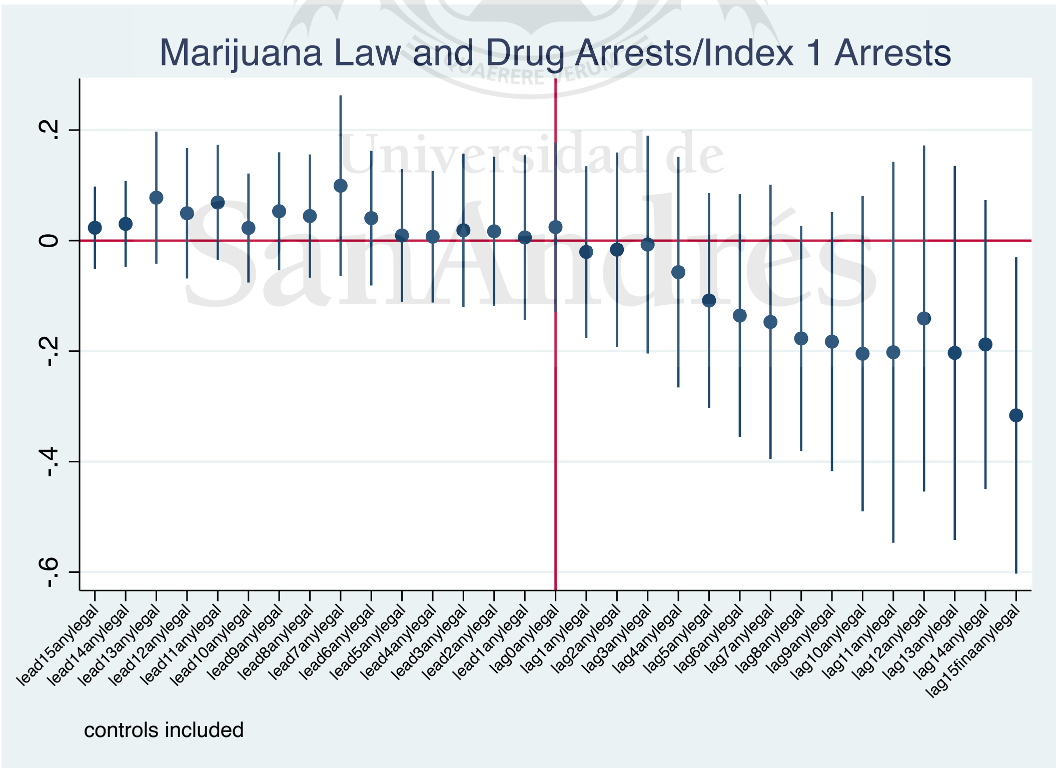
Since index 1 crimes are severe, the definitions of them do not vary across states and this gives us a homogeneous proxy for our regressions. The other classes of arrests (curfew and loitering, runaways, suspicion, etc.) often have different definitions across different states; this subjective component makes them a less robust way of estimating resource allocation.

Benson et. al predicts a more relaxed drug policy generates a shift of resources towards Index 1 crimes. The relationship between MLs and our proxy can be because of several reasons. Firstly, marijuana arrests ceteris paribus should decrease, the crime definition is now less strict[35]. Secondly, since laws generally reflect public opinion, a passing of marijuana law might mean police are less disapproving of marijuana users, and therefore prosecute all marijuana related crimes less.

To estimate a trustworthy model we need to control for variables that might affect both the dependent variable and our treatment, in order to isolate the effect of MLs on. Figure 8 shows equation 1 repurposed to analyze the effect of ML on Resource Allocation towards Drug Arrests. This evaluates how the passing of marijuana laws impacts the amount of resources police allocate towards drug arrests relative to other types of arrests.

The point of this proxy is that if the amount of drug arrests grows relative to index 1 arrests this would be a reflection of police destining more resources and attention to drug crime. The same is true the other way around.

__Figure 8__



[35] This is actually partly confirmed in figure 3

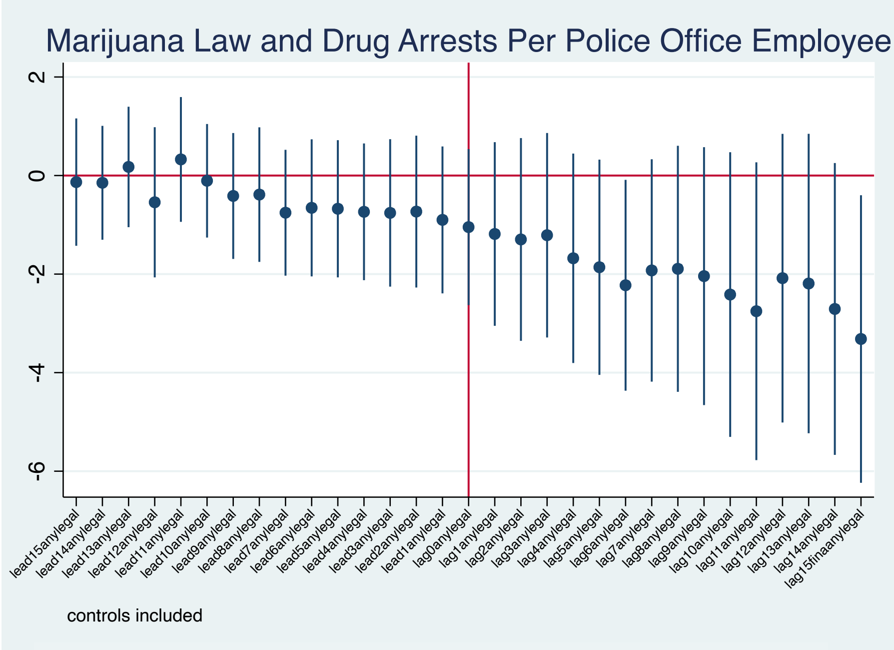
We can confirm Benson et. al results with the results on figure 8. The effect of the treatment on our resource allocation proxy is statistically different from zero at the .1 level and is discernible in the long run. The impact of ML is negative and significant for year 8 and every year after year 15. It appears that police destin resources to other kinds of crimes when more permissive marijuana laws are enacted. This supports the notion of a reduction of crime because of better resource allocation.

The results Benson et al. obtain suggest that criminals, at least while perpetrating property crimes, act rationally. They proxy the probability of arrest and the probability of conviction, and both have a negative impact on the supply of property offences. The probability of arrest is affected by community characteristics and police resources. In order to model the probability of arrest, they use the number of police officers, reports of all other types of crime, socio economic controls and a proxy that represents resource allocation. Their results suggest that when more resources are directed to drug arrests, the probability of arrest for property crime decreases and rational criminals commit more crimes. Taking their results into account, we could predict that a more relaxed drug enforcement policy will cause resources to shift towards other types of crime and our results represented in figure 8 suggest this is what happens. Another argument is made to link drug arrests and crime in Benson et. al (1992). If drug users are over proportionately criminals then drug arrests will very likely reduce the amount of criminals. When observing Florida, of the 45.906 drug related arrests recorded during 1987 80% had never been arrested for burglary and 90% hadn’t been arrested for any other property crime. This leads us to understand that there is two subsets of drug users, those who commit other type of crimes and the overwhelming majority that are only convicted on drug related charges. This idea is reinforced by Kim et al (1990) who show that of the 50% of drug related arrestees that are re-incarcerated or put in probation only 31% are because of non-drug related crimes. Also, the recidivism rate for arrestees who only had drug arrests was significantly lower than that of arrestees with other types of crime as well as drug related crime. This means that arresting and convicting drug users will not have a large effect on the number of property offenders, at least a relevant one. What Benson et. al suggests is that the shifting of police resources to capture drug users is very inefficient at reducing property crime.

Di Tella and Schargrodsky (2004) estimate the deterrence effect of police by exploiting the random allocation of police forces after a terrorist attack. Their results show a fall in crime in the vicinity of new police locations. This leads us to think that police deterrence might also work at a state level considering that police presence, in average, will be greater everywhere. Police no longer spend time arresting drug criminals and now spend this time roaming the streets.

We can also observe this when observing the drug arrests per police officer as seen in figure 9.

Figure 9



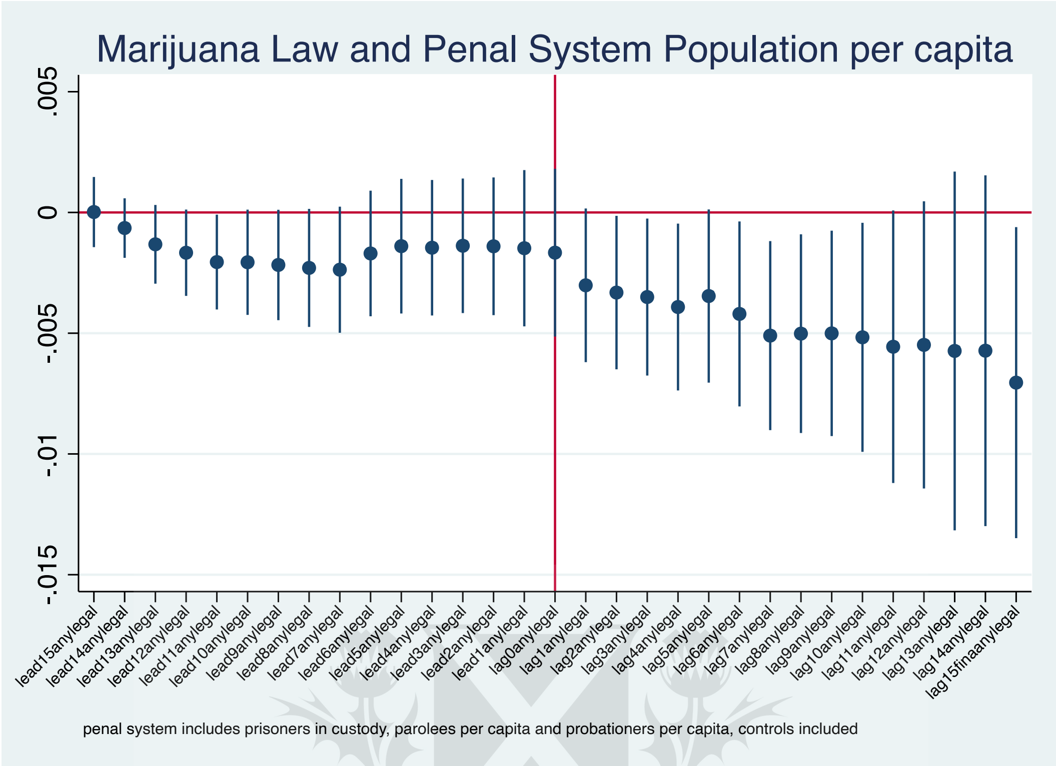
As is shown in table 8 the number of drug arrests per police office employee has a significant decline on most years from year 10 onward, including the dummy variable that takes into account year 15 and all years after. This is especially interesting as it is consistent with our hypothesis that police destine less resources to drug related crime. It is also consistent with our results which show a drop in crime from year 10 onwards, it is only logical that these kinds of laws have a delayed impact.

C) *Penal System, Marijuana Laws and Crime*

When a person is arrested they are either let free for lack of proof to convict or pass on to be part of the penal system. Penal system variables have a wide set of connections to crime. Cullen et al. (2011) suggest that prison terms have a positive impact on recidivism. Drago, Galbiati & Vertova (2011) also find similar evidence of increased recidivism after prison terms. Their study focuses on the impact of harsher prison conditions and they find that these also increase recidivism. This means that an increase in overcrowding that could be brought from more inmates might generate further crime. Pritikin, M. (2008). Enumerates the different links between prison and crime; prison as a school for criminals through new social relations, a severance of ties with family, the brutalization effect of prisons, especially under harsh conditions such as overcrowding and Post carceration consequences such as labeling and diminished employment opportunities.

The number of people in the correctional system either as parolees, probationers or inmates send a signal to criminals and also to police. Penal System Population is a variable that sums up probationers, parolees and inmates in custody for each state anually. The results of analyzing how MLs afect penal system can be seen in figure 10.

Figure 10



The evidence provided by the negative coefficients in penal system per capita is key to the analysis of the mechanisms. We can observe the levels of significance of the 4 variables studied in table 8. This treatment is different to the allocation index and drug arrests. These results are quite consistent. We could hypothesize that, judges and distric attorneys are influenced by politics and public opinion. As soon as the treatment is passed the penal system population per capita falls significantly. The only caveat is that there is a period of 5 years before the treatment from year 12 before the treatment to year 7 before the treatment where there is a fall in penal system population per capita. This could be explained because the judicial system processes information regarding public opinion even before the law is passed. Public opinion and policy are related, and this is indicated by the passing of marijuana laws. As soon as marijuana laws are passed, we see a consistent fall in penal system population per capita for almost every year after the treatment.

Firstly, the convictions fall because the treatment signal reaches judges and district attorneys first. Police continue with their policing practices even when the treatment is passed. When police understand the signals to stop pursuing drug criminals, because public policy has been adopted by the judicial system, they direct their attention to other kinds of crimes, and this impacts crime rates.

All results and significances are consistent with this hypothesis. It appears that penal system population per capita has an average fall of -0,005 for every year after the treatment. With a mean of 0,015 per capita penal system population this means a 34% drop each year after the law is passed. Drug arrests per police officer appear to fall at a pace of around 2,4 arrest less per officer from year 14 onwards. With a mean of 4,8 arrests per police office employee, this means that from year 14 onwards there is a pretty consistent 50% drop in drug arrests processed.

Drug abuse violations arrests per capita don’t show significance from year 10 onwards but from year 14 onwards. The level of coefficients from year 1-10 after the treatment is -0,00061 drug abuse violations arrests per capita and from year 11 to 15 (and onwards) is -0,00111 almost double the precedent years. With a mean of 0,0039 drug abuse violations arrest per capita this is a 28% fall in average through year 11 to 15 (and onwards). Since we see in table 5 a pretty consistent significant fall in crime from year 10 onwards, we present a strong argument to link these mechanisms and the results seen in the drop of crime.

Table 8 – Marijuana Law And Allocation Variables[ii]

VARIABLES	Drug Abuse Violations Per Capita	Allocation Index	Drug Arrests Per Officer	Penal System Per Capita
lead15anylegal	-0.000237	0.0126	-0.300	1.65e-05
	(0.000369)	(0.0298)	(0.602)	(0.000723)
lead14anylegal	-0.000247	0.0214	-0.280	-0.000646
	(0.000322)	(0.0331)	(0.521)	(0.000614)
lead13anylegal	0.000212	0.0698	0.0972	-0.00132
	(0.000350)	(0.0552)	(0.549)	(0.000811)
lead12anylegal	-0.000277	0.0402	-0.579	-0.00167*
	(0.000508)	(0.0558)	(0.735)	(0.000890)
lead11anylegal	0.000489	0.0631	0.332	-0.00205**
	(0.000387)	(0.0471)	(0.589)	(0.000977)
lead10anylegal	8.33e-05	0.0176	-0.0637	-0.00206*
	(0.000376)	(0.0449)	(0.547)	(0.00108)
lead9anylegal	-7.13e-05	0.0486	-0.349	-0.00217*
	(0.000424)	(0.0489)	(0.609)	(0.00114)
lead8anylegal	0.000108	0.0278	-0.254	-0.00230*
	(0.000450)	(0.0500)	(0.639)	(0.00122)
lead7anylegal	-0.000234	0.0870	-0.584	-0.00237*
	(0.000436)	(0.0815)	(0.609)	(0.00130)
lead6anylegal	-9.91e-05	0.0462	-0.507	-0.00170
	(0.000468)	(0.0550)	(0.659)	(0.00129)
lead5anylegal	-9.31e-05	0.0252	-0.480	-0.00140
	(0.000479)	(0.0493)	(0.663)	(0.00139)
lead4anylegal	-0.000256	0.0132	-0.595	-0.00146
	(0.000465)	(0.0525)	(0.654)	(0.00140)
lead3anylegal	-0.000264	0.0344	-0.653	-0.00138
	(0.000509)	(0.0606)	(0.717)	(0.00139)
lead2anylegal	-0.000218	0.0272	-0.610	-0.00140
	(0.000522)	(0.0598)	(0.731)	(0.00142)
lead1anylegal	-0.000388	0.00921	-0.891	-0.00148
	(0.000492)	(0.0648)	(0.716)	(0.00161)
lag0anylegal	-0.000349	0.0264	-0.928	-0.00166
	(0.000524)	(0.0696)	(0.753)	(0.00173)
lag1anylegal	-0.000395	-0.0257	-0.965	-0.00302*
	(0.000614)	(0.0716)	(0.900)	(0.00158)
lag2anylegal	-0.000399	-0.00717	-1.061	-0.00332**
	(0.000646)	(0.0778)	(0.973)	(0.00158)
lag3anylegal	-0.000277	-0.0321	-0.993	-0.00350**
	(0.000679)	(0.0901)	(1.019)	(0.00162)
lag4anylegal	-0.000497	-0.0772	-1.426	-0.00392**
	(0.000657)	(0.0798)	(0.963)	(0.00172)
lag5anylegal	-0.000854	-0.108	-1.716	-0.00346*

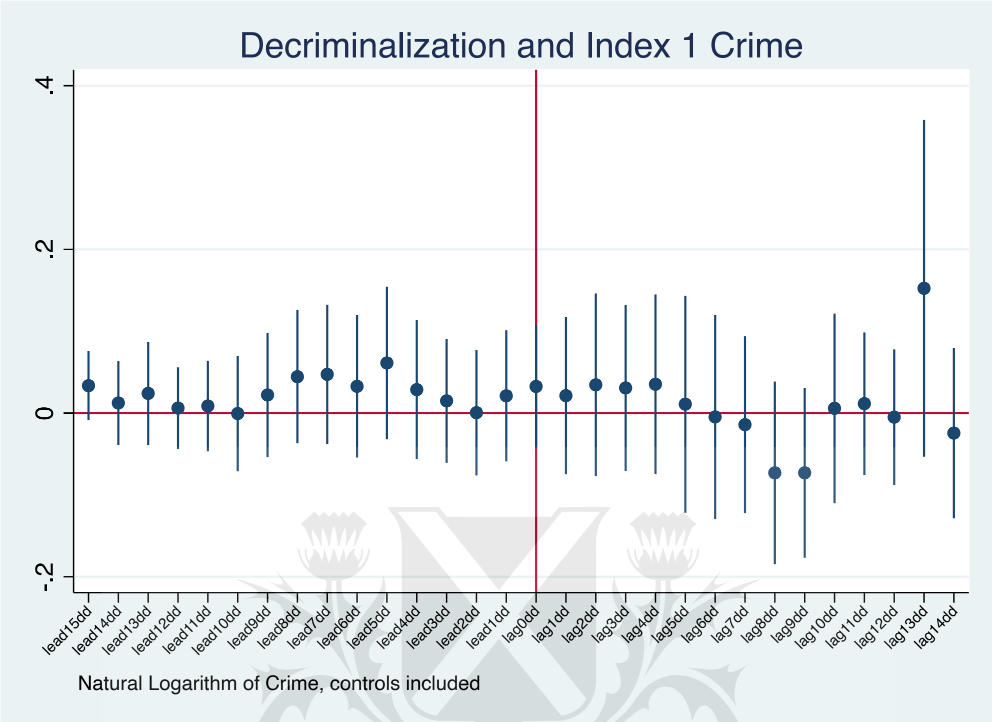
	(0.000751)	(0.0854)	(1.035)	(0.00179)
lag6anylegal	-0.000683	-0.0653	-1.563	-0.00420**
	(0.000672)	(0.0893)	(0.955)	(0.00191)
lag7anylegal	-0.000748	-0.160*	-1.532	-0.00510**
	(0.000726)	(0.0862)	(1.113)	(0.00195)
lag8anylegal	-0.000730	-0.165*	-1.461	-0.00502**
	(0.000756)	(0.0895)	(1.193)	(0.00205)
lag9anylegal	-0.000574	-0.153	-1.513	-0.00501**
	(0.000828)	(0.100)	(1.257)	(0.00212)
lag10anylegal	-0.000997	-0.174	-1.718	-0.00517**
	(0.000908)	(0.131)	(1.407)	(0.00236)
lag11anylegal	-0.000892	-0.145	-1.787	-0.00556*
	(0.000908)	(0.151)	(1.259)	(0.00281)
lag12anylegal	-0.000648	-0.142	-1.653	-0.00548*
	(0.000951)	(0.140)	(1.332)	(0.00296)
lag13anylegal	-0.00109	-0.110	-1.798	-0.00573
	(0.00103)	(0.111)	(1.514)	(0.00370)
lag14anylegal	-0.00140*	-0.179*	-2.223*	-0.00573
	(0.000802)	(0.106)	(1.254)	(0.00362)
lag15finaanylegal	-0.00182*	-0.283**	-2.579*	-0.00705**
	(0.000907)	(0.131)	(1.357)	(0.00321)
GDP Per Capita	-0.00267	1.461	-66.34	-0.165
	(0.0270)	(3.938)	(45.76)	(0.106)
Employment Per Capita	-0.00172	0.531	8.654	0.00943
	(0.00681)	(0.753)	(10.50)	(0.0180)
Sowrn Police Officers Per Capita	0.919***	42.17	-824.9	0.534
	(0.258)	(35.38)	(537.5)	(0.950)
Police Office Employees Per Capita	0.330	61.07		-2.245
	(0.583)	(97.76)		(1.931)
Population Density	-1.73e-05	-0.000610	-0.0216	-0.000148**
	(2.41e-05)	(0.00264)	(0.0341)	(5.93e-05)
Population Growth	5.00e-10	-4.85e-08	9.73e-07	3.97e-09
	(9.87e-10)	(1.46e-07)	(1.60e-06)	(3.57e-09)
Gallons of Ethanol Consumed Per Capita	0.00173*	0.0583	1.878	0.000488
	(0.000884)	(0.101)	(1.521)	(0.00265)
Index Crimes Per Capita	-0.119	-39.49	-23.43	-0.232
	(0.204)	(28.40)	(308.4)	(0.507)
Penal System Population	0.0255	1.478	54.35	
	(0.0245)	(2.243)	(45.64)	
Constant	0.00108	0.186	2.032	0.0354***
	(0.00327)	(0.507)	(4.779)	(0.0104)
Observations	1,021	1,019	1,021	1,074
R-squared	0.737	0.789	0.666	0.888

Note.—All standard errors are in brackets clustered at the state level. * Statistically different from zero at the .1 level. ** Statistically different from zero at the .05 level*** Statistically different from zero at the .01 level. Regressions include controls. All regressions include year and state fixed effects. [i] Any Legal Law represents any change of legality, be it medical marijuana legalization, decriminalization or recreational marijuana legalization. [ii] All analysis was conducted with Stata (Version 13), and standard errors for the model were clustered at the state level.

D) *Is Decriminalization different?*

Some further analysis demonstrates how when analyzing decriminalization separately from medical marijuana and marijuana legalization laws results are somewhat different. We can see in figure 11 that no significant or clear effect can be seen of decriminalization on crime.

Figure 11



What is more interesting, property crime sees a significant fall in year 8 and 9 as shown by figure 12.

Figure 12

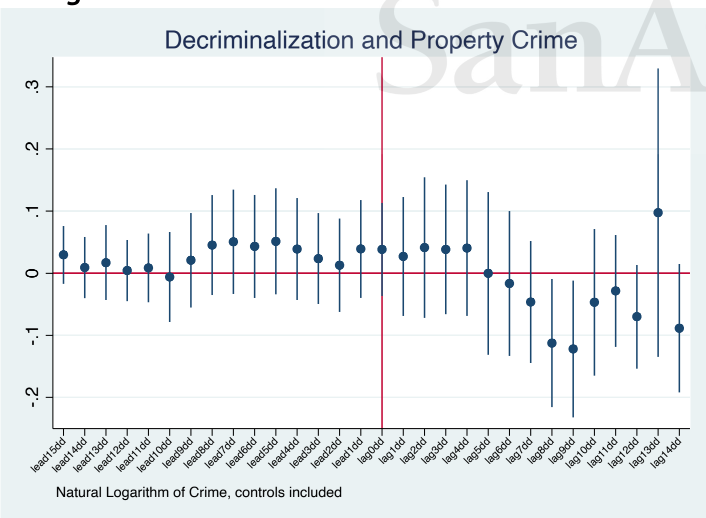


Figure 13

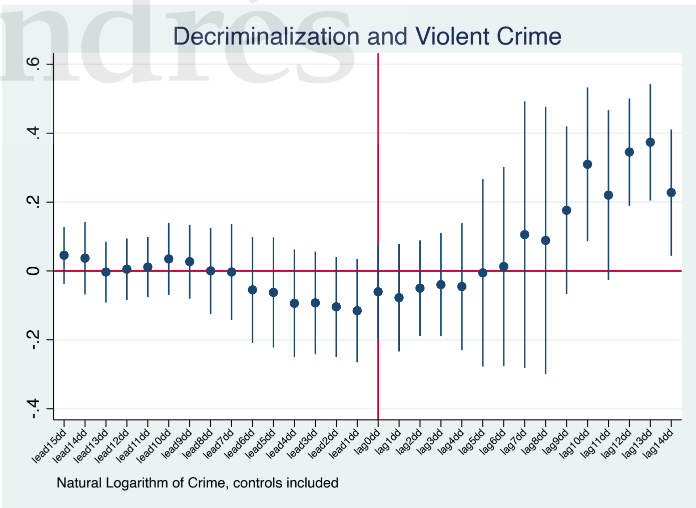


Figure 8 shows an increase in violent crimes which is not coherent with our earlier hypothesis and doesn't seem to eliminate significance when analyzing all marijuana laws together. It is interesting to analyze how the mechanisms we analyze work when only observing decriminalization.

Figure 14

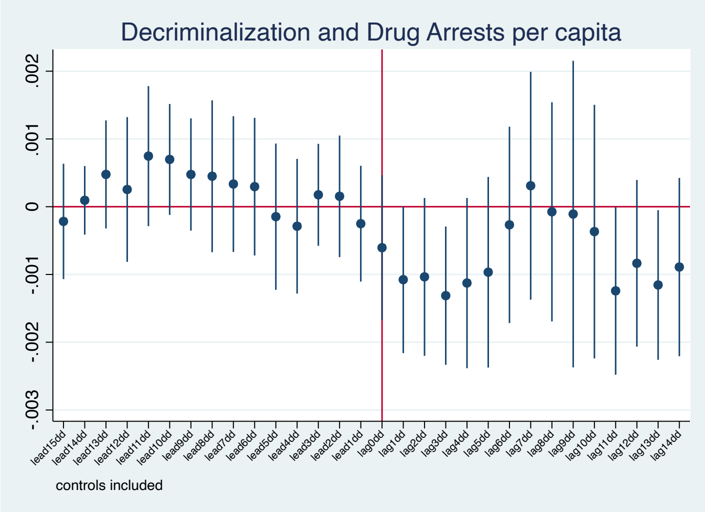


Figure 15

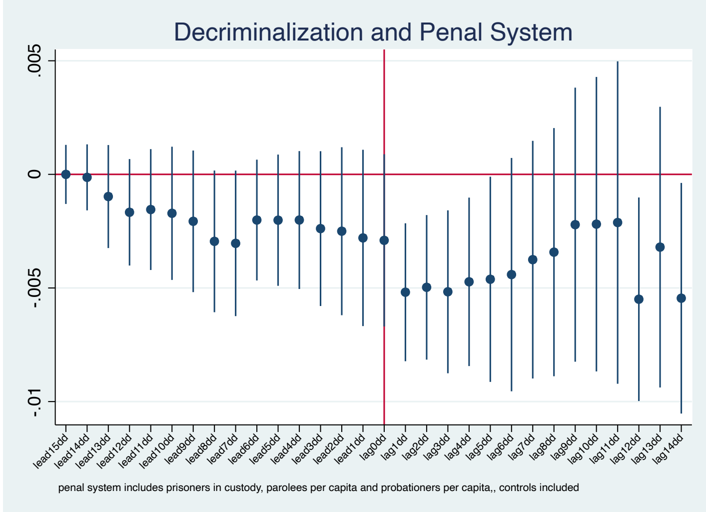


Figure 16

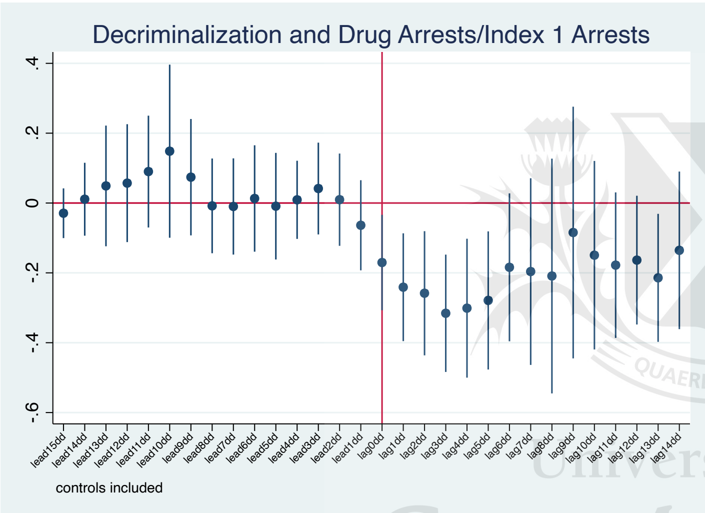
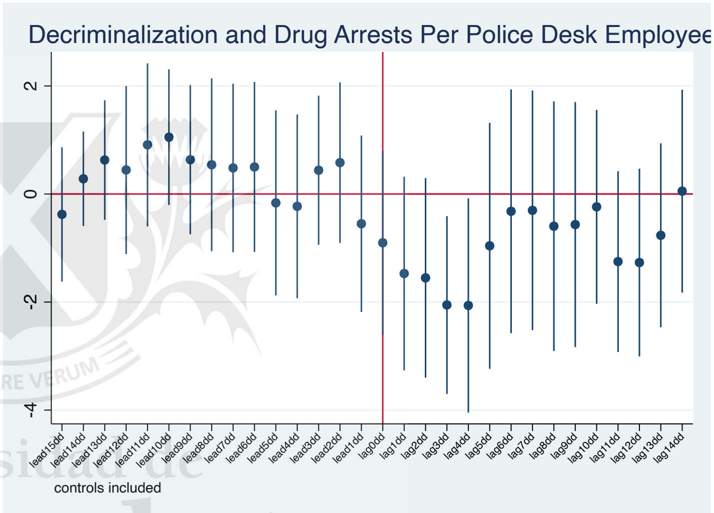


Figure 17



All mechanisms previously analyzed seem to react in the same way. We could argue that resource allocation is deviated away from drug related crime. This is also coherent with the fall in property crime. The question to answer is, why do violent crimes increase? The treatments appear to have some differences and these might explain the inconsistency in results. Going back to section 4A we identified two main mechanisms linking marijuana laws and crime, systemic violence and resource allocation. Systemic violence refers to the black market behind marijuana.

When decriminalizing there is a shift in drug resource allocation but it also becomes more difficult for drug suppliers to get caught. Since posession is no longer a crime drug sellers could sometimes be mistaken with drug users. Before decriminalization both drug users and sellers would be sent to prison, now some drug sellers might get off. When legalizing medical marijuana or recreational marijuana the states regulates the supply of marijuana creating a new competitor which creates desincentives for drug sellers as it makes the business more competitive. Decriminalization could have a positive effect on black markets and medical marijuana and recreational marijuana legalization a negative effect. We can find clear links between black markets in drugs and violent crimes. Single (1989) analyzed the 11 states that decriminalized from 1973, he finds that drug arrests for posessions went down but drug arrests for posession with intent to sell or traficking did not decline and even surged for some states. What is important to understand is that even when financial

expenditures on posession cases went down posessing marijuana is still classified as an offense. This means that police still expend resources on search and seizure. There are other adverse consequences for citizens from being fined for posession such as the creation of a criminal record.
In this case we could hypothesize that two mechanisms are at play.

1. Resource Allocation
2. Systemic Violence

Decriminalization could have a positive impact on the black market and a positive impact on resource allocation. When only analyzing this treatment we can perceive a positive impact on violent crimes. Another possible extension of this work would delve deeper into the impact of decrminalization on the ilegal supply side of drugs.

5. Conclusion

We have shown that more permissive marijuana laws show a connection with a drop on property crimes. In average these crimes fall 15,6% from year 10 to year 14 after the treatment.

We have found interesting results regarding hypothetical mechanisms at work. These give consistent evidence that resource allocation might be at the core of this fall in crime through more efficient policing mechanisms. We find that penal system population falls significantly almost every year after the treatment. Resource allocation towards drugs declines almost at the same time crime falls, not immediately after the treatment. The difference between the significant fall of penal system population and other crime could be explained by a better processing of public policy signals of the judicial system, before policing resources are more efficiently allocated. Reduced conviction rates of drug criminals could be adding to the signal police already receive from public policy. This information better allocates police resources which in turn generates a fall in crime.

Both our mechanisms and the actual crime study results suggest that marijuana laws have a delayed effect on crime. This is consistent with the kind of mechanism we propose as the main culprit of this fall in crime as well as the evidence put forward through the study of these mechanisms.

We believe this framework of analysis adds value and more has to be done to fine tune the approach via more specific and complete control variables. It is important to recognize this works limitations. There is plenty of further analysis to be pointed out. It would add a lot of value to analyze the interactions between different treatments and the timing of treatments. Differences are definitely expected to happen between states that have decriminalized or legalized medical marijuana first and others that have not. Decriminalization appears to have a negative impact on property crimes but a positive impact on violent crimes. Further analysis would have to be made on the matter, but this doesn't appear to show that decriminalization per se is a policy that should be ill considered. It shows that decriminalization isn't enough to reduce crime. Policies regarding drug laws should attack both the supply and the demand of marijuana. Black markets appear to generate crime, and this is the real problem behind drug laws. To further understand this, more analysis should be done on gang activity and black-market activities which could give more evidence to justify this hypothesis. This could be specially interesting when regarding the different effects recreational marijuana laws can have on states with no type of marijuana legality and states with some kind of legality. In "Crime and the Legalization of Recreational Marijuana" (Dragone, Prarolo, Vanin and Zanella, 2019) a spatial regression discontinuity focuses on county level analysis regarding recreational marijuana legalization and finds evidence that crime is reduced specially rapes and thefts. With all new recreational marijuana laws, it is not long until this kind of analysis can be replicated at the state level with the framework we have used.

There is an interesting but more detailed analysis, maybe at a qualitative level, of studying differences between enactment and effect and different details on law implementations. We have segmented public policies into big groups (decriminalization, medical marijuana legalization, recreational marijuana legalization) but each state chose different ways of passing and implementing these laws. For example, some states charge fines for possession and others don't when they are decriminalizing. This kind of analysis could be useful as a tool to accompany econometric interpretations.

Concluding, it would be a stretch to use this analysis to justify legalization of all types of drugs because the psycho-active effects of marijuana are not the same as other harder drugs such as heroin, cocaine, etc. Backed by our results and with current evidence from several studies we would recommend that even the more paternalistic states should evaluate taking a more permissive drug policy towards marijuana use and sale, decriminalizing consumption but also regulating provision. We have intended to explain how marijuana state laws affect crime and shed some empirical light on this subject. We have found and tried to explain how and why marijuana laws are efficient. at tackling the supply and demand side of the drug equation by generating a more efficient resource allocation.

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Appendix

Offense Definitions taken from
Crime in the United States, 2012. **U.S.Department of Justice**—Federal Bureau of Investigation (Released Fall 2013)[36]

The Uniform Crime Reporting (UCR) Program divides offenses into two groups, Part I and Part II crimes. Each month, participating law enforcement agencies submit information on the number of Part I offenses that become known to them; those offenses cleared by arrest or exceptional means; and the age, sex, and race of persons arrested for each of the offenses. Contributors provide only arrest data for Part II offenses.
The UCR Program collects data about Part I offenses in order to measure the level and scope of crime occurring throughout the nation. The program's founders chose these offenses because they are serious crimes, they occur with regularity in all areas of the country, and they are likely to be reported to police. The Part I offenses are:
Criminal homicide—a.) Murder and nonnegligent manslaughter: the willful (nonnegligent) killing of one human being by another. Deaths caused by negligence, attempts to kill, assaults to kill, suicides, and accidental deaths are excluded. The program classifies justifiable homicides separately and limits the definition to: (1) the killing of a felon by a law enforcement officer in the line of duty; or (2) the killing of a felon, during the commission of a felony, by a private citizen. b.) Manslaughter by negligence: the killing of another person through gross negligence. Deaths of persons due to their own negligence, accidental deaths not resulting from gross negligence, and traffic fatalities are not included in the category Manslaughter by Negligence.
Forcible rape—The carnal knowledge of a female forcibly and against her will. Rapes by force and attempts or assaults to rape, regardless of the age of the victim, are included. Statutory offenses (no force used—victim under age of consent) are excluded.
Robbery—The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.
Aggravated assault—An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm. Simple assaults are excluded.
Burglary (breaking or entering)—The unlawful entry of a structure to commit a felony or a theft. Attempted forcible entry is included.
Larceny-theft (except motor vehicle theft)—The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. Examples are thefts of bicycles, motor vehicle parts and accessories, shoplifting, pocket-picking, or the stealing of any property or article that is not taken by force and violence or by fraud. Attempted larcenies are included. Embezzlement, confidence games, forgery, check fraud, etc., are excluded.
Motor vehicle theft—The theft or attempted theft of a motor vehicle. A motor vehicle is self-propelled and runs on land surface and not on rails. Motorboats, construction equipment, airplanes, and farming equipment are specifically excluded from this category.
Arson—Any willful or malicious burning or attempt to burn, with or without intent to defraud, a dwelling house, public building, motor vehicle or aircraft, personal property of another, etc.

[36] "FBI" FBI. http://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2013/preliminary-semiannual-uniform-crime-report-january-june-2013 (accessed May 28, 2014).

The Part II offenses, for which only arrest data are collected, are:
Other assaults (simple)—Assaults and attempted assaults where no weapon was used or no serious or aggravated injury resulted to the victim. Stalking, intimidation, coercion, and hazing are included.
Forgery and counterfeiting—The altering, copying, or imitating of something, without authority or right, with the intent to deceive or defraud by passing the copy or thing altered or imitated as that which is original or genuine; or the selling, buying, or possession of an altered, copied, or imitated thing with the intent to deceive or defraud. Attempts are included.
Fraud—The intentional perversion of the truth for the purpose of inducing another person or other entity in reliance upon it to part with something of value or to surrender a legal right. Fraudulent conversion and obtaining of money or property by false pretenses. Confidence games and bad checks, except forgeries and counterfeiting, are included.
Embezzlement—The unlawful misappropriation or misapplication by an offender to his/her own use or purpose of money, property, or some other thing of value entrusted to his/her care, custody, or control.
Stolen property: buying, receiving, possessing—Buying, receiving, possessing, selling, concealing, or transporting any property with the knowledge that it has been unlawfully taken, as by burglary, embezzlement, fraud, larceny, robbery, etc. Attempts are included.
Vandalism—To willfully or maliciously destroy, injure, disfigure, or deface any public or private property, real or personal, without the consent of the owner or person having custody or control by cutting, tearing, breaking, marking, painting, drawing, covering with filth, or any other such means as may be specified by local law. Attempts are included.
Weapons: carrying, possessing, etc.—The violation of laws or ordinances prohibiting the manufacture, sale, purchase, transportation, possession, concealment, or use of firearms, cutting instruments, explosives, incendiary devices, or other deadly weapons. Attempts are included.
Prostitution and commercialized vice—The unlawful promotion of or participation in sexual activities for profit, including attempts. To solicit customers or transport persons for prostitution purposes; to own, manage, or operate a dwelling or other establishment for the purpose of providing a place where prostitution is performed; or to otherwise assist or promote prostitution.
Sex offenses (except forcible rape, prostitution, and commercialized vice)—Offenses against chastity, common decency, morals, and the like. Incest, indecent exposure, and statutory rape are included. Attempts are included.
Drug abuse violations—The violation of laws prohibiting the production, distribution, and/or use of certain controlled substances. The unlawful cultivation, manufacture, distribution, sale, purchase, use, possession, transportation, or importation of any controlled drug or narcotic substance. Arrests for violations of state and local laws, specifically those relating to the unlawful possession, sale, use, growing, manufacturing, and making of narcotic drugs. The following drug categories are specified: opium or cocaine and their derivatives (morphine, heroin, codeine); marijuana; synthetic narcotics—manufactured narcotics that can cause true addiction (demerol, methadone); and dangerous nonnarcotic drugs (barbiturates, benzedrine).
Gambling—To unlawfully bet or wager money or something else of value; assist, promote, or operate a game of chance for money or some other stake; possess or transmit wagering information; manufacture, sell, purchase, possess, or transport gambling equipment, devices, or goods; or tamper with the outcome of a sporting event or contest to gain a gambling advantage.
Offenses against the family and children—Unlawful nonviolent acts by a family member (or legal guardian) that threaten the physical, mental, or economic well-being or morals of another family member and that are not classifiable as other offenses, such as Assault or Sex Offenses. Attempts are included.
Driving under the influence—Driving or operating a motor vehicle or common carrier while mentally or physically impaired as the result of consuming an alcoholic beverage or using a drug or narcotic.

Liquor laws—The violation of state or local laws or ordinances prohibiting the manufacture, sale, purchase, transportation, possession, or use of alcoholic beverages, not including driving under the influence and drunkenness. Federal violations are excluded.
Drunkenness—To drink alcoholic beverages to the extent that one's mental faculties and physical coordination are substantially impaired. Driving under the influence is excluded.
Disorderly conduct—Any behavior that tends to disturb the public peace or decorum, scandalize the community, or shock the public sense of morality.
Vagrancy—The violation of a court order, regulation, ordinance, or law requiring the withdrawal of persons from the streets or other specified areas; prohibiting persons from remaining in an area or place in an idle or aimless manner; or prohibiting persons from going from place to place without visible means of support.
All other offenses—All violations of state or local laws not specifically identified as Part I or Part II offenses, except traffic violations.
Suspicion—Arrested for no specific offense and released without formal charges being placed.
Curfew and loitering laws (persons under age 18)—Violations by juveniles of local curfew or loitering ordinances.

Table 1A Marijuana Law and Violent Crime Variables[ii]

VARIABLES	Murder Violent Crime	Rape Violent Crime	Robbery Violent Crime	Aggravated Assault Violent Crime
lead15Marijuana Law	-0.0210	0.0215	-0.00722	0.0289
	(0.0288)	(0.0376)	(0.0380)	(0.0355)
lead14Marijuana Law	-0.0631	-0.0300	-0.00500	-0.00727
	(0.0399)	(0.0348)	(0.0430)	(0.0388)
lead13Marijuana Law	-0.0320	-0.0507	-0.0108	0.0313
	(0.0416)	(0.0429)	(0.0524)	(0.0604)
lead12Marijuana Law	-0.0594	-0.0681	0.0208	0.0536
	(0.0412)	(0.0593)	(0.0650)	(0.0795)
lead11Marijuana Law	-0.0504	-0.0504	-0.00150	0.0789
	(0.0459)	(0.0491)	(0.0557)	(0.0713)
lead10Marijuana Law	-0.0613	-0.0435	-0.00208	0.0811
	(0.0440)	(0.0485)	(0.0646)	(0.0713)
lead9Marijuana Law	-0.0339	-0.0296	0.0107	0.0612
	(0.0493)	(0.0488)	(0.0708)	(0.0857)
lead8Marijuana Law	-0.0336	-0.0277	0.00824	0.0316
	(0.0471)	(0.0509)	(0.0581)	(0.0783)
lead7Marijuana Law	0.00201	-0.0386	-0.0221	-0.00683
	(0.0541)	(0.0532)	(0.0638)	(0.0838)
lead6Marijuana Law	0.0214	-0.0486	-0.0332	-0.00563
	(0.0631)	(0.0565)	(0.0686)	(0.0822)
lead5Marijuana Law	0.0248	-0.0156	0.00375	0.0274
	(0.0584)	(0.0544)	(0.0666)	(0.0870)
lead4Marijuana Law	-0.0179	-0.0404	0.0165	-0.0229
	(0.0564)	(0.0564)	(0.0717)	(0.0872)
lead3Marijuana Law	0.0125	-0.0719	0.0262	0.0113
	(0.0655)	(0.0560)	(0.0710)	(0.0953)
lead2Marijuana Law	-0.0185	-0.0496	0.0216	0.0263
	(0.0585)	(0.0582)	(0.0745)	(0.0953)
lead1Marijuana Law	0.0720	-0.0550	-0.0326	0.0203
	(0.0679)	(0.0652)	(0.0799)	(0.106)
lag0Marijuana Law	0.0566	-0.0404	-0.0316	-0.0160
	(0.0553)	(0.0709)	(0.0880)	(0.0974)
lag1Marijuana Law	-0.00185	0.00317	-0.00743	0.0355
	(0.0889)	(0.0750)	(0.0873)	(0.0959)
lag2Marijuana Law	-0.00949	-0.0334	-0.0301	0.0178
	(0.0829)	(0.0731)	(0.0889)	(0.0997)
lag3Marijuana Law	-0.00278	-0.0845	-0.0538	0.0137
	(0.0890)	(0.0743)	(0.0886)	(0.105)
lag4Marijuana Law	0.0468	-0.0835	-0.0801	-0.00315
	(0.0816)	(0.0856)	(0.0978)	(0.115)
lag5Marijuana Law	-0.161	-0.0619	-0.0465	0.00975
	(0.107)	(0.0914)	(0.0990)	(0.109)
lag6Marijuana Law	-0.130	-0.0307	-0.0803	0.0476
	(0.0973)	(0.0835)	(0.116)	(0.122)
lag7Marijuana Law	-0.173	-0.0278	-0.0341	0.0962
	(0.103)	(0.0892)	(0.106)	(0.126)
lag8Marijuana Law	-0.184**	-0.0648	-0.0385	0.0993
	(0.0914)	(0.102)	(0.118)	(0.140)
lag9Marijuana Law	-0.112	-0.0728	0.00141	0.154
	(0.0904)	(0.0948)	(0.123)	(0.141)

lag10Marijuana Law	-0.126	-0.0627	-0.0669	0.128
	(0.114)	(0.135)	(0.109)	(0.178)
lag11Marijuana Law	-0.280*	-0.0156	0.0180	0.180
	(0.151)	(0.128)	(0.113)	(0.189)
lag12Marijuana Law	-0.141	-0.0804	0.0758	0.224
	(0.0995)	(0.113)	(0.124)	(0.171)
lag13Marijuana Law	-0.223*	-0.122	0.0649	0.249
	(0.116)	(0.132)	(0.118)	(0.166)
lag14Marijuana Law	-0.135	-0.0830	0.110	0.239
	(0.117)	(0.0916)	(0.124)	(0.176)
lag15finaMarijuana Law	-0.206*	-0.0917	0.0817	0.273
	(0.117)	(0.145)	(0.129)	(0.180)
gdppc	2.930	-2.643	1.794	-1.894
	(4.886)	(3.870)	(6.023)	(5.778)
employmentpc	1.118	1.992*	0.621	2.783*
	(1.416)	(1.071)	(0.978)	(1.574)
swornpc	81.86*	77.37	110.0**	136.3*
	(42.26)	(52.32)	(54.19)	(67.96)
policeofficeemployeespc	45.48	-18.88	-90.72	58.28
	(107.0)	(70.44)	(115.8)	(160.1)
probationpc	1.833	5.744*	3.964	2.137
	(4.693)	(3.366)	(3.227)	(3.909)
parolepc	15.01	21.38	5.325	2.549
	(17.87)	(23.46)	(16.87)	(25.17)
prisonerscustodypc	0.315	31.63	27.83	67.03*
	(24.84)	(28.71)	(33.86)	(36.17)
popdens	0.00355	-0.00895*	-0.00265	-0.00614
	(0.00258)	(0.00500)	(0.00382)	(0.00463)
popgrowthh	1.61e-07	1.56e-07	1.65e-07	1.72e-07
	(1.94e-07)	(1.76e-07)	(2.05e-07)	(1.57e-07)
gallonspc	0.402*	0.0619	0.486***	0.620***
	(0.203)	(0.156)	(0.153)	(0.204)
Constant	-0.673	2.712***	2.934***	2.497*
	(0.849)	(0.759)	(0.889)	(1.394)
Observations	1,074	1,074	1,074	1,074
R-squared	0.914	0.866	0.973	0.917

Note.—All standard errors are in brackets clustered at the state level. * Statistically different from zero at the .1 level. ** Statistically different from zero at the .05 level*** Statistically different from zero at the .01 level. Regressions include controls for employment per capita, Gross Domestic Product per capita, number of police personnel per capita, number of adults on parole per capita, number of adults on probation per capita, estimated number of people in custody of federal or state prison per capita, population density per square kilometer, yearly population growth and estimated gallons of alcohol consumed per capita. Information on medical marijuana legality was taken from NORML. All regressions include year and state fixed effects. [i] Any Legal Law represents any change of legality, be it medical marijuana legalization, decriminalization or recreational marijuana legalization. [ii] All crime variables are natural logarithms of the actual crime rate per 100.000 people. All analysis was conducted with Stata (Version 13), and standard errors for the model were clustered at the state level.

Table 2A Marijuana Law and Property Crime Variables[ii]

VARIABLES	Burglary Property Crime	Larceny Theft Property Crime	Vehicle Theft Property Crime
lead15anylegal	0.0194	0.0105	0.0253
	(0.0291)	(0.0227)	(0.0480)
lead14anylegal	-0.00126	0.0103	-0.00238
	(0.0287)	(0.0232)	(0.0529)
lead13anylegal	0.00146	0.000918	-0.00465
	(0.0334)	(0.0279)	(0.0646)
lead12anylegal	0.00302	-0.0121	-0.0179
	(0.0401)	(0.0352)	(0.0680)
lead11anylegal	0.00133	-0.0175	0.0178
	(0.0348)	(0.0324)	(0.0691)
lead10anylegal	-0.0143	-0.0483	0.00379
	(0.0394)	(0.0327)	(0.0675)
lead9anylegal	0.0100	-0.0141	0.0195
	(0.0375)	(0.0325)	(0.0728)
lead8anylegal	-0.00217	-0.0255	-0.0105
	(0.0369)	(0.0321)	(0.0734)
lead7anylegal	-0.0199	-0.0280	-0.0249
	(0.0412)	(0.0317)	(0.0828)
lead6anylegal	-0.0212	-0.0338	-0.0361
	(0.0425)	(0.0312)	(0.0865)
lead5anylegal	-0.0226	-0.0141	-0.0261
	(0.0403)	(0.0340)	(0.0903)
lead4anylegal	-0.0313	-0.0248	-0.0623
	(0.0420)	(0.0352)	(0.0933)
lead3anylegal	-0.0310	-0.0254	-0.0718
	(0.0437)	(0.0352)	(0.0969)
lead2anylegal	-0.0170	-0.0330	-0.0563
	(0.0434)	(0.0363)	(0.0934)
lead1anylegal	-0.0559	-0.0482	-0.125
	(0.0489)	(0.0420)	(0.102)
lag0anylegal	-0.0593	-0.0506	-0.157
	(0.0512)	(0.0422)	(0.106)
lag1anylegal	-0.0286	-0.0407	-0.122
	(0.0502)	(0.0409)	(0.104)
lag2anylegal	-0.0376	-0.0489	-0.124
	(0.0537)	(0.0411)	(0.109)
lag3anylegal	-0.0484	-0.0566	-0.151
	(0.0528)	(0.0400)	(0.115)
lag4anylegal	-0.0228	-0.0489	-0.119
	(0.0552)	(0.0427)	(0.124)
lag5anylegal	-0.0156	-0.0482	-0.124
	(0.0572)	(0.0425)	(0.131)
lag6anylegal	-0.0384	-0.0733	-0.153
	(0.0616)	(0.0440)	(0.155)
lag7anylegal	-0.0201	-0.0626	-0.0525
	(0.0618)	(0.0513)	(0.134)
lag8anylegal	-0.0232	-0.106**	-0.157

	(0.0644)	(0.0516)	(0.151)
lag9anylegal	-0.0361	-0.0860	-0.0848
	(0.0630)	(0.0614)	(0.174)
lag10anylegal	-0.150**	-0.195***	-0.293
	(0.0718)	(0.0488)	(0.182)
lag11anylegal	-0.103	-0.195***	-0.278
	(0.0884)	(0.0652)	(0.223)
lag12anylegal	-0.112	-0.132**	-0.223
	(0.101)	(0.0550)	(0.200)
lag13anylegal	-0.183*	-0.165***	-0.296**
	(0.0981)	(0.0475)	(0.140)
lag14anylegal	-0.101	-0.168***	-0.252*
	(0.0994)	(0.0483)	(0.139)
lag15finaanylegal	-0.0197	-0.0805	-0.0681
	(0.116)	(0.0595)	(0.149)
gdppc	-6.564	-4.093	5.150
	(4.838)	(2.890)	(6.439)
employmentpc	0.145	0.495	-0.572
	(0.958)	(0.571)	(1.123)
swornpc	92.37*	85.72**	74.39
	(47.11)	(35.02)	(73.44)
policeofficeemployeespc	-79.96	-78.40	-17.21
	(83.07)	(53.07)	(146.8)
probationpc	2.506	-1.350	0.737
	(2.938)	(1.749)	(3.885)
parolepc	34.02	16.65	7.841
	(21.06)	(14.07)	(24.24)
prisonerscustodypc	22.24	7.457	18.22
	(20.66)	(15.30)	(47.61)
popdens	-0.000359	0.00105	-0.00876
	(0.00278)	(0.00152)	(0.00548)
popgrowthh	8.24e-08	1.43e-07	4.10e-07
	(1.69e-07)	(1.15e-07)	(3.16e-07)
gallonspc	0.0622	0.0610	0.0462
	(0.144)	(0.110)	(0.154)
Constant	6.279***	7.239***	6.236***
	(0.591)	(0.267)	(1.015)
Observations	1,074	1,066	1,074
R-squared	0.934	0.930	0.922

Note.—All standard errors are in brackets clustered at the state level. * Statistically different from zero at the .1 level. ** Statistically different from zero at the .05 level*** Statistically different from zero at the .01 level. Regressions include controls for employment per capita, Gross Domestic Product per capita, number of police personnel per capita, number of adults on parole per capita, number of adults on probation per capita, estimated number of people in custody of federal or state prison per capita, population density per square kilometer, yearly population growth and estimated gallons of alcohol consumed per capita. Information on medical marijuana legality was taken from NORML. All regressions include year and state fixed effects. [i] Any Legal Law represents any change of legality, be it medical marijuana legalization, decriminalization or recreational marijuana legalization. [ii] All crime variables are natural logarithms of the actual crime rate per 100.000 people. All analysis was conducted with Stata (Version 13), and standard errors for the model were clustered at the state level.

Table 3A Control Checks[ii]

VARIABLES	LN INDEX	LN INDEX	LN INDEX	LN INDEX	LN INDEX	LN INDEX	LN INDEX	LN INDEX	LN INDEX	LN INDEX
lead15anylegal	0.0129	-0.0988***	0.0148	0.0141	0.0116	0.00929	0.0164	0.0140	0.0182	-0.0187
	(0.0204)	(0.0362)	(0.0212)	(0.0242)	(0.0218)	(0.0207)	(0.0219)	(0.0209)	(0.0207)	(0.0201)
lead14anylegal	0.00517	-0.111***	0.00655	0.00144	0.00501	0.00139	0.00905	0.00488	0.00908	-0.0198
	(0.0227)	(0.0403)	(0.0226)	(0.0244)	(0.0232)	(0.0224)	(0.0228)	(0.0231)	(0.0224)	(0.0226)
lead13anylegal	-0.00279	-0.120***	-0.000935	-0.00497	-0.00259	-0.00458	0.00195	-0.00406	0.00126	-0.0372
	(0.0274)	(0.0393)	(0.0265)	(0.0282)	(0.0275)	(0.0268)	(0.0265)	(0.0277)	(0.0262)	(0.0280)
lead12anylegal	-0.0105	-0.102**	-0.00724	-0.0192	-0.0104	-0.0101	-0.00444	-0.0135	-0.00537	-0.0416
	(0.0336)	(0.0413)	(0.0329)	(0.0352)	(0.0333)	(0.0337)	(0.0324)	(0.0332)	(0.0323)	(0.0312)
lead11anylegal	-0.00978	-0.121***	-0.00740	-0.0191	-0.0102	-0.0135	-0.00625	-0.0130	-0.00614	-0.0300
	(0.0281)	(0.0450)	(0.0274)	(0.0339)	(0.0290)	(0.0300)	(0.0280)	(0.0280)	(0.0270)	(0.0323)
lead10anylegal	-0.0215	-0.140***	-0.0209	-0.0312	-0.0223	-0.0258	-0.0213	-0.0229	-0.0201	-0.0553
	(0.0299)	(0.0476)	(0.0298)	(0.0364)	(0.0308)	(0.0317)	(0.0305)	(0.0301)	(0.0299)	(0.0361)
lead9anylegal	-0.00248	-0.131**	-0.00121	-0.00607	-0.00375	-0.00329	-0.000867	-0.00540	0.00101	-0.0457
	(0.0295)	(0.0490)	(0.0293)	(0.0367)	(0.0304)	(0.0320)	(0.0300)	(0.0300)	(0.0292)	(0.0359)
lead8anylegal	-0.0117	-0.141***	-0.0103	-0.0132	-0.0131	-0.0109	-0.00917	-0.0136	-0.00699	-0.0517
	(0.0291)	(0.0492)	(0.0292)	(0.0368)	(0.0301)	(0.0318)	(0.0299)	(0.0292)	(0.0289)	(0.0356)
lead7anylegal	-0.0308	-0.145***	-0.0290	-0.0284	-0.0325	-0.0280	-0.0283	-0.0332	-0.0257	-0.0583*
	(0.0290)	(0.0486)	(0.0291)	(0.0383)	(0.0301)	(0.0324)	(0.0299)	(0.0291)	(0.0289)	(0.0345)
lead6anylegal	-0.0320	-0.144***	-0.0301	-0.0317	-0.0340	-0.0313	-0.0294	-0.0341	-0.0265	-0.0559*
	(0.0297)	(0.0490)	(0.0300)	(0.0376)	(0.0312)	(0.0324)	(0.0309)	(0.0300)	(0.0296)	(0.0332)
lead5anylegal	-0.00875	-0.132***	-0.00659	-0.00516	-0.0110	-0.00547	-0.00584	-0.00977	-0.00255	-0.0293
	(0.0332)	(0.0485)	(0.0332)	(0.0412)	(0.0353)	(0.0364)	(0.0346)	(0.0332)	(0.0329)	(0.0375)
lead4anylegal	-0.0329	-0.143***	-0.0307	-0.0293	-0.0353	-0.0316	-0.0309	-0.0337	-0.0275	-0.0552
	(0.0335)	(0.0508)	(0.0334)	(0.0427)	(0.0360)	(0.0365)	(0.0354)	(0.0334)	(0.0332)	(0.0388)
lead3anylegal	-0.0344	-0.137**	-0.0314	-0.0324	-0.0369	-0.0301	-0.0299	-0.0357	-0.0264	-0.0543
	(0.0343)	(0.0515)	(0.0337)	(0.0423)	(0.0375)	(0.0373)	(0.0364)	(0.0341)	(0.0335)	(0.0388)
lead2anylegal	-0.0376	-0.143***	-0.0347	-0.0371	-0.0400	-0.0359	-0.0333	-0.0397	-0.0298	-0.0566
	(0.0349)	(0.0517)	(0.0343)	(0.0419)	(0.0368)	(0.0384)	(0.0363)	(0.0353)	(0.0344)	(0.0377)
lead1anylegal	-0.0650	-0.160***	-0.0619	-0.0590	-0.0677	-0.0606	-0.0603	-0.0674	-0.0563	-0.0816*
	(0.0408)	(0.0544)	(0.0399)	(0.0474)	(0.0438)	(0.0446)	(0.0428)	(0.0411)	(0.0400)	(0.0433)
lag0anylegal	-0.0694	-0.160***	-0.0666	-0.0719	-0.0722	-0.0703	-0.0639	-0.0697	-0.0597	-0.0997**
	(0.0426)	(0.0557)	(0.0420)	(0.0516)	(0.0454)	(0.0470)	(0.0440)	(0.0428)	(0.0415)	(0.0484)
lag1anylegal	-0.0505	-0.169***	-0.0486	-0.0674	-0.0529	-0.0477	-0.0432	-0.0487	-0.0393	-0.122**
	(0.0402)	(0.0561)	(0.0399)	(0.0533)	(0.0415)	(0.0444)	(0.0394)	(0.0404)	(0.0383)	(0.0492)
lag2anylegal	-0.0465	-0.160***	-0.0428	-0.0534	-0.0489	-0.0479	-0.0367	-0.0459	-0.0332	-0.0988**
	(0.0404)	(0.0565)	(0.0403)	(0.0515)	(0.0412)	(0.0464)	(0.0392)	(0.0400)	(0.0382)	(0.0460)
lag3anylegal	-0.0653	-0.174***	-0.0605	-0.0672	-0.0678	-0.0647	-0.0552	-0.0661	-0.0518	-0.0951*
	(0.0398)	(0.0549)	(0.0386)	(0.0500)	(0.0409)	(0.0441)	(0.0380)	(0.0397)	(0.0367)	(0.0475)
lag4anylegal	-0.0548	-0.179***	-0.0501	-0.0771	-0.0573	-0.0546	-0.0427	-0.0534	-0.0393	-0.108**
	(0.0427)	(0.0559)	(0.0422)	(0.0505)	(0.0437)	(0.0463)	(0.0407)	(0.0420)	(0.0395)	(0.0483)
lag5anylegal	-0.0531	-0.183***	-0.0471	-0.0444	-0.0565	-0.0486	-0.0448	-0.0566	-0.0403	-0.0697

	(0.0418)	(0.0567)	(0.0407)	(0.0498)	(0.0438)	(0.0453)	(0.0423)	(0.0420)	(0.0398)	(0.0496)
lag6anylegal	-0.0680	-0.186***	-0.0608	-0.0701	-0.0710	-0.0623	-0.0584	-0.0720	-0.0547	-0.0825*
	(0.0468)	(0.0599)	(0.0457)	(0.0540)	(0.0488)	(0.0505)	(0.0474)	(0.0464)	(0.0450)	(0.0490)
lag7anylegal	-0.0483	-0.202***	-0.0422	-0.0572	-0.0508	-0.0377	-0.0407	-0.0526	-0.0377	-0.0716
	(0.0480)	(0.0609)	(0.0460)	(0.0529)	(0.0491)	(0.0512)	(0.0489)	(0.0467)	(0.0467)	(0.0511)
lag8anylegal	-0.0868*	-0.191***	-0.0806	-0.0779	-0.0897*	-0.0736	-0.0813	-0.0915*	-0.0778	-0.0653
	(0.0499)	(0.0669)	(0.0482)	(0.0555)	(0.0513)	(0.0535)	(0.0527)	(0.0498)	(0.0501)	(0.0513)
lag9anylegal	-0.0607	-0.192***	-0.0565	-0.0808	-0.0625	-0.0527	-0.0534	-0.0673	-0.0512	-0.0702
	(0.0582)	(0.0707)	(0.0568)	(0.0582)	(0.0595)	(0.0589)	(0.0594)	(0.0566)	(0.0578)	(0.0523)
lag10anylegal	-0.181***	-0.218***	-0.180***	-0.135*	-0.183***	-0.171***	-0.179***	-0.180***	-0.176***	-0.0947
	(0.0522)	(0.0726)	(0.0518)	(0.0726)	(0.0533)	(0.0539)	(0.0530)	(0.0512)	(0.0521)	(0.0638)
lag11anylegal	-0.170**	-0.175**	-0.170**	-0.187***	-0.172**	-0.165**	-0.165**	-0.165**	-0.162**	-0.111
	(0.0693)	(0.0730)	(0.0696)	(0.0681)	(0.0701)	(0.0708)	(0.0703)	(0.0677)	(0.0693)	(0.0669)
lag12anylegal	-0.123*	-0.192***	-0.124*	-0.134*	-0.125*	-0.120*	-0.119*	-0.120*	-0.116*	-0.0989
	(0.0633)	(0.0690)	(0.0639)	(0.0687)	(0.0644)	(0.0653)	(0.0661)	(0.0627)	(0.0649)	(0.0620)
lag13anylegal	-0.164***	-0.188***	-0.165***	-0.155**	-0.166***	-0.156***	-0.163***	-0.169***	-0.160***	-0.107
	(0.0501)	(0.0673)	(0.0503)	(0.0731)	(0.0512)	(0.0545)	(0.0539)	(0.0480)	(0.0530)	(0.0670)
lag14anylegal	-0.140***	-0.184**	-0.140***	-0.144**	-0.142***	-0.130**	-0.138***	-0.146***	-0.134***	-0.0827
	(0.0462)	(0.0708)	(0.0465)	(0.0554)	(0.0475)	(0.0504)	(0.0494)	(0.0447)	(0.0484)	(0.0628)
lag15finaanylegal	-0.0529	-0.249**	-0.0544	-0.0685	-0.0552	-0.0310	-0.0577	-0.0601	-0.0537	-0.131*
	(0.0490)	(0.114)	(0.0500)	(0.0610)	(0.0500)	(0.0505)	(0.0493)	(0.0480)	(0.0492)	(0.0730)
GDP Per Capita	-3.358		-2.387	-3.040	-3.445	-3.098		-3.250		-9.524***
	(3.174)		(2.844)	(3.393)	(3.093)	(3.301)		(3.288)		(2.949)
Employment Per Capita	0.360			0.126	0.389	0.330	-0.0344	0.609		-0.165
	(0.582)			(0.595)	(0.568)	(0.607)	(0.496)	(0.483)		(0.441)
Sowrn Police Officers Per Capita	89.14**		88.56**		89.66**		87.76**	97.68***	86.98**	
	(36.18)		(36.54)		(36.14)		(36.84)	(31.76)	(36.90)	
Police Office Employees Per Capita	-69.84		-76.88	0.827	-69.48	-3.461	-79.01	-62.15	-78.05	
	(65.76)		(70.56)	(50.25)	(66.11)	(50.48)	(67.65)	(67.09)	(70.67)	
probationpc	-0.00271		0.0766		0.0401	0.0518	0.295	-0.102	0.210	
	(1.887)		(1.859)		(1.931)	(2.011)	(1.906)	(1.823)	(1.858)	
parolepc	21.95		21.46		22.89	21.47	25.02*	23.58	23.66	
	(15.20)		(15.26)		(14.82)	(15.61)	(14.29)	(14.21)	(15.18)	
prisonerscustodypc	15.03		14.83	26.79	15.73	18.02	18.04	16.40	17.00	19.10
	(16.11)		(16.00)	(18.12)	(15.72)	(17.82)	(16.94)	(15.92)	(17.01)	(11.96)
Population Density	-0.000428		-0.000627	-0.00196		-0.000621		-0.000328	-0.000662	-0.00155***
	(0.00198)		(0.00193)	(0.00198)		(0.00190)		(0.00211)	(0.00197)	(0.000371)
Population Growth	1.56e-07		1.68e-07	1.65e-07	1.55e-07	1.52e-07	1.65e-07	1.80e-07	1.62e-07	2.79e-08
	(1.29e-07)		(1.32e-07)	(1.23e-07)	(1.30e-07)	(1.30e-07)	(1.29e-07)	(1.33e-07)	(1.29e-07)	(1.24e-07)
Gallons of Ethanol Consumed Per Capita	0.0925		0.110	0.119	0.0915	0.125	0.0874		0.0842	0.307***
	(0.109)		(0.0928)	(0.105)	(0.109)	(0.108)	(0.104)		(0.0838)	(0.0733)
Constant	7.761***	8.266***	7.930***	8.091***	7.705***	7.840***	7.819***	7.744***	7.873***	8.258***
	(0.350)	(0.0238)	(0.269)	(0.367)	(0.272)	(0.353)	(0.263)	(0.357)	(0.263)	(0.252)
Observations	1,074	3,004	1,074	1,136	1,074	1,074	1,074	1,074	1,074	2,008
R-squared	0.943	0.882	0.943	0.938	0.943	0.941	0.943	0.943	0.943	0.913

Note.—All standard errors are in brackets clustered at the state level. * Statistically different from zero at the .1 level. ** Statistically different from zero at the .05 level*** Statistically different from zero at the .01 level. Regressions include controls. All regressions include year and state fixed effects. [i] Any Legal Law represents any change of legality, be it medical marijuana legalization, decriminalization or recreational marijuana legalization. [ii] All analysis was conducted with Stata (Version 13), and standard errors for the model were clustered at the state level. Coefficients rounded to 1 significant figure. Standard errors rounded to 3 decimal places.

Table 4A - Control Checks[ii]

VARIABLES	lnindex	lnindex	lnindex	lnindex	lnindex	lnindex	lnindex	lnindex
anylegallaw	-0.0290*	-0.0822*	-0.0278*	-0.0259	-0.0341**	-0.0281*	-0.0278*	-0.0246*
	(0.0154)	(0.0477)	(0.0150)	(0.0290)	(0.0165)	(0.0156)	(0.0157)	(0.0141)
GDP Per Capita	-3.318		-2.211	-1.789	-2.837	-2.994	-3.229	
	(2.932)		(2.707)	(2.976)	(3.159)	(3.050)	(3.034)	
Employment Per Capita	0.425			-0.239	0.155	0.393	0.655	
	(0.551)			(0.432)	(0.567)	(0.572)	(0.456)	
Sowrn Police Officers Per Capita	85.62**		84.84**				93.16***	82.74**
	(34.71)		(35.22)				(31.19)	(35.63)
Police Office Employees Per Capita	-63.77		-71.35		-0.550	-1.043	-56.23	-71.11
	(62.94)		(67.28)		(49.74)	(49.61)	(64.22)	(67.46)
probationpc	0.429		0.524			0.403	0.389	0.672
	(1.865)		(1.837)			(1.961)	(1.817)	(1.827)
parolepc	21.36		20.84			21.01	22.87*	23.08
	(14.53)		(14.62)			(14.83)	(13.62)	(14.67)
prisonerscustodypc	16.30		16.04		27.82	19.13	17.53	17.99
	(16.89)		(16.73)		(18.74)	(18.28)	(16.78)	(17.53)
Population Density	-0.000704		-0.000903	-0.000632*	-0.00215	-0.000854	-0.000615	-0.000875
	(0.00209)		(0.00199)	(0.000355)	(0.00203)	(0.00197)	(0.00221)	(0.00202)
Population Growth	1.32e-07		1.48e-07	-2.95e-08	1.35e-07	1.27e-07	1.54e-07	1.42e-07
	(1.30e-07)		(1.32e-07)	(1.02e-07)	(1.24e-07)	(1.31e-07)	(1.33e-07)	(1.28e-07)
Gallons of Ethanol Consumed Per Capita	0.0863		0.108	0.333***	0.111	0.115		0.0849
	(0.102)		(0.0862)	(0.0771)	(0.0995)	(0.102)		(0.0807)
Constant	7.734***	8.211***	7.929***	7.936***	8.074***	7.815***	7.717***	7.869***
	(0.359)	(0.0109)	(0.271)	(0.248)	(0.381)	(0.359)	(0.372)	(0.260)
Observations	1,074	3,004	1,074	2,433	1,136	1,074	1,074	1,074
R-squared	0.940	0.876	0.940	0.872	0.935	0.938	0.940	0.939

Note.—All standard errors are in brackets clustered at the state level. * Statistically different from zero at the .1 level. ** Statistically different from zero at the .05 level*** Statistically different from zero at the .01 level. Regressions include controls. All regressions include year and state fixed effects. [i] Any Legal Law represents any change of legality, be it medical marijuana legalization, decriminalization or recreational marijuana legalization. [ii] All analysis was conducted with Stata (Version 13), and standard errors for the model were clustered at the state level. Coefficients rounded to 1 significant figure. Standard errors rounded to 3 decimal places.