Is Legal Pot Crippling Mexican Drug Trafficking Organizations? The Effect of Medical Marijuana Laws on US Crime[*]

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Abstract

We examine the effect of medical marijuana laws (MML) on crime treating the introduction of MML as a quasi-experiment and using three different data sources. First, using data from the Uniform Crime Reports, we show that introduction of MML leads to a decrease in homicides, aggravated assaults and robberies in states that border Mexico. We show that the reduction in violent crimes is strongest for counties close to the border, while there is no significant impact of MML on crime for counties located further inland. Second, using Supplementary Homicide Reports' data we show that the decrease in homicides can largely be attributed to a drop in drug-law and juvenile-gang related homicides. Third, using STRIDE data, we show that the introduction of MML in Mexican border states decreases the quantity of cocaine seized, while it increases its price. All three results are consistent with the theory that the introduction of MML reduces activity by Mexican drug trafficking organizations (DTOs) and their affiliated gangs in the border region. MML exposes DTOs to legitimate competition, and substantially reduces their profits in one of their most lucrative drug markets. This results in a decrease in drug- and gang-related crime in the Mexican border area. Our results survive a large variety of robustness checks. The results indicate that decriminalization of the production and distribution of drugs may lead to a reduction in violence in markets where organized drug criminals are replaced by licit competition.

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Michael Braun, the former chief of operations for the D.E.A., told me a story about the construction of a high-tech fence along a stretch of border in Arizona. "They erect this fence," he said, "only to go out there a few days later and discover that these guys have a catapult, and they're flinging hundred-pound bales of marijuana over to the other side." He paused and looked at me for a second. "A catapult," he repeated. "We've got the best fence money can buy, and they counter us with a 2,500-year-old technology." New York Times, Keefe (2012)

1 Introduction

Most illicit drugs in the US are supplied through Mexico and every year around 6 billion dollars find their way back across the border as profit for the large drug trafficking organizations (DTOs) (Kilmer et al., 2014). DTOs are a major contributors to crime in US border states. Their namesake activity - the smuggling of illicit drugs - is known to be paired with violence as they are willing to protect their products with lethal force. On the US side of the border they are allied with local gangs, which also contribute to crime in the border region (National Gang Intelligence Center NGIC, 2011). It is no surprise that US law enforcement has focused a large part of its efforts and resources on deterring DTOs from importing their drugs into the US. A prime example of this is given in the quote on the top of this page. Yet, the quote by Micheal Braun indicates that even the most advanced technologies can often be circumvented by Mexican DTOs.

In this paper we argue that a different policy may have inadvertently been more effective in decreasing the role of Mexican DTOs within the US. Medical marijuana laws (MML) have been introduced in more than twenty states across the US. The primary purpose of MML is to allow the consumption and production of marijuana for medical purposes. However, medical purposes are very broadly defined, and can range from severe conditions such as cancer to much milder conditions such as (perceived) headaches or back pain. As a result, MML *de facto* decriminalize small-scale consumption *and* production of marijuana within the US.

We argue that the main difference between states with and without MML is not the availability of marijuana. Many studies show marijuana is widely available in states without MML in place (e.g. National Drug Threat Assessment Report NDIC, 2011, Kilmer et al., 2014). Moreover, a large number of states have decriminalized the use of marijuana in policies dating back to the 1970's. Instead the main difference between states with MML, and states without MML lies in the origin of the drug. Traditionally, marijuana markets have been firmly in the hands of Mexican DTOs. MML create legitimate competition to the DTOs by increasing the local production of marijuana within the US.

Note that MML is different from earlier decriminalization policies in the US and other countries. These policies typically decriminalize the use of marijuana. However, they do not legalize production and distribution of marijuana. MML is the first policy that legalizes production and distribution of the drug, as long as the drug is intended for medical purposes. This gives us a unique opportunity to evaluate what the impact of such a policy is on previous illicit suppliers of marijuana.

There is a large amount of anecdotal evidence that suggests MML have indeed increased marijuana production within the US. Turning first to production in the US: production of marijuana has increased more than twofold in the period 2005-2009, according to the 2011 National Drug Threat Assessment Report (NDIC, 2011), coinciding with the introduction of

MML in many states.[1] In addition, price data indicates that the quality-adjusted price of marijuana has decreased by 6 percent in the period 2009-2012 alone (UNODC, 2014). In the background section we present self-collected data on the number of marijuana dispensaries in MML states, which shows that take-up of medical marijuana indeed appears to be substantial.

Several articles in popular media suggest that the increase in production that results from MML and the later legalization of marijuana in Colorado and Washington negatively affected the activity of Mexican DTOs (e.g. articles from the Washington and Huffington Post Khazan, 2012, Miroff, 2014, Knafo, 2014). The title of our paper was inspired by an article in Vice News which proclaims that "Legal Pot in the US is Crippling Mexican Drug Cartels" (O'Hara, 2014).

If MML have indeed crippled Mexican DTOs in the US, we should see that the introduction of MML leads to a decrease in violent crimes committed by DTOs and the gangs with which they form alliances. Since DTOs and their affiliated gangs conduct most of their activities in counties close to the Mexican border, it follows that the reduction in crime should be strongest when an MML is introduced within the border region.

To test our theory we use crime data from several different sources. First, we use the Uniform Crime Report (UCR) data which records felony crime rates for all US counties. UCR is a panel data set with violent and property crime rates for each state, split into seven crime categories. Our analysis focuses on homicides, aggravated assaults, and robberies as these crimes are often connected to activities of DTOs and their affiliated gangs (see NGIC, 2011). Second, we use the Supplementary Homicide Reports (SHR) data, which gives information on the circumstances surrounding homicides committed in the US. This data allows us to see whether homicides are related to drug violence. Both data sets cover the time period 1994-2012.

Our main analysis applies a difference-in-difference-in-difference (DDD) methodology where we divide counties in four groups depending on i.) whether the county is located in a Mexican-border state or an inland state, and ii.) whether the state introduced MML or not. The DDD methodology allows us to fully control for all shocks to the crime rate that affect all states on the border. Examples of such shocks are increases in border patrols, and increases in Mexican law enforcement. In addition, we explicitly control for observable confounding factors that may be correlated to both the introduction of MML and the crime rate, and we include state-linear time trends to control for possible unobservable confounding factors. Finally, we augment the analysis, by adding a specification where we interact the treatment dummy for the introduction of MML with the distance to the border. This allows us to verify that within Mexican-border states the effect of MML on crime is strongest for counties located close to the border.

As with any DDD analysis, identification relies on a common-trend assumption. We test the common-trend assumption using a placebo test in the spirit of Autor (2003). Evidence from the placebo test shows that trends prior to the introduction of MML follow a similar trend in treatment and control states.

Our main result shows that MML lead to a strong reduction in the violent crime rate for counties in the Mexican-border states. In these counties the violent crime rate decreases by between 10-20 percent depending on the specification. The decrease is strongest in robberies which decrease by 26 percent, followed by homicides at 11 percent and aggravated assaults with 10 percent. When we consider the distance to the border, we find that the strongest decrease in the violent crime rate occurs in counties in close proximity to the border while

[1] This estimate likely represents a lower bound, since production is measured as plants eradicated by law enforcement, while many farms are protected from eradication by MML.

the effect weakens with the distance of a given county from the border. We find no robust significant effect of MML on crime in counties that are located more than 350 kilometer from the border.

Our point estimates suggest that MML decreases crime in all 3 border states that have introduced MML. However, the effect is most robust in California. This may be the result of t

The SHR data reveals that MML decrease drug-law and juvenile-gang-related homicides by 46, and 34 percent, respectively within states on the Mexican border. This result is strongly suggestive of the fact that MML in the Mexican-border region is effective in reducing crimes related to drugs and drug trade.

Since DTOs sell a number of other illegal drugs we also investigate whether there are spillover effects to other drug markets using a third data source: the System to Retrieve Information from Drug Evidence (STRIDE) from the Drug Enforcement Administration (DEA) for the period 1994 - 2007. This data records narcotic seizures and prices of drugs, thereby allowing us to investigate the effect of MML on the market for illicit drugs. We find evidence that MML in Mexican border states has decreased the quantity of powdered cocaine seized, while simultaneously increasing its price. This implies that MML leads to a negative supply shock in the market for powdered cocaine, consistent with the theory that MML reduces the activity of Mexican DTOs. The supply shock could for example be explained if marijuana and cocaine are often smuggled together, or if proceeds for marijuana are used to invest in cocaine purchases from cocaine-producing countries. However, we do not find consistent evidence for negative supply shocks for any of the other drugs in the STRIDE sample. This could imply that those negative shocks are absent, or that they are obscured by other interactions between MML and the demand or supply of other drugs.[2]

We perform several robustness checks to confirm our results. First, we exclude counties with more than 250,000 inhabitants as crime trends in metropolitan areas follow a strong downward trend during the period we study (see Levitt, 2004; Kneebone and Raphael, 2011). This does not affect our main result significantly. Second, we allow for spillover effects between states with MML and states without MML. We show that when a neighbor introduces MML this creates a negative spillover on crime in states that border Mexico. This is consistent with the theory that MML reduces the profitability of drug smuggling routes. In this specification our point-estimate for the direct effect of MML on crime is virtually unaffected. Third, we estimate our model in one - to five-year differences, instead of levels. The effect of MML on crime is not significant in one-year differences, indicating that MML have no effect on crime in the first year after introduction. However, the effect becomes significantly negative in a specification using two-year differences. When we use four- or more-year differences, the estimated effect is indistinguishable from our main result, indicating that it takes around 4 years for the effect of MML on crime to appear. Fourth, we study the effect of heterogeneity in MML between states. In particular, Pacula et al. (2015) and Alford (2014) note that there may be a difference between MML that only allow for home cultivation and MML that allow for marijuana dispensaries. This would be a concern, if differences in the specific allowances of MML are correlated with their geographical proximity to the border as this would contaminate our results. We find that when we control for differences in MML, the negative effect of MML on crime at the Mexican border remains. In particular, we show that violent crimes at the Mexican border decrease when an MML allows for home cultivation, and this decrease becomes stronger after the opening of the first licensed dispensary. We should note that the identification of the latter effect is weak since all MML states at the Mexican border open

[2]One such interaction could be the gateway drug hypothesis, which would imply that MML leads to an increase in the demand for other drugs.

their first licensed dispensary one or two years after the adoption of MML.

Our research is of importance to policy makers who consider legalizing or decriminalizing marijuana production in their jurisdiction. We find that MML strongly decrease crime in regions where violent Mexican DTOs and their affiliated gangs are effective. We expect even stronger effects of full legalization of marijuana production, since this will allow for large-scale production by corporations, likely pushing the DTOs completely out of the profitable market for marijuana. Thus, legalization might prove to be a way to reduce violent crime, in regions where marijuana and organized crime are strongly interlinked.

The remainder of this article is organized as follows. The next section discusses related literature. The third section provides a theoretical link between MML and crime. The fourth section describes the data while the fifth section discusses methodology and the results. The sixth section presents robustness checks. The final section concludes.

2 Related Literature

MML have recently become a popular instrument for a variety of societal issues related to drug consumption (See e.g. Anderson et al., 2013; Chu, 2012, 2013; Pacula et al., 2015; Morris et al., 2014; Alford, 2014). Most related to our study are Morris et al. (2014), and Alford (2014) which investigate the relationship between MML and crime. Using state UCR data, Morris et al. (2014) find a non-significant negative relationship between MML and violent crime. The only exception is homicides for which the relationship with MML is significantly negative. Using county data and county controls, we show that there is also a negative relationship between MML and other violent crime. Moreover, we show that this negative relationship is driven entirely by counties in proximity to the Mexican border.

Alford (2014) studies the effect of the specifics of MML on crime. She finds that MML which allow for dispensaries have a positive effect on both violent and property crimes. We partly replicate her result. We show that violent crime is positively related to MML that explicitly allow for dispensaries. However, in some states, including the largest MML state California, a large number of dispensaries received a license at the county level prior to the amendment of the MML that allows dispensaries to open throughout the state (see also the discussion in Anderson and Rees, 2014). In Mexican border states we find that both MML that allow for home cultivation, as well as the opening of the first dispensary have a negative effect on crime in Mexican border states.

There have been a number of studies abroad on the effect of the decriminalization of marijuana possession on crime. Adda et al. (2014) look at the effect of marijuana decriminalization on crime in a London borough. They find that crime falls after marijuana is decriminalized. However, marijuana possession offenses increase, and this effect persists even after the policy ends. In another UK quasi-experiment, Braakman and Jones (2014) find no effect of the 2004 decriminalization in the UK on crime and drug consumption. The main difference between these studies and our study is that marijuana decriminalization does not affect the supply chain, as both growing and distributing marijuana remain an illegal activity when marijuana is decriminalized. On the other hand, MML do affect the supply chain, as they allow local farmers to grow marijuana, and to sell it at marijuana dispensaries.

The market for marijuana is strongly interlinked with the market for other illicit drugs. It is often argued that marijuana is a complement to the demand of other drugs, in a theory known as the gateway drug hypothesis. According to the theory, after consumption of marijuana users are more likely to consume other illicit drugs habitually, making marijuana act as a gateway into addiction. However, empirical evidence is mixed, with some papers finding that consumption of marijuana causally increases the demand for other drugs (e.g. DeSimone, 1998; Ramful and Zhao, 2009), while others find no effect (e.g. Van Ours, 2003; Morral et al., 2002; Chu, 2013), and some even indicating that marijuana is a substitute to the consumption of other drugs(e.g. Model, 1993). Chu (2013) uses MML to test the gateway drug hypothesis and finds no significant effect of MML on the arrests for possession of other drugs. Moreover, using substance treatment admission data, he rather finds that MML may decrease heroin treatment admissions.

We add to this literature by showing that MML lead to a reduction in seizures of other illicit drugs which is consistent with a negative supply shock. This complicates any test for the gateway drug hypothesis, since when supply chains of illicit drugs are interlinked, a change in the demand of marijuana may affect the supply of other drugs.

In addition to the relationship between marijuana and other illicit drugs, there is another strand of the literature which examines the complementarity in demand between marijuana and alcohol use. Anderson et al. (2013) find a significant negative effect of MML on alcohol-related accidents and survey-reported alcohol use. Both results indicate that marijuana and alcohol are demand substitutes. This finding corresponds with earlier results in DiNardo and Lemieux (2001) who show that an increase in the drinking age increases marijuana consumption. On the other hand, Pacula (1998) shows that marijuana consumption decreases with the beer tax, indicating that the two goods are complements. Additionally, Pacula et al. (2015) finds no evidence for an effect of MML on alcohol abuse, using various survey measures of alcohol use. We add indirectly by studying the degree of complementarity in demand between alcohol and marijuana through the effect of MML on alcohol-related homicides. With our data we do find a positive relationship between MML and alcohol-related homicides in Mexican border states. This could indicate that the passing of MML increases alcohol consumption. However, the effect is only significant at the ten percent level, and the number of alcohol-related homicides is very small. Hence, this result should be interpreted with caution.

3 Background

In this section we introduce our theoretical framework. First, we describe the legal impact of MML on marijuana consumption and production. Second, we explain the link between MML, DTOs and the demand and supply of illicit drugs.

3.1 Legal Impact of MML

Prior to MML marijuana was strictly prohibited in some states and decriminalized in other states in a policy that typically dates back to the 1970's.[3] If the drug is prohibited, this means that even possession and use of small quantities of marijuana could lead to punishment in jail. If the drug is decriminalized this implies that the penalty for possession of small quantities is limited to a small fine. In either case, prior to MML no state allowed for any form of production or distribution of the drug.

When a state introduces an MML it allows patients to consume marijuana for medicinal purposes. The most important of these purposes is pain reduction. Most states with MML allow doctors to prescribe marijuana as a pain killer for general complaints related to pain, such as migraines and back pain. Since it is difficult for doctors to verify whether pain complaints are real, MML *de facto* make marijuana legally available for a large group of 'patients'.

[3]Nevada in 2002 and Massachusetts in 2008 are the only states that decriminalized marijuana during the time span we study in this paper. We control for decriminalization in Nevada and Massachusetts in our analysis.

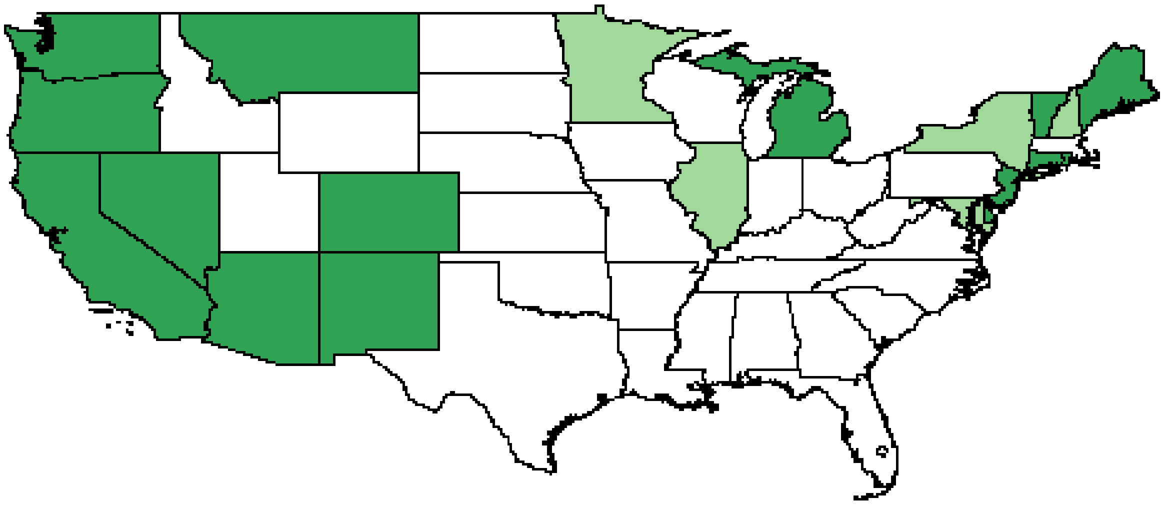

Figure 1: Map of Medical Marijuana Laws

Notes: This graph shows the states in which MML have been introduced. Not shown are Alaska and Hawaii, which have also introduced MML. Dark shade corresponds to states that have introduced MML until the end of 2012, while light shaded are state that have introduced MML after the beginning of 2013.

Patients with a prescription for marijuana can generally obtain the drug in two ways. First, they are allowed to grow a limited number of plants in their own homes. Second, in some states patients can obtain marijuana from marijuana dispensaries.

Dispensaries are typically organized as co-operative associations (collectives). Members of the collective can either be producers, consumers or both. If a dispensary has x patients, the producers of the dispensary are on aggregate allowed to grow x times the number of plants allowed for a single patient. In some states/counties producers can be a member of multiple dispensaries allowing them to scale up their production substantially, but in other states/counties this is not allowed.

At the federal level all usage, sales and production of marijuana are felony offenses subject to imprisonment. However, the large majority of law enforcement is employed at the state or county level. As such, the risk of federal prosecution is relatively small for small-scale operations. Hence overall, MML significantly reduces the risk of prosecution for both consumers, producers and distributors of marijuana.

In figure 1 we present a map of the United States, where states with MML are shaded. Most relevant for our study is the Mexican border region. As can be seen, in this region all states except Texas have adopted an MML.

Table 1 presents an overview of the MML. A dummy for the introduction of MML serves as the main independent variable in most of our analysis. However, in some of our robustness checks we also consider the specifics concerning each MML. In particular, we consider whether an MML allows for home cultivation, and dispensaries, and we consider whether dispensaries are actually in place in a state.

As can be seen in Table 1, MML in most states have a provision for home cultivation from the moment they are enacted, with only a few exceptions. However, not all MML have a provision for dispensaries. This does not necessarily imply that the state does not have licensed dispensaries. For example, the initial MML that was introduced in California in 1996 did not specifically allow nor disallow dispensaries. Statewide regulations for dispensaries were only adopted in 2004. Prior to 2004 many counties had already licensed dispensaries. As far

Table 1: Medical Marijuana Laws

State	Date Active	Home Cultivation	Dispensaries	Dispensaries Open	Number of Dispensaries per 100,000
Alaska	04.03.1999	Yes	No	No	NA
Arizona	14.12.2010	Yes	Yes	2012[a]	0.42
California	06.11.1996	Yes	2004	1997[b]	5.11
Colorado	01.06.2001	Yes	2009	2009[a]	8.79
Connecticut	01.10.2012	No	No	No	NA
DC	27.07.2010	No	Yes	No	NA
Delaware	01.07.2011	No	Yes	No	NA
Hawaii	28.12.2000	No	No	No	NA
Maine	22.12.1999	Yes	2009	2011[a]	0.82
Michigan	04.12.2008	Yes	No	2010[a]	0.85
Montana	02.11.2004	Yes	No	2009[a]	1.27
Nevada	01.10.2001	Yes	No	2011[a]	0.07
New Jersey	18.07.2010	No	Yes	2012[a]	0.07
New Mexico	01.07.2007	Yes	Yes	2009[c]	0.62
Oregon	03.12.1998	Yes	No	2010[a]	1.56
Rhode Island	03.01.2006	Yes	2009	No	0.47
Vermont	01.07.2004	Yes	2011	No	NA
Washington	03.11.1998	Yes	No	2010[a]	1.88

Notes: The Table presents MML and their specific provisions up to the year 2012. The second column presents the date the law became active, the third column shows whether there is a statewide allowance for home cultivation, the fourth column gives the same information about dispensaries, the fifth column shows the date when the first licensed dispensary opened, and the final column gives the number of dispensaries per 100,000 inhabitants in each states. "No" means that the original MML does not allow for the feature in question, while "Yes" means that it does. Whenever some feature is allowed in a later amendment to original law the year is given. For example, in California MML became active in 1996. Home cultivation was immediately allowed, while dispensaries were not allowed statewide until 2004. 1997 is the date in which the first licensed dispensary opened. All information except the final two columns comes from `procon.org`. For the fifth column the sources are listed below. The final column contains self-collected data through the website `weedmaps.com` on January 26th 2014.
[a] Source: Anderson and Rees (2014)
[b] Source: Novack (2012)
[c] Source: DEA (2013)

as we know, the first county-licensed dispensary opened in San Francisco in 1997, and there were at least 55 licensed dispensaries by 2003 in California, (Gieringer, 2003). On the other hand, some MML do allow for dispensaries but there is often a time-lag between the passing of the MML, and the first opening of a dispensary. Therefore, we have added a column to the Table with the date in which the state first opened a licensed dispensary. These dates are partly the result of work by Anderson and Rees (2014) and of a report by DEA (2013) which documents the opening of dispensaries for some states. In the case of California these sources could not confirm the first opening of a licensed dispensary. Therefore, we conducted a Google search to see when the state opened its first licensed dispensary. Several sources, among which Novack (2012), confirmed that the first licensed dispensary opened in 1997 in San Francisco.

MML appear to have increased the supply and demand of both legal (medical), and illegal marijuana within the US. Turning first to demand, Pacula et al. (2015) find that MML lead to an increase in self-reported use of marijuana. Chu (2012) shows there is a positive relationship between MML and marijuana-related arrests, indicating that when MML are in place, illegal demand for marijuana increases. Although we are not aware of a causal evidence in the US, Walsh et al. (2013) show that MML in Canada also substantially increase the demand for (legal) medical marijuana. On the supply side, NDIC (2011) shows that the illegal production of marijuana within the US as measured by plants eradicated has increased twofold in the period 2005-2009.[4]

To our knowledge no data is available on the production of (legal) medical marijuana. However, in the final column of Table 1 we present self-collected data on the number of dispensaries in each MML state in 2014 per 100,000 inhabitants. The data is collected through the website `weedmaps.com`, which is dedicated to locating the nearest marijuana dispensary. Not all dispensaries are listed on Weedmaps. As a result, the numbers presented in column 6 of Table 1 should be seen as a lower bound for the number of dispensaries available. Unfortunately, to our knowledge, there is no panel information on the number of dispensaries in each state. Nevertheless, the number of dispensaries listed in Table 1 can be seen as a rough measure for the take-up rate of MML.

As can be seen from the table, the average number of dispensaries in states for which we found data is around 1.7 per 100,000 inhabitants. For comparison, the number of Walmarts per 100,000 inhabitants in the US is around 0.5. As such, in states that list dispensaries on Weedmaps, the number of dispensaries outnumbers the number of Walmarts by a factor of 3 on average. Underlying this average is substantial heterogeneity. In California and Colorado have a very high number of dispensaries, whereas there are very few listings in Minnesota and New Jersey. Importantly for our research question, in the border states Arizona, and New Mexico the number of dispensaries is about as large as the number of Walmarts. If we proxy the take-up rate by the number of dispensaries per 100,000 inhabitants, then take-up at the Mexcian border is by far largest in California, and a lot smaller in Arizona and New Mexico.

3.2 DTOs, Drugs and Crime

In Mexico there are 7 major DTOs that control almost all the drug trade between Mexico and the US (NDIC, 2011). Through most of our sample the Arallano Felix Organization, also known as the Tijuana cartel, located on the Mexican West-Coast, is the largest DTO. However, in recent years this DTO is falling into decay, and the Sinola Cartel located in the center of Mexico has replaced its role as Mexico's largest drug cartel. Sinola's annual revenue

[4]The increase in illegal marijuana production may be explained by the fact that law enforcement agencies within MML states do not have the means to distinguish between medical and illegally grown marijuana.

Figure 2: Map of Territorial Division of DTOs

Notes: The map shows the territorial division of Mexican DTOs in 2011 (source: NDIC, 2011).

is estimated at 3 billion US dollar (Fortune Magazine Matthews, 2014).

The main activity of Mexican DTOs is drug distribution. Within Mexico DTOs are strictly geographically separated, and each controls its own territory and smuggling routes into the US. Figure 2 shows the territorial division of Mexican DTOs in 2011.

Once the drugs enter the US, DTOs sell their drugs to affiliated gangs. The affiliated gangs each have a presence in at least one of the four Mexican border states. This likely indicates that representatives of the DTOs do not often venture further North than the border states.[5] The affiliated gangs distribute the drugs further into the US (NGIC, 2011; NDIC, 2011).

Both DTOs and their affiliated gangs are well-known for their contribution to violent crime along the Mexican border. In particular, they have been known to engage in kidnapping, assaults, robberies and homicides in Mexico and in the US (NGIC, 2011; NDIC, 2011). Therefore, we concentrate our analysis on the latter three crimes for which data is available in the UCR register.

Drugs sold by the DTOs can be roughly categorized into four categories: marijuana, cocaine, opium-based drugs of which heroin is the most important, and synthetic drugs, most prominently methamphetamine. All DTOs are diversified and sell a range of these drug products. This strategy is likely optimal, since DTOs and their owners do not have access to capital markets. In effect, diversification allows drug kingpins to smooth their consumption. Moreover, retained earnings of one drug can be used to pay investment cost on other drugs.

In this respect, marijuana plays a special role. Heroin and other opium-related drugs are

[5]We have established this by cross-checking the list of gangs allied to Mexican DTOs with the list of gangs that are active in each state in NGIC (2011).

usually imported from South-America or Asia. Mexico has recently increased its production of poppy plants (UNODC, 2010, 2014), from which heroin is produced, but even locally produced poppy has to go through laboratory refinement in order to create heroin. Cocaine has to be purchased from Columbian DTOs. Production of synthetics requires laboratory equipment. As such, production of each of these drugs, in particular at the large scale required for the DTOs, requires major investment.

On the other hand, marijuana can be grown in Mexico with almost zero up-front cost. Additionally, marijuana is the largest drug market in the US. Moreover, prior to MML Mexico had a virtual monopoly on marijuana in the sense that they were by far the largest producer of marijuana in North America (UNODC, 2010, 2014). Therefore, marijuana is probably a major cash crop for the DTOs. As such, it is likely that proceeds of marijuana are used for investment in the other drugs[6].

If MML causes states to produce more marijuana this can have severe repercussions on DTOs and their affiliated gangs. Smuggling routes into the US will decrease in value as both the demand and the price of one of their major drugs falls. This could cause DTOs to decrease their activity within the US, as profitability drops. If this indeed occurs, it should decrease crime in the Mexican-border area. Moreover, as DTOs also sell other illicit drugs, a drop in their activity may lead to a negative supply shock in other illicit drugs as well.

Anecdotal evidence supporting this theory is the demise of the Tijuana Cartel. As can be seen in figure 2, the main smuggling routes for the Tijuana cartel lead to California which was the first state to introduce MML in 1996. Part of the demise of this cartel may therefore be explained by MML in California.[7] In addition, articles in popular media suggest that locally produced marijuana is affecting the profits and activities of DTOs as discussed in the introduction.

We study this theory using crime data. In particular, if MML negatively affect the activity of DTOs we expect that MML introduced in a Mexican-border state leads to a reduction in crimes committed within the border region of that state.[8] We would expect that this decrease in crime is related to violent crimes such as homicides, assaults and robberies which are commonly committed by DTOs and their affiliated gangs. In addition, whenever the circumstances behind the crime can be established, we expect the drop in crime to be related to decreases in drug trade and gang related crimes. Finally, the reduction in DTO activity may also result in a negative supply shock in the market for other drugs.

Note that it is unlikely that the decrease in DTO activity occurs immediately after introduction of MML. It takes time to set up marijuana farms within the US. Moreover, the extra competition of local US farms may at first lead to an increase in violence between Mexican DTOs, in an effort to retain market share. Although a lot of this infighting will likely take place in Mexico, some of it may spill over to the US. Finally, some criminal organizations may be able to switch over to other criminal activities such as the trade in other drugs and human trafficking. However, it stands to reason that legal marijuana markets in the US in the medium - to long-run lead to a significant drop in the profitability of drug-related crimes, and will hence, reduce activity by DTOs. In our econometric design we try to carefully separate

[6]This has also been asserted in several media articles, e.g. Keefe (2012)

[7]Other factors have also contributed to the demise of the Tijuana cartel. In particular, Mexican law enforcement started a campaign against the DTO in 2006. Our DDD identification strategy controls for this and other increases in Mexican law enforcement.

[8]On top of the direct effect of MML in a border state on crime in the same state, an MML in an inland state could also influence crime in the border region. To see this note that MML in an inland state may reduce the total amount of marijuana smuggled over the Mexican border. In our Methodology section we explain how we control for this and possible other spillover effects.

between the short - and long-run effects to verify whether the decrease in crime can credibly be attributed to the effect of MML on Mexican DTOs.

3.3 Alternative Mechanisms

MML may affect crime through a number of alternative mechanisms. Goldstein (1985) discusses three main channels through which drugs can affect criminal activity. First, through the 'pharmacological channel' drugs may increase aggression, and therefore, violent crime. Second, there is an 'economic channel' in that drug users may resort to crime in order to finance their drug habit. Finally, there may be a 'systemic channel' because drug contracts cannot be enforced in the courts, and hence, disputes between drug market participants are often solved with violence. Moreover, according to the drug gateway hypothesis, after consumption of marijuana users are more likely to consume habitually other illicit drugs, which itself can again influence crime through the three aforementioned channels.

However, unlike the DTO channel we consider in this paper, these alternative channels do not have a clear geographical dimension. For example, if MML increases crime through the pharmacological channel this will affect states like New Mexico, and Washington alike. However, if MML affects activity by DTOs this should have a strong effect on crimes in New Mexico, and a negligble effect on crimes in Washington, as DTOs are simply not active within Washington. Hence, if we see that MML has a significantly stronger negative effect on crime in the border region of New Mexico, than in Washington, this is an indication that MML are affecting the activity of DTOs. If in addition, the strong reduction in crime in New Mexico can be attributed to crimes habitually committed by DTOs, such as drug-law homicides, this provides even stronger evidence that MML is effective in reducing the role of DTOs.

Hence, for our analysis, we do not need to rule out that MML also affects crime rates through other channels. Instead our strategy is to isolate the DTO-channel by considering the heterogeneity in the 'treatment effect' of MML on crime in counties located close to the border, and counties located inland. This allows us to answer the question whether MML are effective in crippling Mexican drug cartels.

4 Data Description

We use three different data sets to test the effect of MML on crime. First, we use UCR data (1994-2012) for data on overall crime rates. Second, we use SHR data (1994-2012), which allows us to examine the homicides by circumstances. Lastly, STRIDE data (1994-2007) on illicit drug seizures and price allows us to examine the relationship between MML and illicit drug markets. For UCR and SHR data, we primarily use county level data. For STRIDE data the unit of analysis is at the state level. In this section we describe each of our datasets in turn. Summary statistics are presented in Table 2.

4.1 Uniform Crime Reports

All local US law enforcement agencies collect data on reported crimes. Summaries of this data are voluntarily submitted to the FBI and reported as the Uniform Crime Reports (UCR). The data include information on violent and property crimes in seven categories. For the purpose of this study we look at the three crimes most commonly associated to drug violence: the number of homicides, robberies and aggravated assaults per 100,000 inhabitants in each jurisdiction.

Table 2: Summary Statistics

Variable	Mean	Std. Dev	Min	Max	Obs
A. UCR[a]					
Violent Crime	230.53	253.57	0.00	8003.68	59061
Murder Rate	3.34	6.68	0.00	329.49	59061
Robbery Rate	38.73	73.42	0.00	1624.38	59061
Assault Rate	188.46	204.97	0.00	8003.68	59061
Coverage Indicator	89.30	28.05	0.00	100.00	59061
B. SHR[a]					
Robberies	0.35	1.35	0.00	45.33	25767
Drug Law	0.17	0.78	0.00	26.53	25767
Gangland	0.03	0.31	0.00	10.82	25767
Juvenile Gang	0.04	0.31	0.00	11.82	25767
Alcohol Influence	0.15	1.05	0.00	45.69	25767
Drug Influence	0.07	1.04	0.00	136.61	25767
C. STRIDE					
Quantity					
Powder Cocaine	1123.83	4351.10	0.00	61556.32	688
Crack Cocaine	333.53	1216.41	0.00	18292.79	688
Methamphetamine	158.75	553.06	0.00	7804.66	688
Heroin	181.67	663.12	0.00	9332.65	688
Bust Count					
Powder cocaine	129.16	171.94	0.00	1047.00	688
Crack cocaine	185.40	444.95	0.00	3786.00	688
Mehtamphetamine	79.04	163.96	0.00	1555.00	688
Heroin	98.07	174.58	0.00	1268.00	688
Price by Distribution Levels[b]					
Powder Cocaine Street Level	738.76	675.38	41.32	2884.74	464
Powder Cocaine Street Low Distribution	242.86	299.30	8.73	2125.77	529
Powder Cocaine Street High Distribution	64.97	84.12	3.53	1683.39	599
Powder Cocaine Wholesale	31.43	14.08	2.01	85.82	582
Crack Cocaine Street Level	554.77	566.68	17.44	2828.28	483
Crack Cocaine Low Distribution	135.89	143.90	6.93	1504.50	576
Crack Cocaine Wholesale	36.16	16.42	2.16	110.07	577
Methamphetamine Street Level	412.41	456.89	3.54	2952.32	441
Methamphetamine Low Distribution	74.84	72.17	2.22	969.65	469
Methamphetamine Wholesale	22.07	18.20	2.07	138.93	367
Heroin Street Level	1061.05	1318.23	8.05	9266.34	418
Heroin Low Distribution	405.09	648.27	10.33	7305.00	461
Heroin Wholesale	95.95	72.00	8.10	746.04	473
D. Treatment Variables					
MML Mexico Border	0.02	0.14	0	1	59061
MML Inland	0.06	0.24	0	1	59061
Home Cultivation M. Border	0.02	0.14	0	1	59061
Home Cultivation Inland	0.06	0.23	0	1	59061
Dispensary Legalization M. Border	0.01	0.11	0	1	59061
Dispensary Legalization Inland	0.01	0.08	0	1	59061
Dispensary Operating M. Border	0.02	0.13	0	1	59061
Dispensary Operating Inland	0.02	0.13	0	1	59061
Neighbor M. Border State	0.08	0.37	0	4	59061
Neighbor Inland State	0.28	0.72	0	4	59061
E. Control Variables					
Decriminalization	0.22	0.42	0.00	1.00	59061
Portion Males	0.50	0.02	0.43	0.72	59061
Portion of African Americans	0.11	2.56	0.00	542.74	59061
Portion of Hispanics	0.07	0.13	0.00	0.98	59061
Portion of Age 10-19	0.15	0.02	0.03	0.33	59061
Portion of Age 20-24	0.06	0.03	0.00	0.34	59061
Population	92472.91	299080.78	55.00	9951690.00	59061
Poverty Rate	15.14	6.28	2.00	62.00	59061
Median Income	37627.99	10748.70	12451.50	121250.00	59061
Unemployment Rate	6.08	2.86	0.70	38.40	59061
Distance to M. Border (km)	1489.34	633.66	13.29	3401.73	59061

The Table presents the summary statistics of the variables used in the estimation of the results. The first panel present statistics from the Uniform Crime Reports dataset, the second panel presents statistics from the Supplementary Homicide Reports dataset, the third panel present statistics from the System to Retrieve Information from Drug Evidence dataset. The fourth panel presents our MML independent variables, while the last panel presents the control variables.

[a] All UCR and SHR crime statistics are measured as the number of reported crimes per 100,000 inhabitants.

We also consider the violent crime rate which we define as the sum of the three categories.[9] Unfortunately, UCR data does not contain information on drug crimes. We try to circumvent this by using the STRIDE data described below.

UCR has information on almost all counties in the US. Only 2 counties are missing during the years up to 2000, and none are missing after 2000.[10] However, we filter the data to exclude counties in Hawaii and Alaska, as it is likely that drug violence follows a different pattern for both states.

UCR data is collected at the agency level, and aggregated to the county level by the National Archive of Criminal Justice Data (NACJD). UCR is the most commonly used crime data set for county - and state-level crime analysis in the US. However, it has a number of caveats, the most important of which are described below.

First, The NACJD uses imputation techniques to take into account issues such as law-enforcement agencies spanning several counties (e.g. in big cities like Los Angeles), openings and closures of agencies within a county, and agencies failing to report their crime rate. Prior to 1994 the imputation method was flawed, as is noted by Maltz and Targonski (2002). Moreover, the year 1993 is missing from the UCR county series altogether.

In the period from 1994 onwards the flaw in the imputation method was corrected. Moreover, an indicator variable was added to indicate whether crime rates in a county are imputed or based on actual data. Hence, we focus our analysis on the time period 1994-2012. Fortunately for us, we have two years of data prior to introduction of the first MML in 1996. Our main analysis focuses on the full sample, including counties for which data is imputed. However, we try to solve for the imputation problem in two ways. First, as suggested in Maltz and Targonski (2002), we apply population weights in our analysis. In doing so we are assigning less weight to small counties that are likely to report less frequently. Second, in a robustness check we confirm that our results are robust to dropping county-year observations when data is imputed.

Second, crime data is constructed through crime reports. Crime reports are likely to be a lower bound for the number of crimes committed, as not all crimes are reported to the authorities. Additionally, some agencies reduce their major crime numbers through reporting tricks, for example by reporting aggravated assault as a minor assault (Eterno and Silverman, 2012). It is unlikely that this measurement error is correlated to MML, and hence it should not bias our results. Moreover, a large part of our study focuses on homicides for which reporting issues are unlikely to be a major issue.

Table 2 presents summary statistics for the UCR data in panel A. We observe that the average violent crime rate is 230 per 100 000 inhabitants. Murders are least frequent with only 3 occurrences per 100,000 inhabitants, robberies occur 13 times more often - at 39 crimes per 100, 000, and the assaults are the most common form of violent crime, with 188 crimes per 100,000 persons.

During the period we study crime rates follow a strong downward trend. This negative trend tends to be stronger in urban areas, and weaker in rural areas (see Levitt, 2004). We take this issue into account in placebo and robustness tests.

[9]In most studies, forcible rapes are also included in the violent crime rate, but we exclude them for two reasons. First, rape is not commonly associated to drug violence. Second, reporting issues in rape are likely a larger issue than in the other 3 violent crimes. Our main results are not affected if we use the more common definition of violent crimes which includes forcible rapes.

[10]The missing counties are Miami-Dade, Florida and Broomfield, Colorado.

4.2 Supplementary Homicide Reports

The Supplementary Homicide Reports (SHR) data provides incident level information of a homicide, as reported by the UCR agencies, and collected by the FBI. The data include information of the relationship between a victim and an offender, demographic characteristics of both the victim and offender, types of weapon used and circumstances behind the homicide. Of particular interest for our study are the circumstances. The SHR data classify circumstances behind homicides into 21 categories of which we consider the following six in our study (9 percent of the homicides in the SHR): robberies, drug law, juvenile gang, gangland, homicides committed under the influence of drugs and homicides committed under the influence of alcohol. Drug law homicides are homicides that are related to a violation of narcotic drug laws (e.g. drug trafficking or manufacturing), juvenile gang homicides are homicides that are related to a juvenile gang, gangland homicides are all homicides related to organized crime (except juvenile gangs), and the other three categories speak for themselves. Whenever a homicide may fall under multiple categories, for example an organized crime related homicide committed under the influence of drugs, it is only reported under the more serious offense.

We selected these homicide categories, since they are directly related to drug violence. In particular, the first four homicides categories are often related to drug trade. On the other hand, homicides committed under the influence of drugs are related to drug usage. Morris et al. (2014) hypothesizes that MML may reduce homicides, since marijuana acts as a substitute for alcohol. If this is true, we should see that MML leads to a decrease in alcohol-related homicides, which is why we included this category in our analysis as well. By comparing the impact of MML on drug-trade related homicides to the impact of MML on drug - and - alcohol use related homicides, we can assess whether the effect of MML on homicides is related to its impact on drug trade or its impact on drug and alcohol use.

The caveats described above with respect to the UCR data apply also to the SHR data. On top of that, not all counties that report UCR statistics also report statistics for the SHR database. The number of county-year observations in the SHR data is around 50 percent of the number of observations in UCR data. However, since more populous counties are more likely to report SHR data to the FBI, these counties together represent around 77 percent of the population included in the UCR data.

Summary statistics for the relevant categories are presented in panel B of Table 2. As can be seen, the most common type of homicide in our data is homicides committed during robberies, with 0.73 per 100,000 inhabitants. This number is far less than the average number of robberies committed, presented in panel A and it shows that most robberies end without a death. Following are drug law homicides of which on average 0.63 occur per 100,000 inhabitants, or 3.9 percent of all homicides committed, followed by killings under the influence of alcohol and under the influence of drugs.

4.3 STRIDE Data

To gain information on drug trade in the US we use the STRIDE data, provided by the DEA, which records seizures and (undercover) purchases of drugs by law enforcement officers. The data contains the number of seizures, the quantity seized and the price for each purchase, provided samples of the drug purchase or seizure are sent to the DEA lab for analysis. We have records on drugs in 4 categories: powdered cocaine, crack cocaine, methamphetamine and heroin.[11]

Unfortunately, not all drugs seized in the US are sent to the DEA lab for analysis. To partly resolve measurement issues that come with non-reporting, we aggregate the STRIDE data to the state level. By using state, rather than county data, we resolve issues that result from counties that report zero seizures/purchases during a given year. In the extreme event where an entire state reports zero seizures we treat this as missing observation, rather than an actual zero in our analysis, as we do not believe that any state has zero drug seizures in any drug category during an entire calendar year. Finally, in our regression equation we take care to always take the log of any variable we use from the STRIDE data to ensure that the estimated coefficients are not unduly influenced by outliers. Nevertheless the reader should be aware that date obtained from STRIDE data are not necessarily representative for the US as a whole, and can generally be quite noisy.

In addition to these issues, the literature has identified several issues that apply only to the price data in STRIDE (Arkes et al., 2008). First, the data contains some outliers which are likely the result of a mistake at data entry. Therefore, for powdered and crack cocaine, and methamphetamine, prices per gram less than $2 as well as more than $3000 are excluded. For heroin, prices per gram less than $7.5 and more than $ 10000 are excluded. Second, the price of drugs differs significantly by the distribution level at which the drugs are purchased. Drugs purchased at the wholesale level tend to be cheaper than the same drug sampled at the retail (street) level for the simple reason that each distribution level takes a profit margin. Hence, a comparison of price data between states and over time is not possible unless we classify the price by the distribution level at which the drug is seized. We follow the recommendations given in Arkes et al. (2008), who show that their classification scheme leads to consistent pattern in price comparison between metropolitan areas and over time. In particular, we distinguish between small seizures which are likely the result of seizures at the retail level, medium seizures which we classify as distribution level seizures, and large seizures which we classify as wholesale level seizures.[12]

Our STRIDE data runs from 1994 up to 2007. Unfortunately, we could not obtain more recent data, as the DEA does not distribute data from cases for which the decision in court is still pending. In the first part of panel C of Table 2 we report the quantities of the four drugs we consider. The sizes of the standard error relative to the mean attests to the noise present in the data. On average authorities seize more than 1,000 kg of powder cocaine, 260 kg of crack cocaine, 128 kg of Methamphetamine and 145 kg of Heroin. In the second subpanel we show the number of drug seizures subdivided by each drug. Crack cocaine is most often seized, followed by powdered cocaine, heroin and methamphetamine. The third subpanel shows that heroin commands the highest prices at all level of distribution. At the street level, heroin is followed by cocaine, crack cocaine and methamphetamine. At the wholesale, crack cocaine is more expensive than powder cocaine.

[11] STRIDE can also provide information on marijuana purchases and seizures. However, MML likely has a mechanical effect on the seizures of marijuana, and therefore we have not requested this data.

[12] To be precise, powdered cocaine quantities smaller than 2 grams are classified as street level, quantities between 2 and 10 grams are low distribution level, quantities between 10 and 50 gram are high distribution level, and quantities larger than 50 are considered wholesale level. For crack cocaine quantities smaller than 1 gram are street level, quantities between 1 and 15 gram are distribution level and quantities greater than 15 are wholesale level. For methamphetamine quantities smaller than 0.1 gram are excluded, quantities between 0.1 and 10 gram are considered street level, quantities between 10 and 100 grams are distribution level and quantities greater than 100 grams are wholesale level. For heroin quantities quantities smaller than 0.1 gram are excluded, quantities between 0.1 and 1 gram are considered retail level, quantities between 1 and 10 grams are distribution level and quantities greater than 10 grams are wholesale level.

4.4 MML and Control Variables

In panels D and E of Table 2 we report the main independent variable, and the control variables. Our main independent variable is a dummy variable for the introduction of MML, coded as 1 from the year in which MML was introduced. We differentiate between MML introduced in Mexican Border states and MML introduced in other states. Additionally, we have extracted some of the characteristics of MML, related to the allowance for home cultivation and marijuana dispensaries. We have coded the latter in two ways to account for the whether dispensaries are regulated in the MML, as used in the previous literature, and for the whether dispensaries are actually operating. The higher mean for Dispensaries Operating reflects the fact that in some states dispensaries were opened before the MML regulated dispensaries. These dispensaries typically received a license at the county level. Finally, we have coded a variable Neighbor that should capture spillover effects due to the introduction of MML. The variable is a count for the number of neighboring states that have introduced MML. An overview of the relevant dates and characteristics of each law can be found in Table 1 in section 3.1.

Control variables in our analysis come from the following data sources: the U.S. Census Bureau, Bureau of Labor Statistics and the Bureau of Economic Analysis. We include as control variables for our analysis the shares in the population of: males, African Americans, Hispanics, people aged between 10-19 and people aged between 20-25. Furthermore, we add unemployment rates, poverty rates, median income per capita and a dummy when a state introduces a marijuana decriminalization policy (instead of an MML). Each of these variables is known to correlate with the crime rate (see e.g. Tauchen, 2010). Moreover, we consider it plausible that these variables may be correlated with the introduction of MML. Hence, if we do not control for them, they may bias our estimates. We alsohave data on the minimum distance between the US Mexican border and the center of a each county in our sample, which we use to uncover distance effects.

An average county in our data has a 22 percent likelihood to be in a state where marijuana has already been legalized during the time period under consideration, an even sex ration and small portions of 0.11 percent African-Americans and 0.07 percent Hispanics. Additionally, the portion of inhabitants aged between 10-19 is 15 percent, while for the rest of the 5-year age shares it is 6 percent. An average county has a population of a little less than 100 thousand inhabitants, a poverty rate of 15 percent and a median income of 37 thousand dollars per year. The unemployment rate hovers around 6 percent, and the distance to the Mexican Border is close to 15 hundred km.

5 Methodology and Results

5.1 Empirical Strategy

In our empirical analysis we use two specifications to test our hypothesis. First, we consider whether crime rates in counties located in Mexican border states react differently to the introduction of MML than counties in inland states. We estimate this relationship using the following regression equation:

$$y_{cst} = \beta^{MB} D_{st} B_s + \beta^{inland} D_{st}(1 - B_s) + \alpha_c + \gamma_t + B_s \eta_t + \nu X_{cst} + \sum_{s=1}^{S} \delta_s t + \varepsilon_{cst}, \qquad (1)$$

where y_{cst} is the outcome variable of county c in state s in period t. D_{st} is the treatment dummy which takes value zero if a state has not (yet) enacted MML in period t and one otherwise. B_s is a dummy which takes value one if a county is located in a Mexican border state and zero otherwise. α_c are county-fixed effects. γ_t are time-fixed effects. $B_s\eta_t$ are border-time fixed effects. X_{cst} is a vector of control variables at the county level. The term $\sum_{s=1}^{S}\delta_s t$ are state-linear time trends. Finally, ε_{cst} is the error term. The outcome variables we use are crime rates taken from the UCR, SHR and STRIDE data and are outlined in detailed in the previous section.

In the regression equation parameter β^{MB} captures the effect of an MML on the outcome variable in counties in Mexican border states, while β^{inland} measures the effect of an MML in counties in inland states. Our theory states that MML should have a more negative impact on crime in states on the Mexican border, than in inland states, since MML reduces the activity of Mexican DTOs. We test our theory empirically by establishing whether the treatment effect, β^{MB}, is significantly smaller than β^{inland}.

Following the literature (e.g. Morris et al., 2014, Alford, 2014), we estimate the regression equation using weighted-least squares (WLS), where we weight observations using county population. We are aware of the issues involved with using WLS (see e.g. Solon et al., 2015), and hence also report our main results using OLS instead.

To understand our identification strategy in more detail, first consider the simplest possible specification that does not include border-time fixed effects, control variables, and state-linear time trends. In that case, regression equation (1) estimates a simple difference-in-difference (DiD) model with two treatment groups, i.) counties in Mexican-border states with MML, and ii.) counties in inland states with MML, and one control group consisting of counties in states without MML. In this case, identification of the coefficients β^{MB} and β^{inland} relies on a common-trend assumption, which states that crime rates follow a similar trend in treatment and control counties.

One particular reason why the common trend assumption may fail to hold is if there are common shocks that affect crime rates in all Mexican border states, independent of whether these states have an MML. An example of such a shock could be an increase in law enforcement on the Mexican side of the border, as in Dell (2015). If an increase in law enforcement over our time period decreases crimes committed by DTOs in the US, this may bias β^{MB} downward, as most of the control states are located inland, and hence there crime rates are not as strongly affected by Mexican law enforcement efforts. Other examples of shocks that likely affect crime in the border area are US investment in border controls, and shocks to Mexican DTOs, such as changes in world drug market prices. To account for this, we include border-time dummies, η_t, in our regression equation. The border-time dummies absorb all shocks to the dependent variable that are common to the border area. When we include border-time dummies we effectively identify the causal effect of interest through a DDD specification, where we make use of the fact that we can further divide treatment and control states into two groups: border states, and inland states.

We further include control variables X_{it}, in the regression equation which allows us to control for heterogeneity in crime trends that is correlated to observable variables. The control variables we use are listed in section 4.4, and are all known to be correlated to crime rates. Finally, the state-linear time trends allow us to control for unobserved heterogeneity in crime trends between states, as long as the heterogeneity evolves linearly with time. Note that a further inclusion of county-linear time trend would not affect our estimate of the treatment effect, since the MML dummy only changes value at the state level.

Even in the fully parsimonious model, unobserved heterogeneity in crime trends between states may lead to a violation of our identifying assumptions. Therefore, we test the common-trend assumption explicitly through a placebo test in the spirit of Autor (2003). Moreover, in a robustness check we estimate (1) in 1- to 5-year differences, which allows us to estimate the effect of MML on crime using only the 1-5 year window around the reform.

5.1.1 Distance to the border

Our theory states that the effect of MML on crime is stronger in counties that are closer to the Mexican border. In the empirical strategy described above we use the fact that a county is located in a Mexican-border state as a proxy for a county being close to the Mexican border. The upside of this approach is that it increases the efficiency of our estimates as a relatively large amount of counties are located in Mexican border states. The downside is that some counties in Mexican-border states are closer to the Mexican border than others. For instance, we do not expect that DTO activity plays a major role in crimes committed in Northern California, as this region is relatively far away from the border. Therefore, in our second empirical strategy we explicitly interact distance to the border with the treatment dummy, and estimate the following regression equation:

$$y_{cst} = \beta D_{st} + \beta_2 \log(dist_c) D_{st} + \gamma_t + \log(dist_c)\eta_t + \nu X_{ct} + \sum_{s=1}^{S} \delta_s t + \varepsilon_{cst}, \tag{2}$$

where $dist_c$ denotes the minimum distance of the center of a county from the border measured in kilometers, and log denotes the natural logarithm. Note that we can include the interaction between distance and MML, without additionally controlling for distance, since distance is absorbed by the county-fixed effect. However, by including $\log(dist_c)\eta_t$ we do allow the time-fixed effect to vary with the logarithm of distance from the border. The role of this term is equivalent to the inclusion of border-time dummies in the previous specification.

The treatment effect of MML in this specification is given by $\beta + \beta_2 \log(dist_c)$. Intuitively, β measures the impact of MML on a county that is located at 1 km from the border. β_2 measures the marginal increase in the treatment effect when distance from the border increases by 1 percent. If MML negatively affects Mexican DTOs activity this implies that β is negative, and β_2 is positive.

Taking the log of distance, rather than including it linearly provides a strong test for our theory. To see this, suppose that MML reduces crime in Mexican border states, but it does so by reducing crimes in Los Angeles and San Francisco, without actually reducing crime rates in counties that are close to the border. In log distance terms, Los Angeles is closer to Canada than it is to Mexico. Hence, in that case we are likely to find a positive, or non-significant value for the MML intercept β and a negative or non-significant value for the interaction coefficient β_2, contradicting our main hypothesis. The only way we will find a negative value for the intercept, and a positive intercept for the slope coefficient, is if MML are really effective at reducing crime in the border area. Nevertheless, to ensure that our results are not driven by the functional form assumption we also include a non-parametric specification where distance is subdivided into splines.

5.1.2 Spillover Effects

Identification of the causal effect of MML on crime may be confounded by a number of spillover effects. First, MML may have spillover effects on neighboring states. Legally produced marijuana may be smuggled out of the MML state to neighboring states, which may influence crime rates in these states. Moreover, DTO activity from MML states may be diverted to the neighboring states. In a robustness check we control for this spillover effect by including a count variable which counts the number of neighboring states with MML.

Second, MML in states away from the Mexican border may affect crime rates in Mexican border states. To see this note that MML in an inland state may reduce the demand for marijuana of Mexican DTOs. This could lead to a decrease in the overall amount of marijuana smuggled over the Mexican border, which in turn may reduce crime in Mexican border states. In our empirical specification this spillover effect does not affect our estimates if the reduction in demand affects all four border states at the same rate, since in that case the effect is absorbed by our border-time dummies. However, in practice it is unlikely that this spillover effect spread out exactly along the border. In particular, it is likely that the effect in Texas is stronger than in the other 3 border states. To see this note that Texas has a much longer border than each of the other 3 states, and most of the DTOs have smuggling routes into Texas, as can be seen in figure 2. Since Texas does not have an MML, and is hence part of the control group, this spillover effect implies that our empirical approach may underestimate the reduction in crime related to MML in Mexican border states.

5.1.3 Reverse Causality

One possible channel of reverse causality is that states introduce MML in reaction to a decrease in (drug-related) crime rates. In particular, a state may decide to legalize medical marijuana after observing that trade in drug markets has become less violent. We do not consider this a very plausible channel, as the discussion surrounding the introduction of MML has been mainly focused on the medical arguments, and not on its impact on crime. Moreover, even if states have introduced MML in a response to crime rates, this likely affects both Mexican-border states and inland states. Hence, it should not lead to a heterogeneous treatment effect of MML on crime at the border. Finally, if reverse causality affects our results we should be able to identify this in our placebo test, as in that case the reduction of crime should precede the introduction of MML.

5.2 UCR Results

5.2.1 Placebo Test

Before we present our main result, we first present a placebo test to verify that our econometric specification is able to identify the causal effect of MML on crime. The estimated treatment coefficient in our main analysis may potentially be biased if crime rates follow a different trend in treatment and control states, in the absence of treatment. We test whether the common-trend assumption is satisfied by creating a placebo test where we include the lead of the MML dummy in our regression. The test works under the premise that the lead of MML cannot causally affect the crime rate. This implies that we assume there is no announcement effect. This assumption is plausible, since all MML in Mexican border states were enacted immediately after a public vote, which for each of the three Mexican border states with MML was a close call. Moreover, even if criminals anticipated the enactment of MML, it is not clear what kind of different behavior they would exhibit during the announcement period.

Therefore, if we do find a significant effect of the lead of MML on the crime rate, this implies that crime rates follow a different trend in treatment states, than in control states, and that these differences are not properly controlled with our control variables. If the coefficient on the lead is non-significant and moreover small in magnitude with respect to the contemporaneous

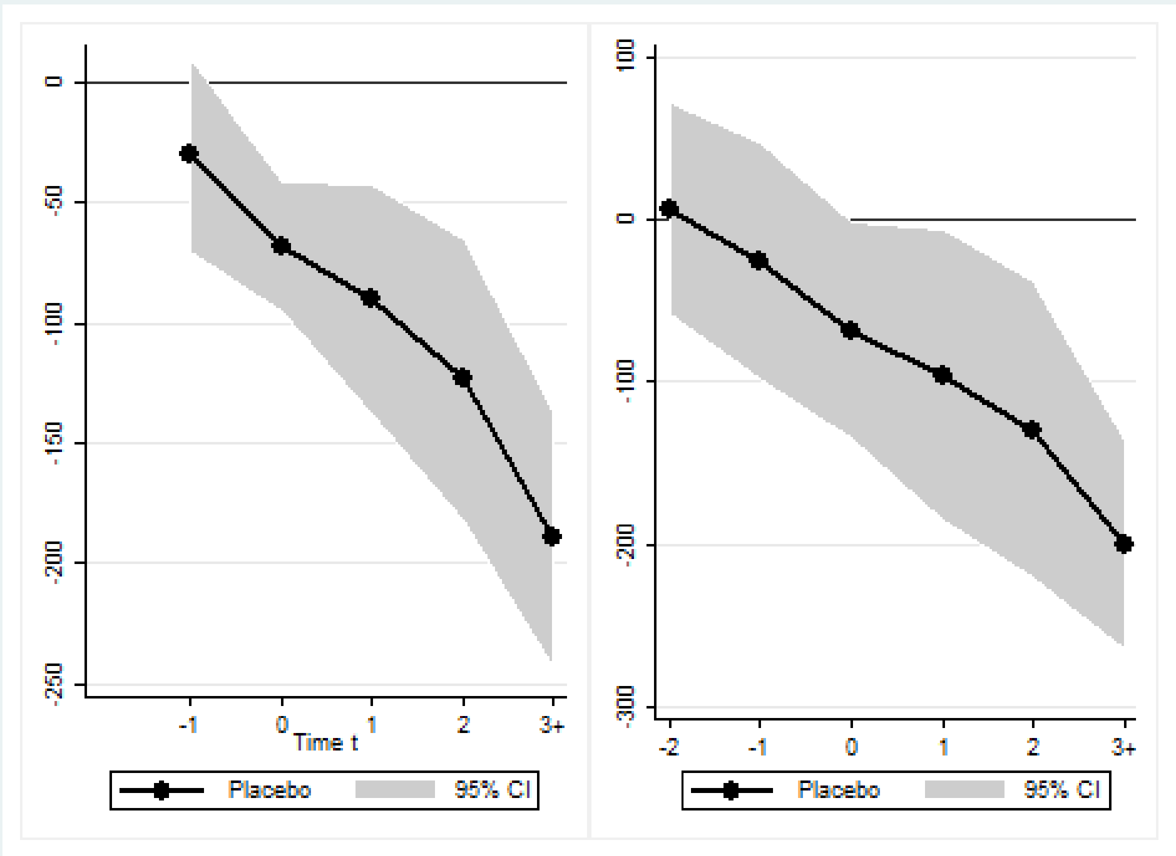

Figure 3: Placebo Tests
Notes: This figure plots the coefficients on MML from the last two columns in Table 3

and lagged effect of MML on crime, we can conclude that trends in the outcome variable are similar in treatment and control states prior to the introduction of MML.

Results are presented in Table 3 and figure 3. The dependent variable in each column is the violent crime rate.[13] The first four columns in Table 3 present estimates from our main sample. Following Autor (2003) we code the MML variables as taking value 1 for the period for which they are labeled and 0 otherwise. The only exception is the three times lagged MML variable which takes value 1 from the period of 3 years after adoption of MML until the end of the sample. The first four columns differ by the number of control variables included, as noted at the bottom of the table.

In column one we estimate a simple difference-in-difference model. We observe that the lead on the MML variable in both Mexican border states, and inland states is approximately zero. This implies that prior to MML, violent crime rates follow a very similar trend in treatment and control states. In Mexican border states we find that crime rates start reducing significantly in the year MML is introduced. The effect of MML on crime becomes stronger with time. This is fully consistent with our theory, as it likely takes time to set up productive capacity that competes with Mexican DTOs. We also test whether the one-year lagged effect of MML on crime is significantly different from the one-year lead effect to verify that crime rates are indeed significantly lower one year after the introduction of MML, then they were

[13]For reasons of brevity we do not present results for placebo tests of the individual crime categories. However, the results are very similar.

Table 3: Placebo Test

VARIABLES	(1) Violent Crime	(2) Violent Crime	(3) Violent Crime	(4) Violent Crime	(5) Violent Crime
L(3). MML M. Border	-237.288***	-222.782***	-189.494***	-185.195***	-200.337***
	(82.823)	(64.341)	(26.608)	(48.281)	(32.182)
L(2). MML M. Border	-125.589***	-78.197***	-123.473***	-111.774***	-129.311***
	(40.347)	(20.172)	(29.262)	(40.653)	(45.610)
L(1). MML M. Border	-77.542***	-38.417**	-89.609***	-80.024*	-95.513**
	(26.462)	(15.282)	(23.826)	(41.986)	(45.138)
MML M. Border	-26.223*	-19.590	-67.938***	-95.410**	-67.762**
	(14.655)	(21.500)	(13.377)	(43.240)	(33.387)
F(1).MML M. Border	-9.649	16.639	-30.422	-54.123	-24.727
	(25.226)	(37.399)	(20.213)	(41.251)	(36.320)
F(2).MML M. Border					7.374
					(32.904)
L(3). MML Inland	43.823*	35.606	-11.342	-26.146**	-6.239
	(25.294)	(26.221)	(20.462)	(10.462)	(22.743)
L(2). MML Inland	20.069	15.888	6.117	-2.334	19.506
	(17.286)	(18.092)	(15.848)	(8.938)	(17.167)
L(1). MML Inland	19.630	15.554	5.729	-5.505	19.943
	(16.033)	(16.661)	(14.232)	(8.074)	(15.377)
MML Inland	16.468	10.343	3.513	-3.803	12.568
	(15.509)	(15.584)	(11.512)	(6.390)	(14.401)
F(1).MML Inland	8.178	2.471	-3.226	7.324	4.541
	(16.053)	(16.067)	(11.574)	(6.730)	(14.287)
F(2).MML Inland					12.006
					(13.158)
Observations	59,061	59,061	59,061	59,061	68,382
R-squared	0.861	0.862	0.882	0.745	0.857
County fixed effects	x	x	x	x	x
Year fixed effects	x	x	x	x	x
Control variables	-	-	x	x	x
State specific trends	-	-	x	x	x
Bordertime	-	x	x	x	x
Weighting	x	x	x	-	x
Sample	1994-2012	1994-2012	1994-2012	1994-2012	1990-2012

Note: The dependent variable in columns 1-4 is the log of the violent crime rate per 100,000 inhabitants of the crime listed above in state s at time t. The MML variables are dummies which take value one for the year MML are enacted. The variables "1 year before MML" are dummies which take a value one a year before the introduction of MML. The regressions underlying the presented results were all estimated with county and year fixed effects, border $\times$ year fixed effects, control variables and state-specific linear time trends. The included control variables are: an indicator for decriminalization policy, logged population, poverty rate, the unemployment rate, logged median income, the share of males, African-Americans, Hispanics, ages 10-19, ages 20-24 in the population. The panel covers the period 1994-2012, except for the last column when it covers the period 1990-2012. Standard errors in parenthesis are clustered at the county level. Regressions are population weighted. Asterisks denote: $***p < 0.01, **p < 0.05, *p < 0.1$.

one year. On the other hand, in inland states we find that MML has a slight positive after three years, although the treatment coefficient is small.

In column two we include border-time dummies, and in column three we also add control variables. As can be seen this has almost no effect on the lead coefficient on MML at the Mexican border, while contemporaneous and lagged coefficients remain significantly negative, and increasing with time. In inland states MML appears to have no impact on crime whatsoever, as all coefficients are non-significant and very close to 0. These results combined provide strong evidence that our identification strategy is able to pick up the causal effect of MML on crime, as in all 3 specifications under consideration pre-trends for treatment and control states are similar.

In the fourth column we use OLS instead of WLS. In this case it is no longer clear that the common-trend hypothesis is satisfied. Although the lead-coefficient of MML on crime is not significant, the size of the coefficient is very large in Mexican border states. In particular, we can no longer reject the null hypothesis that the one-year lead effect is significantly different from the one-year lag effect. This implies that with unweighted data, crime grows at a lower rate in treatment states at the Mexican border than in control states in the absence of treatment. Hence, OLS estimates should be interpreted with caution.

Unfortunately, our main sample starts in 1994 and the first MML is introduced in 1996 in California. In this sample we can therefore only include one lead of the MML, without seriously affecting the identifying assumptions of our model.[14] In the fifth column we use the sample from 1990-2012. There are two downsides of using this sample. First, there is significant measurement error as discussed in the Data section in the period 1990-1992. Second, data from 1993 is missing entirely. Nonetheless if we are willing to assume the measurement error is uncorrelated to introduction of MML, we can append the sample 1990-1992 to the sample from 1994-2012 to evaluate the common-trend assumption over a pre-treatment time horizon. As can be seen, results are not significantly affected when we consider the sample over a longer horizon. The two - and one-year lead on MML have no effect on the crime rate, while crime starts reducing in Mexican border states immediately after the introduction of MML.

In figure 3 we visualize the results on MML at the Mexico Border from column 3 and 5, corresponding to the first and second panel in the figure. We observe that the lead of the treatment effect is non-significant, as the 95 % confidence interval includes 0. However, in the year MML is introduced, as well as in the years afterwards, crime starts reducing significantly.

5.2.2 Main Results

Table 4 shows the effect of MML on violent crime. The dependent variable in each specification is the violent crime rate per 100,000 inhabitants. In column 1 we see that a general MML dummy slightly decreases the violent crime rate. This finding contradicts earlier results in Morris et al. (2014) and Alford (2014) who find a negative, but non-significant effect of MML on violent crime rates. The reason is that we include county-level control variables which increases the precision of our estimates, while Morris et al. (2014) and Alford (2014) only use state-level data.

In columns 2-5 we estimate the treatment effect of MML on crime separating between Mexican-border states and inland states. In the simple DiD model presented in column 2 the estimates suggest that the introduction of MML reduces the violent crime rate in Mexican-

[14]If we would include a two-year lead coefficient, the set of MML coefficients at the Mexican border would be collinear to the fixed effect for California up to the introduction of MML in New Mexico in 2007. Hence, this would effectively remove all causal evidence of MML on crime from the largest MML state.

Table 4: The Effect of Medical Marijuana Laws on Crime

VARIABLES	(1) Violent Crime	(2) Violent Crime	(3) Violent Crime	(4) Violent Crime	(5) Violent Crime	(6) Violent Crime	(7) Violent Crime
MML	-35.789***						
	(11.895)						
MML Mexico Border		-175.491**	-140.762***	-107.984***	-99.066***		
		(70.256)	(49.963)	(20.452)	(28.364)		
MML Arizona						-66.516***	-34.191*
						(24.155)	(20.589)
MML California						-87.517***	-144.358***
						(25.445)	(21.923)
MML New Mexico						-131.810*	-57.922
						(71.257)	(37.454)
MML Inland		38.249**	24.025	2.806	-9.361	-9.356	3.069
		(18.910)	(18.051)	(11.061)	(5.996)	(5.996)	(11.067)
Observations	59,061	59,061	59,061	59,061	59,061	59,061	59,061
R-squared	0.881	0.857	0.860	0.882	0.744	0.744	0.882
County fixed effects	x	x	x	x	x	x	x
Year fixed effects	x	x	x	x	x	x	x
Control variables	x	-	-	x	x	x	x
State specific trends	x	-	-	x	x	x	x
Bordertime	-	-	x	x	x	x	x
Weighting	x	x	x	x	-	x	-
Elasticity	-0.0707						
Elasticity M Border		-0.254	-0.204	-0.156	-0.207		
Elasticity Inland		0.0874	0.0549	0.00641	-0.0419	-0.0214	0.0138
Elasticity AZ						-0.131	-0.0905
Elasticity CA						-0.0938	-0.222
Elasticity NM						-0.207	-0.119

Notes: The dependent variable in all columns the violent crime rate per 100,000 inhabitants in county c at time t as measured in the UCR data. The MML variables are dummies which take value one from the year MML are enacted. The included control variables are: an indicator for decriminalization policy, logged population, poverty rate, the unemployment rate, logged median income, the share of males, African-Americans, Hispanics, ages 10-19, ages 20-24 in the population. The panel covers the period 1994-2012. Standard errors in parenthesis are clustered at the county level. Regressions are populations weighted where noted. Asterisks denote: $***p < 0.01, **p < 0.05, *p < 0.1$.

border states significantly. The size of the effect decreases slightly when we include border-year fixed effects as can be seen in column 3, and it becomes even smaller in a specification that also includes state-linear time trends and control variables, as can be seen in column 4. However, even in the most parsimonious specification, the treatment effect of MML on crime remains significantly negative at the Mexican border. Our estimates suggest that MML in border states reduce the violent crime rate by approximately 108 crimes per 100,000 inhabitants.

On the other hand, the simple DiD model presented in column 2 suggests that the effect of MML on crime in inland states is positive, and significant at the 10 percent level. However, when we include border-time dummies and control variables the effect in inland states becomes non-significant. In each model, the null hypothesis stating that the effect of MML on crime is the same in inland, and border states is rejected at the 5 percent significance level. This provides support for our theory, because it shows that MML leads to a stronger reduction in crime at the Mexican border than in inland states. This could be consistent with MML in Mexican-border states reducing violent activity by Mexican DTOs.

The specification in column 5 considers the same model using OLS instead of WLS. When we do not weight the data, the treatment effect of MML on crime in Mexican-border states becomes slightly smaller, but remains significant. Moreover, the treatment coefficient remains more negative in Mexican-border states, than it is in inland states.

In column 6 and 7 we look at the effect of MML in the three different states that border Mexico. Column 6 shows that the effect is significant in each of the 3 states when we use OLS. Column 7 shows that with WLS the effect of MML on violent crime is negative in each border state. However, the effect is only significantly at the ten percent level in Arizona, and despite the large coefficient it is not significant in New Mexico.

The fact that the effect of MML on crime is most robust in California can easily be explained. First, since California is, by a large margin, the most populous MML state at the Mexican border, crime data in California is less noisy. Second, Arizona has only introduced MML during the last two years in our sample. Hence, the full effect of MML may not yet be measurable in that state. Last, as discussed in the background section, take-up rates of MML are likely much larger in California than in the other two states.

To estimate the magnitude of the effect of MML on violent crime, we also report semi-elasticities in Table 4, which we only interpret if the estimated coefficient is significant. The semi-elasticities use the treatment coefficient to measure the relative decrease in crime associated to introduction of MML.[15] The effect of MML on crime in Mexican-border states is very large. Semi-elasticities range between -15 to -25 percent depending on the specification. In the population-weighted model, the effect size is largest in California with a 22 percent decrease, and smallest in Arizona. The effect of MML on violent crime rates in inland states is negligible.

5.2.3 Distance from the border

Table 5 represents the effect of MML on violent crime using specification (2) where we interact MML with the distance from a county's midpoint to the border. In column 1-3 we use a parametric specification where we interact MML with the logarithm of distance from the border. Column 1 represents a simple DiD model where we estimate the effect of MML on crime using a generic control group consisting of all counties in states without MML. In column 2 we allow the time-fixed effects to differ by the log of the distance to the border. In column 3 we further saturate the model by including control variables and state-linear time trends.

In column 4-6 we present a non-parametric specification where we divide the US into 10 zones, depending on the distance to the border. Each zone is a little below 340 kilometers long. Hence, zone 1 represents the counties whose midpoints are located between 13-353 kilometers from the border.[16] Zone 10 represents those counties that are located furthest away from the border. In column 4 we present a DiD specification where we identify the treatment effect of MML by comparing the treatment counties in each zone to a generic control group consisting of all counties without MML. In column 5 we include year-zone fixed effects. This implies that we compare treatment counties within each zone to control counties within the same zone. Note that luckily for us each of the ten zones include both treatment and control counties. Hence, the treatment effect is identified for each zone. Finally, in column 6 we saturate the model by also including control variables and state-linear trends.

Figure 4 shows the model-predicted effect of MML on crime as a function of the distance to the border. The solid line represents the predicted effect of MML on crime using the parametric specification in column 3 of Table 5. The gray area around the line represents a 95 percent confidence interval around the central estimate. The horizontal lines represent the non-parametric specification in column 6 of the same table, and the drop lines represent a 95 percent confidence interval around these estimates.

[15] When we calculate the semi-elasticity in a geographic area, e.g. Mexican border states, we divide the treatment coefficient in that geographic area by the average violent crime rate in in the geographic area *prior* to the introduction of MML. When we calculate the average crime rate we weight counties by population weights when we use WLS. In the OLS specification we use an unweighted average instead.

[16] 13 kilometers is the minimum distance between the midpoint of a county and the Mexican border in our sample.

Table 5: Log Distance from the Border

VARIABLES	(1) Violent Crime	(2) Violent Crime	(3) Violent Crime	(4) Violent Crime	(5) Violent Crime	(6) Violent Crime
MML	-592.512**	-438.083***	-326.836***			
	(244.362)	(153.544)	(89.104)			
MML X Log distance	81.932**	60.052***	42.687***			
	(33.167)	(20.841)	(12.375)			
MML in zone 1				-239.035**	-146.483***	-131.528***
				(94.373)	(56.074)	(31.066)
MML in zone 2				-47.390	-45.688	-38.738
				(33.278)	(33.160)	(34.054)
MML in zone 3				23.189	13.822	-4.300
				(29.668)	(29.676)	(29.571)
MML in zone 4				85.031***	-11.110	13.008
				(22.232)	(29.177)	(71.508)
MML in zone 5				14.840	-19.880	-126.788***
				(52.227)	(54.923)	(35.228)
MML in zone 6				73.863***	58.052	52.680*
				(26.531)	(44.160)	(31.853)
MML in zone 7				14.223	-30.407	22.584
				(26.357)	(24.019)	(20.868)
MML in zone 8				5.623	48.063	-34.051
				(37.071)	(47.301)	(50.659)
MML in zone 9				69.279***	36.604*	17.924
				(18.696)	(22.220)	(18.442)
MML in zone 10				115.508***	-59.072***	-34.035
				(21.154)	(17.723)	(21.128)
Observations	59,061	59,061	59,061	59,061	59,061	59,061
R-squared	0.857	0.858	0.882	0.858	0.867	0.890
County fixed effects	x	x	x	x	x	x
Year fixed effects	x	x	x	x	x	x
Control variables	-	-	x	-	-	x
State specific trends	-	-	x	-	-	x
Logdistance x time	-	x	x	-	-	-
Zone x Time	-	-	-	-	x	x
Weighting	x	x	x	x	x	x

Note: The dependent variable in each column is the log of the violent crime rate per 100,000 inhabitants in county c at time t. The MML is a dummy which take value one from the year MML are enacted. Log distance is the logarithm of distance from the border measured in kilometers. In column 4-6 we subdivide the US in 10 zones with a length of around 340 kilometers. Zone 1 is the zone closest to the Mexican border, zone 10 is furthest away. The included control variables are: an indicator for decriminalization policy, logged population, poverty rate, the unemployment rate, logged median income, the share of males, African-Americans, Hispanics, ages 10-19, ages 20-24 in the population. The panel covers the period 1994-2012. Standard errors in parenthesis are clustered at the county level. Regressions are populations weighted. For this specification, Alaska was excluded from the data. Asterisks denote: $***p < 0.01, **p < 0.05, *p < 0.1$.

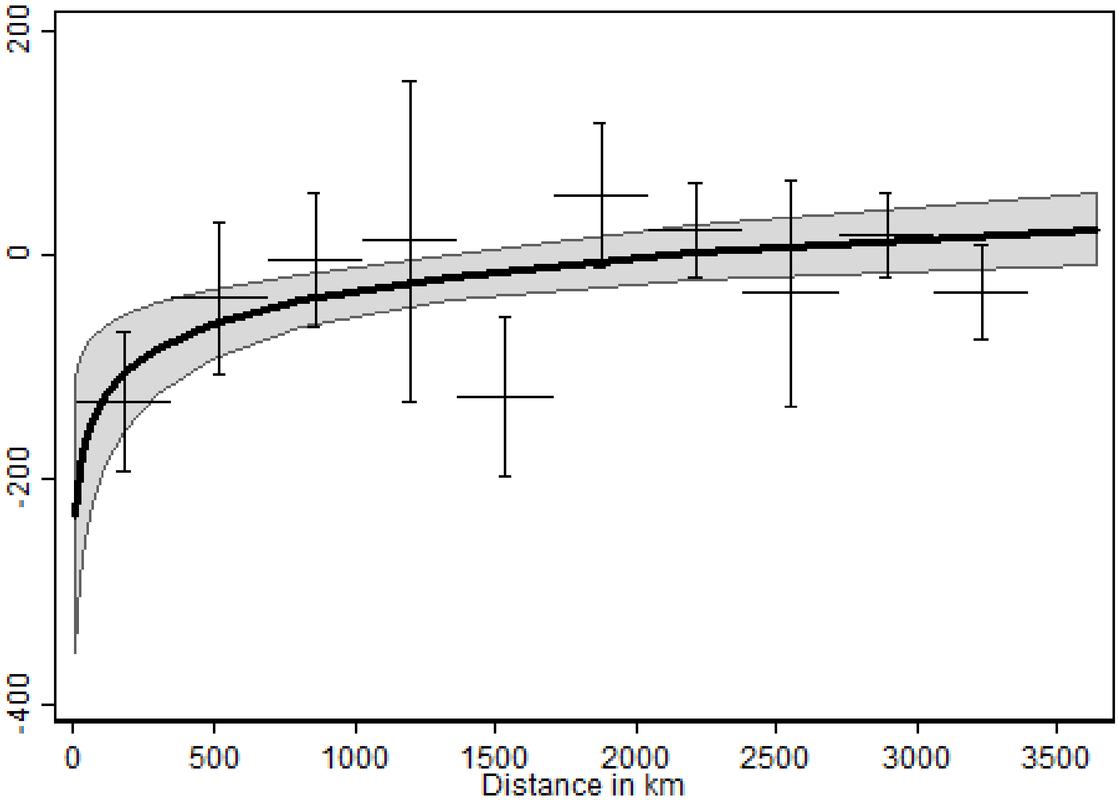

Figure 4: The Effect of MML on Crime by Distance from the Mexican Border
Notes: The solid curve in black plots the effect of the log distance of MML on crime, surrounded in gray with 95% confidence interval. The horizontal lines represent the coefficients on the non-parametric model. The corresponding drop line represents the 95% confidence interval. The vertical axis represents the size of the marginal effect of MML.

As can be seen, both models predict a large negative effect of MML on crime in counties that are located close to the border. However, the effect rapidly dissipates for counties further away, and becomes non-significant for inland counties. In the parametric specification, the effect of MML on crime is no longer significant at approximately 1500 kilometers inland, although the predicted impact on the crime rate is already four times smaller for counties located 500 kilometers inland, than for the counties closest to the border. In the non-parametric specification, the effect is no longer significant in zone 2, which represents counties located from 353-693 kilometers from the border.

One potential downside of using a non-parametric specification is that it may provide too much flexibility. In particular, since we estimate 10 treatment coefficients chances are that at least one of them is significant at the 5-percent level, even when there is no treatment effect. Moreover, this type I error is even larger when you consider the fact that we run a number of different specifications which each have different identifying assumptions. We indeed encounter this issue in the specification shown in the figure. In particular, the estimated treatment effect is significantly negative in zone 5 and zone 10, even though these zones are very far from the Mexican border. However, by comparing specifications 4-6 in Table 5, we verify that i.) the estimated treatment effect in zone 1 is largest in absolute value in each specification, ii.) the treatment effect in zone 1 is the only treatment effect that is significant in each specification, and iii.) unlike the treatment effect in zone 1, even the sign of the treatment coefficients in zone 5 and 10 depends on the specification. Hence, we conclude that MML has most likely reduced crime rates in the counties closest to the border, while the estimated effect of MML on crime in zone 5 and 10 may be attributable to noise. Apart from zone 5 and 10, the parametric model and the non-parametric model give very similar predictions. The central estimate of the parametric model always falls within the 95-percent confidence bounds of the non-parametric model.

The size of the effect we find in each specification appears to be consistent with our earlier estimates presented in Table (4). Both the parametric, and the non-parametric specification predict a large negative effect of MML on crime in the border region, that is stronger than the average effect of MML on crime identified in Table (4). On the other hand, in the Northern regions of Mexican border states, the distance specifications predict that MML has a smaller effect on crime rates, than the effect identified in Table (4).[17] Hence, the estimated average effect of MML on crime in Table (4) is the result of a strong drop in crime in the border-region, and a must smaller reduction in the Northernmost parts of MML states.

The results in Table 5 and figure 4 confirm the results obtained in the previous subsection, by showing that MML significantly reduce crime rates in counties that are close to the Mexican border. Moreover, they strongly suggest that the heterogeneity in the treatment effect is causally driven by proximity to the border. In particular, the results obtained in the previous subsection are consistent with MML reducing violent crime in the border-region, but there could also be other mechanisms that distinguish the 3 treatment states that border Mexico from other treatment states. The results in Table 5 and figure 4 show that even within Mexican-border states, the treatment effect is strongest in the counties closest to Mexico. This provides strong evidence for our theory that MML reduces crimes committed by Mexican DTOs and their affiliated gangs.

5.2.4 Results by Different Crimes

Table 6 splits our main result up by detailed crime category. The dependent variable in each column is the crime rate reported in the column head. As can be seen, MML at the border has a significant negative effect on all three crimes. The semi-elasticities show that robberies decrease by 26 percent, while both homicides and assaults drop by around 11 percent.

The model suggests MML increases robberies in inland states, although the effect is only significant at the 10 percent level. There is no significant effect of MML on crime in any of the other categories. For each crime category, the treatment coefficient for Mexican-border states is significantly smaller (more negative), than the treatment coefficient in inland states.

The fact that each of the three individual crimes respond to the introduction of MML is consistent with our theory. Both DTOs and their affiliated gangs are known for their involvement in homicides, aggravated assaults and robberies around the border (see e.g NGIC, 2011). The results also show that MML leads to a decrease in overall DTO activity, rather than a substitution from involvement in marijuana trade to, for example, involvement in robberies.

[17] Del Norte California is the northernmost county in a Mexican-border state with MML. It is approximately 1184 kilometers from the border. At that distance, the parametric model in column 3 of Table 5 predicts a very small negative effect of MML on crime, while the non-parametric model in column 6 predicts an insignificant effect of MML on crime.

Table 6: The Effect of MML Split per Crime

VARIABLES	(1) Violent Crime	(2) Murder Rate	(3) Robbery Rate	(4) Assault Rate
MML Mexico Border	-107.984***	-1.005***	-57.990***	-48.988***
	(20.452)	(0.320)	(16.413)	(15.241)
MML Inland	2.806	-0.153	10.265*	-7.306
	(11.061)	(0.148)	(5.855)	(7.184)
Observations	59,061	59,061	59,061	59,061
R-squared	0.882	0.789	0.900	0.835
Elasticity M Border	-0.156	-0.113	-0.267	-0.105
Elasticity Inland	0.00641	-0.0265	0.0659	-0.0265

Note: The dependent variable in each column is the log of the crime rate per 100,000 inhabitants of the crime listed in the column header in county c at time t. The MML variables are dummies which take value one from the year MML are enacted. The included control variables are: an indicator for decriminalization policy, logged population, poverty rate, the unemployment rate, logged median income, the share of males, African-Americans, Hispanics, ages 10-19, ages 20-24 in the population. The panel covers the period 1990-2012. Standard errors in parenthesis are clustered at the county level. All regressions are population weighted. Asterisks denote: $***p < 0.01, **p < 0.05, *p < 0.1$.

5.3 SHR Results

Table 7 further disaggregates the effects of MML on crime using SHR data. The dependent variable in the reported regressions is the homicide rate in the category listed in the column header. As can be seen, the introduction of MML at the Mexican border significantly reduces homicides related to narcotic drug laws, juvenile gangs, and robberies. Homicides under the influence of alcohol increase slightly, although the effect is only significant at the 10 percent level. Gangland homicides and homicides under the influence of drugs are not affected in Mexican-border states.

Table 7: The Effect of Medical Marijuana Laws on Different Types of Homicide: SHR

VARIABLES	(1) Drug Law	(2) Juvenile Gang	(3) Gangland	(4) Robberies	(5) Alcohol Influence	(6) Drug Influence
MML Mexico Border	-0.232***	-0.361**	0.015	-0.211***	0.039*	0.047
	(0.049)	(0.179)	(0.030)	(0.059)	(0.023)	(0.029)
MML Inland	0.020	-0.049**	0.032	0.044*	-0.023	0.012
	(0.048)	(0.024)	(0.028)	(0.026)	(0.015)	(0.012)
Observations	25,767	25,767	25,767	25,767	25,767	25,767
R-squared	0.482	0.903	0.254	0.546	0.224	0.229
Elasticity M Border	-0.463	-0.345	0.261	-0.301	0.261	1.708
Elasticity Inland	0.0846	-0.835	0.682	0.110	-0.344	0.497

Note: The dependent variable in each column is the homicide rate per 100,000 inhabitants of the type of homicide listed above in county c at time t. The MML variables are dummies which take value one from the year MML are enacted. The included control variables are: an indicator for decriminalization policy, logged population, poverty rate, the unemployment rate, logged median income, the share of males, African-Americans, Hispanics, ages 10-19, ages 20-24 in the population. The panel covers the period 1994-2012. Standard errors in parenthesis are clustered at the county level. All regressions include county and year fixed effects, control variables, state specific trends, border × time fixed effects and populations weights. Asterisks denote: $***p < 0.01, **p < 0.05, *p < 0.1$.

In inland states, the introduction of MML leads to a significant reduction in juvenile gang homicides, and an increase in homicides related to robberies, although the latter effect is only significant at the 10 percent level. Other homicides are not affected in inland states.

The results are broadly consistent with our theory. As is shown in column 2 of Table 6 the overall reduction in the homicide rate at the Mexican border after introduction of MML is approximately 11 percent. Table 7 shows that part of the decrease can be attributed to a reduction in drug-law by 46 percent, juvenile gang homicides by 34 percent, and robbery related homicides by 30 percent. Each of these categories can credibly be connected with activities relating to DTOs, and their affiliated gangs.

However, our theory does not provide an explanation for the reduction in juvenile-gang homicides in inland states. This could perhaps be interpreted as MML reducing juvenile-gang activity in inland states, although more research is required to verify this result.

In addition, the results in Table 7 allow us to rule out a number of competing hypotheses. Morris et al. (2014) suggest that the decrease in the homicide rate in UCR data may have been caused by a decrease in alcohol use in MML states. They hypothesize that MML facilitated a substitution from alcohol to marijuana. This may in turn lead to a decrease in homicides committed under the influence of alcohol. We find no evidence for this hypothesis in the supplementary homicide data, as homicides committed under the influence of alcohol increase after introduction of MML. To be clear, we do not rule out the possibility that MML leads people to substitute alcohol for marijuana as suggested in Anderson et al. (2013), but we find no evidence of this hypothesis using crime data. In addition, we also find no evidence that MML affects homicides committed under the influence of drugs, ruling out that homicides decreased through the pharmacological channel.

5.4 STRIDE Results

Table 8 reports the results of MML on drug seizures using the STRIDE data. In sample underlying the estimates we removed data for Los Angeles, as Los Angeles exhibits a very strongly decreasing trend in drug seizures which starts in the period prior to the introduction of MML. After removing Los Angeles from the data we confirm that crime trends follow a similar trend in treatment and control states prior to the introduction of MML using a placebo test.[18]

The dependent variable in the first 4 columns is the log of the quantity seized of the drug in the column header. Columns 5-8 report the log of the count of seizures. As can be seen, at the Mexican border MML decrease the amount seized for powdered and crack cocaine, as well as the number of seizures.

To interpret the effect size we calculate semi-elasticities using the methodology of Kennedy (1981) to create semi-elasticities in a log-dummy regression equation.[19] The central estimate indicates that the amount of powdered cocaine seized in states at the Mexican border have decreased by 67 percent as a result of MML, while the number of seizures decreased by 45 percent. The amount of crack cocaine seized decreased by 85 percent, while the number of seizures decreased by 86 percent. We also find strong effects of MML on the number of heroin seizures in Mexican border states, but given the extremely noisy nature of STRIDE data, and given that the drop in heroin seizures does not coincide with a corresponding drop in the amount seized, this result should be interpreted with caution. Finally, we also see a drop in the amount of cocaine seized in inland states, but this effect is only significant at the 10 percent level.

[18] The results of the test are available upon request.

[19] To be precise, for an estimated coefficient, c the semi-elasticity ϵ_c is calculated as $\epsilon_c = \exp(c - se_x^2) - 1$, where se_c is the standard error of the estimate.

Moreover, the effect of MML on drug seizures appears to be stronger in border states than in inland states. In particular, the coefficient for the amount of powder cocaine seized, and the count of powder and cracked cocaine seizures, is significantly smaller (more negative) in Mexican border states than in inland states. However, the same cannot be said for the effect of MML on the amount of crack cocaine seized, as for this drug the coefficient in Mexican-border states and inland states are approximately the same.

The observed drop in seizures does not appear to be consistent with a theory where law enforcement agencies shift resources from marijuana to other drugs. In that case we would expect an increase in other drug seizures, whereas we actually observe a decrease. Thus, these results may be interpreted as statistical evidence that MML at the Mexican border has decreased drug trafficking of cocaine.

Table 9 reports the estimated effect of MML on the price of drugs as measured by the STRIDE data, at various distribution levels. As can be seen, MML at the Mexican border significantly increase the price of powdered cocaine at all distribution levels. Effects are again large, but also very noisy. For the other drugs we do find effects at different distribution levels. For example, MML appear to have reduced the price of crack cocaine at the middle distribution level, and appears to have increased the price of methamphetamine at the wholesale level. However, since these results are not consistent across distribution levels, the results should be interpreted with extreme caution. Prices in states that are not at the Mexican border are unaffected, except for powdered cocaine at the street level, and heroin at the wholesale level. The price of both drugs decrease significantly after the introduction of MML.

The result on powdered cocaine is in line with our hypothesis that MML have decreased the supply of illicit drugs in Mexican border states. A negative supply shock leads to a decrease in quantity traded as well as an increase in the price, and as we show in Table 8 and Table 9, this appears to be the case for powder cocaine.

We do not obtain equally supportive evidence for our theory from the other drugs. This could be the result of the quality of the STRIDE data which may be too noisy to pick up these effects. Alternatively, it may be that other effects are obscuring the effect of MML on drug supply. For example, if the gateway drug hypothesis is correct, MML may have simultaneously increased the demand for other drugs. On the other hand, marijuana may act as a substitute to drugs like heroin or crack cocaine. Moreover, DTOs are known to have replaced marijuana plants with poppy plants (Miroff, 2014; UNODC, 2010, e.g.). Hence, we do not expect the supply of this drug to decrease very much as a result of MML. Each of these alternative mechanisms complicate the identification of the causal effect of MML on the supply of other drugs.

6 Robustness Analysis

In our robustness analysis we focus on several issues. We present the results in Table 10. First, we test whether the heterogeneity in the treatment effect between Mexican-border states and inland states may be driven by differences in the characteristics of the MML, rather than proximity to Mexican DTOs. Second, we test the sensitivity of our results with respect to different subsamples and a slightly differently coded treatment variable. Finally, we estimate our regression model in differences rather than levels.

In the first two columns of Table 10 we assess the robustness of our results with respect to the characteristics of different MML. Alford (2014) shows that MML which allow for dispensaries increase the violent and property crime rate, while MML which only allow for home cultivation have a non-significant impact on crime. If the differences in the characteristics of

Table 8: The Effect of Medical Marijuana Laws on Drugs Seized

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quantity				Count-Seizures			
	Powder Cocaine	Crack Cocaine	Methamphetamine	Heroin	Powder Cocaine	Crack Cocaine	Methamphetamine	Heroin
MML Mexico Border	-0.983***	-1.579**	0.808	-0.345	-0.582***	-1.259***	0.478	-0.670**
	(0.336)	(0.607)	(0.677)	(0.507)	(0.084)	(0.137)	(0.383)	(0.262)
MML Inland	0.111	-0.717	-0.559	-1.195*	-0.100	-0.094	-0.202	-0.078
	(0.567)	(1.129)	(0.431)	(0.613)	(0.282)	(0.136)	(0.212)	(0.243)
Observations	677	654	623	636	677	654	623	636
R-squared	0.883	0.754	0.762	0.801	0.956	0.923	0.909	0.918
Elasticity M Border	-0.666	-0.857	0.419	-0.452	-0.445	-0.721	0.393	-0.522
Elasticity Inland	-0.190	-0.863	-0.525	-0.792	-0.164	-0.106	-0.219	-0.128

Notes: The dependent variable in the first 4 columns is the logged quantity seized by the police of the drug reported in the column header, while the dependent variable in the last 4 columns is the logged count of seizures of these drugs in state s at time t as measured in the STRIDE data. The MML variables are dummies which take value one from the year MML are enacted. The included control variables are: an indicator for decriminalization policy, logged population, poverty rate, the unemployment rate, logged median income, the share of males, African-Americans, Hispanics, ages 10-19, ages 20-24 in the population. The panel covers the period 1994-2012. Standard errors in parenthesis are clustered at the county level. All regressions include county and year fixed effects, control variables, state specific trends, border $\times$ time fixed effects and populations weights. Asterisks denote: $***p < 0.01, **p < 0.05, *p < 0.1$.

Table 9: The Effect of Medical Marijuana Laws on Prices of Drugs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Powder Cocaine				Crack Cocaine			Methamphetamine			Heroin		
MML Mexico Border	0.848***	1.214***	0.334**	0.186*	0.123	-0.766***	0.326	-0.333	0.013	1.079***	-0.093	0.312	-0.133
	(0.275)	(0.237)	(0.148)	(0.104)	(0.245)	(0.142)	(0.280)	(0.295)	(0.119)	(0.333)	(0.528)	(0.362)	(0.142)
MML Inland	-0.903**	-0.020	0.038	-0.054	0.251	0.115	0.121	0.103	-0.272	0.225	-0.501	0.012	-0.253*
	(0.337)	(0.480)	(0.211)	(0.225)	(0.567)	(0.456)	(0.334)	(0.621)	(0.239)	(0.251)	(0.316)	(0.691)	(0.146)
Observations	464	529	599	582	483	576	577	441	469	367	418	461	473
R-squared	0.567	0.563	0.360	0.361	0.567	0.538	0.414	0.500	0.524	0.440	0.475	0.334	0.569
Elasticity M Border	1.164	2.182	0.367	0.191	0.0654	-0.545	0.281	-0.343	-0.00101	1.633	-0.311	0.199	-0.142
Elasticity Inland	-0.638	-0.222	-0.00681	-0.0991	-0.0678	-0.0889	0.00971	-0.246	-0.280	0.176	-0.451	-0.372	-0.240
Street Level	x				x			x			x		
Low Distribution		x				x			x			x	
High Distribution			x										
Wholesale				x			x			x			x

Notes: The dependent variable is the logged price of the drugs purchased, each supercolumn is disaggregated into several distribution levels as outlined in Table 2. The distribution level of each column is marked at the bottom. The MML variables are dummies which take value one from the year MML are enacted. The included control variables are: an indicator for decriminalization policy, logged population, poverty rate, the unemployment rate, logged median income, the share of males, African-Americans, Hispanics, ages 10-19, ages 20-24 in the population. The panel covers the period 1994-2012. Standard errors in parenthesis are clustered at the county level. All regressions include county and year fixed effects, control variables, state specific trends, border × time fixed effects and populations weights. Asterisks denote: $***p < 0.01, **p < 0.05, *p < 0.1$.

MML correlate with proximity to the Mexican border, our estimated treatment effect may be biased.

To test whether this is the case we use four dummy variables. The first takes value 1 when MML are introduced. The second takes value 1 the moment a state allows for home cultivation. The third treatment dummy takes value 1 when an MML regulates dispensaries and the fourth takes value 1 when dispensaries start operating. The treatment effect is again split between states at the Mexican border, and other states, with the exception of the MML dummy, since all MML states at the Mexican border immediately allowed for home cultivation, implying that the MML dummy at the Mexican border is collinear to the home cultivation dummy at the Mexican border.

Table 10 presents our results. Column 1 shows the results for violent crime when we use the date at which dispensaries were regulated in an MML, as a proxy for when dispensaries start operating. This variable was used previously in Pacula et al. (2015) and Alford (2014). With this dummy we partly replicate the results by Alford (2014). We show that allowing for dispensaries is positively correlated to violent crime in border and non-border states. Nonetheless, our main result, which shows that MML decrease overall violent crime in the Mexican border states, remains unaffected. To see this note that the overall treatment effect of MML, the sum of the coefficient of home cultivation and for dispensaries, is significantly negative at the Mexican border.

Table 10: The Effect of MML on Crime by MML Characteristics and Robustness Checks

VARIABLES	(1) Violent Crime	(2) Violent Crime	(3) Violent Crime	(4) Violent Crime	(5) Violent Crime	(6) Violent Crime
Dispensary Legalization M. Border	56.576***					
	(14.440)					
Dispensary Legalization Inland	1.878					
	(16.995)					
Dispensary Operating M. Border		-104.132***				
		(16.722)				
Dispensary Operating Inland		-7.106				
		(12.581)				
Home Cultivation M. Border	-119.254***	-50.718***				
	(15.925)	(14.459)				
Home Cultivation Inland	-64.192**	-68.156**				
	(30.064)	(28.354)				
MML Mexico Border			-111.971***	-73.044***		-106.465***
			(22.901)	(22.266)		(14.821)
MML Inland	48.547*	52.335**	15.563	-16.415**		1.169
	(28.060)	(26.573)	(13.429)	(6.779)		(11.578)
MML M. Border Weighted					-119.010***	
					(22.992)	
MML Inland Weighted					0.248	
					(12.572)	
Neighbor M. Border State						-50.899***
						(12.638)
Neighbor Inland State						9.659
						(9.251)
Observations	59,061	59,061	40,488	54,675	59,061	59,061
R-squared	0.882	0.882	0.893	0.789	0.882	0.882

Note: The dependent variable in all columns is the log of the violent crime rate per 100,000 inhabitants of the crime listed above in county c at time t. The MML variables are dummies which take value one from the year MML are enacted. The included control variables are: an indicator for decriminalization policy, logged population, poverty rate, the unemployment rate, logged median income, the share of males, African-Americans, Hispanics, ages 10-19, ages 20-24 in the population. The panel covers the period 1994-2012. All regressions include county and year fixed effects, control variables, state specific trends, border $\times$ time fixed effects and populations weights. The variables are defined as follows: Dispensary Legalization is a dummy that takes a value one when dispensaries are legalized in state s at time t, separately for states at the Mexican Border and all the other states. Dispensary Operating is a dummy that takes a value one when licensed dispensaries are operating regardless of the legal framework in state s at time t, similarly separated for states at the Mexican border and all the rest. Home Cultivation is a dummy that takes a value one when home cultivation has been legalized in state s at time t, for Mexico border states and the rest. MML Rest variable is a dummy which takes value one from the moment MML are enacted in states not at the Mexican border. An MML variable for Mexican border states is not included because it is collinear to Home Cultivation at Mexico Border. The variable MML Weighted are the same as the normal MML variables, except in the first year of MML introduction where they take value $\frac{1}{12}$ if the MML was introduced in December, value $\frac{2}{12}$ if the MML was introduced in November and so on.The variables Neighbor take a value 1 if the neighbour of state s passed MML, it takes a value of 2 when a second neighbour of state s passes a MML and so on. Neighbour takes a value 0 if state s itself passes a MML. In column 3 the underlying subsamples includes counties with full coverage of the crime rate. Standard errors in parenthesis are clustered at the county level. Asterisks denote: $***p < 0.01, **p < 0.05, *p < 0.1$.

In column 2 we replace the dummy for the statewide regulation of dispensaries with a dummy for the opening of the first dispensary within the state. In this case the result of Alford (2014) disappears. Dispensaries at the Mexican border have a negative effect on violent crime, and dispensaries in inland states do not affect the crime rate at all. Additionally, the effect of home cultivation at the Mexican border on crime becomes smaller. In both columns 1 and 2 home cultivation seems to decrease crime in non-border state. However, the net effect of a full MML that includes home cultivation and dispensaries remains insignificant in non-border states.

We should note that identification on the differential effect of home cultivation and dispensaries is rather weak. Almost all states with MML allow for home cultivation. Moreover, for the three states at the Mexican border, California's first licensed dispensary opened one year after the adoption of MML. For New Mexico and Arizona this occurred two years after MML were adopted. If we take into account that MML may have a delayed impact on crime, we cannot be certain whether the estimated coefficients for home cultivation and dispensaries are related to home cultivation and dispensaries, or to a delayed effect of the adoption of the MML itself. Hence, to find out if certain provisions in MML lead to an increase or a decrease in crime further research, and possibly further policy experiments, are required. Yet, we can conclude that accounting for the characteristics of MML does not affect our main results.

In the remainder of Table 10 we present additional robustness to our main result. In column 3 we drop all observations were the crime rate was imputed by the NACJD rather than based on actual crime reports. We find that the coefficient -111.8 is not statically different from what we obtained using the full sample.

In column 4 we drop from the sample counties with population higher than 250 thousand inhabitants. This robustness check has two purposes. First, we know that metropolitan areas have seen strongly declining crime rates in the last 30 years (see e.g. Levitt, 2004). If states with MML contain larger cities than control states this could potentially bias the estimated effect of MML on crime downwards. Second, some large cities are known to actively misreport crimes in the UCR system in order to make it appear that crime rates are lower (Eterno and Silverman, 2012). This reporting bias is likely smaller in rural areas. We find a slightly smaller effect of MML on crime in Mexican-border states of 73.3 decline in violent crimes. However, the difference is not statistically significant. Moreover, in this sample we also find a statistically significant effect of MML on crime in non-border states. However, the difference between the coefficient for border states, and non-border states does remain significant in this sample, indicating that MML leads to a sharper reduction in crime in Mexican border states than in inland states.

In column 5 we recode the MML variables. In the baseline, in accordance with the literature, our MML dummy variable takes value 1 for a given year if MML was introduced in that year. This likely attenuates our estimated treatment effect, since when MML are introduced in, for example, December 2010, it is unlikely that it has a significant effect on crime during 2010. Therefore in this robustness check we weight the MML by the fraction of months in a year in which it has been in effect. In the example of December 2010, the MML dummy will take value $\frac{1}{12}$ for the year 2010 and 1 for the following years. In this specification, we find a slightly larger effect of MML on crime than the baseline of 119.1, but the difference is not statistically significant.

Finally, in column 6 we control for spillovers from neighboring states. In particular, we code the variable neighbor which counts the number of neighboring states that have introduced MML, and interact the variable with a dummy for whether a state is located at the Mexican border.[20] In doing so, we effectively remove neighboring states from the pool of control states.

[20]In an unreported robustness check we also use a dummy variable which takes value 1 when at least one

Instead, we estimate the effect of MML on crime by comparing treatment states to control states that do not border treatment states. We find that including the neighboring count does not have a significant impact on the estimated effect of MML on crime. However, we do find a negative effect of MML on crime rates in neighboring states when those neighboring states border Mexico. This might indicate that MML leads to the smuggling of marijuana over state borders, thereby reducing DTO activity, and hence crime rates in the border region of the neighboring state.

6.1 Estimation in Differences

Identification of the treatment effect in equation (1) requires a strong common-trend assumption, as it requires that violent crime rates follows a common trend in treatment and control states during the entire estimation period from 1994 to 2012. One possible way to relax this assumption is by estimating (1) in first differences, as identification in that case only requires the common-trend assumption during the year before and after the reform. However, the downside of using first differences is that the effect of MML on crime is unlikely to appear in the first year after the reform. Therefore, in Table 11 we provide a robustness check where we estimate regression equation (1) in x-year differences rather than levels. This relaxes the common-trend assumption, as identification in each case only requires the common trend assumption to hold in the x-year window around the reform, while still allowing us to estimate the long-term impact of MML on crime by choosing a large enough value for x.

As can be seen from the results in column 1, MML at the Mexican border do not significantly reduce violent crime when we estimate the model in one-year differences. This is to be expected, as it takes time for Mexican-border states to set up local competition to Mexican DTOs. However, the effect of MML on crime in Mexican-border states already appears when we estimate the model in 2-year differences. The estimated effect of MML on crime is no longer significantly different from our main result obtained in section 5.2.2 when we use 3-year differences, and the same continues to hold when we estimate the model in 4 - and 5-year differences.

Table 11: Dynamic Effects of MML

VARIABLES	(1) Violent Crime	(2) Violent Crime	(3) Violent Crime	(4) Violent Crime	(5) Violent Crime
D. MML M. Border	-26.286	-46.578***	-70.000***	-104.333***	-118.505***
	(20.686)	(17.611)	(23.710)	(25.525)	(22.736)
D. MML Inland	6.921	8.211	12.915	9.793	3.594
	(6.280)	(7.442)	(8.993)	(9.371)	(10.588)
Observations	55,952	52,843	49,734	46,625	43,516
R-squared	0.054	0.098	0.124	0.159	0.184
Differences	1	2	3	4	5
Elasticity M Border	-0.0381	-0.0674	-0.101	-0.151	-0.172
Elasticity Inland	0.0158	0.0188	0.0295	0.0224	0.00821

Note: The dependent variable in all columns is the log of the violent crime rate per 100,000 inhabitants of the crime listed above in county c at time t. The MML variables are dummies which take value one from the year MML are enacted. The included control variables are: an indicator for decriminalization policy, logged population, poverty rate, the unemployment rate, logged median income, the share of males, African-Americans, Hispanics, ages 10-19, ages 20-24 in the population. The panel covers the period 1994-2012. Standard errors in parenthesis are clustered at the county level. All regressions include state and year fixed effects, control variables, border × time fixed effects and populations weights. Asterisks denote: $***p < 0.01, **p < 0.05, *p < 0.1$.

neighboring state introduces MML. Results of this robustness check are similar.

The results obtained in Table 11 together with the results obtained in Table 3 strongly suggest that what we are measuring the causal effect of MML on crime. To see this, suppose to the contrary that crime trends follow a different trend in treatment states than in control states prior to the introduction of MML. In that case, the lead coefficient in Table 3 would have been significant. Now suppose that MML states at the Mexican border were affected by another shock to crime rates that appears more than 3 years after the introduction of MML. In that case, the estimates for the 3-year differenced model would have been significantly different from the model estimated in levels.

7 Conclusion

In this paper we provide indirect evidence for the theory that Medical Marijuana Laws (MML) decrease crimes committed by Mexican DTOs in the US. We exploit the quasi-experimental variation of MML, that comes from the fact that these laws are introduced in several states at different points in time. We explore the causal effect of MML on crime at Mexican Border states through the lenses of three different datasets. First, we use the Uniform Crime Reports to find the overall effect of MML introduction on crime. We find that MML have significantly reduced violent crimes in Mexican border states, most prominent among them, robberies and homicides. We find that the reduction is strongest in counties at the Mexican border, and that the effect decreases with distance from the border. We find no robust effect of MML on crimes in inland states. Second, we explore the circumstances under which homicides were committed through the Supplementary Homicides Reports data. We find that the drop in homicides is driven by a drop in drug law and juvenile gang related homicides, lending support to the hypothesis that the drop in crime is related to activity in drug markets. Third, we look at the effect of MML on drug seizures and prices as recorded by the STRIDE dataset. We find evidence for a negative supply shock in the market of powdered cocaine in Mexican border states. All these results are consistent with the theory that MML are negatively affecting the large Mexican DTOs.

The magnitude of each of the identified effects is surprisingly large. Our estimates suggests the introduction of an MML reduces the violent crime rate in Mexican-border states by between 15-25 percent, even though MML only open the door for small- and medium-scale production of marijuana. This is consistent with the idea that marijuana is the "bread and butter" of Mexican DTOs. Although there is some evidence that DTOs are switching activity to crimes unrelated to drugs such as human trafficking, none of these activities exhibit the same scale and profit commonly associated with the trafficking of marijuana. Extrapolating from our results, we consider it likely that the full legalization of marijuana in Colorado and Washington will have an even stronger impact on the DTOs as large-scale marijuana production facilities are erected in these states.

The case of MML provides an important lesson for policy makers. Drug markets are well-known for their violence. However, in the case of marijuana when the supply chain of the drug is legalized, or at least decriminalized, a lot of the violence disappears and the business of organized crime structures is hurt.

An important caveat of this study and other studies on crime is the focus on violent crime categories reported in UCR, and on drug crimes reported in STRIDE. To our knowledge, a similar database on crimes such as extortion, human trafficking and fraud is not available. Therefore, our study cannot assert whether these crimes, which are sometimes associated to activity of Mexican DTOs, are affected by MML. Collecting these crimes in a nationwide database would provide researchers in (the economics of) crime with an opportunity to study them in more detail.

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