Correcting for Measurement Error in the Uniform Crime Report With an Application Estimating the Effects of Legalizing Medical Marijuana on Crime Rates

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Abstract:

Federal policy in the United States (U.S.) has historically used prohibition to curb the supply of drugs and thereby reduce crime. However, much of the crime associated with drugs are due to prohibition (Goldstein, 1987; Resignato, 2000). Thus the relationship between supply and crime is not clear. Medical marijuana laws (MMLs) passed in recent years have created a natural experiment to test this relationship. Literature using similar data and empirical methods, however, have produced conflicting results. We provide a simple imputation procedure for reducing the measurement error in the FBI Uniform Crime Report. Once measurement error is accounted for, we find that MML generally reduces crime rates.

1. INTRODUCTION

Drug policy in the United States (U.S.) is predicated on the notion that there is a causal link between crime and drug usage. Drug policy makers have stated 'Efforts to reduce the supply of drugs and enforce the laws of the U.S. are focused on decreasing crime…'[1] Accordingly, U.S. drug policy has been largely focused on prohibition in an effort to stem the supply of drugs. As a result, the number of prisoners incarcerated for drug-related offenses rose 15-fold between 1980 and 2000, far outpacing the number of drug-related arrests (Kuziemko and Levitt, 2004). Still, it is not obvious that prohibition should reduce crime since much of the crime associated with illegal drugs, such as turf wars, punishment and retaliation, robbery, and theft, are due to the illegality of the product itself (Goldstein, 1987; Resignato, 2000). That is, in illegal markets where there is an absence of government provided property rights, market participants must protect themselves from predation and enforce contracts through the threat and use of violence (Rasmussen and Benson, 1994). Moreover, enforcement of drug prohibition can divert scarce resources away from the deterrence of other types of crime (Benson and Rasmussen, 1991; Benson et al., 1992). Indeed, it remains an open empirical question as to whether drug prohibition policies reduce crime.

There is now a growing literature that has focused specifically on the link between marijuana prohibition and crime (Adda, et al., 2014; Huber et al., 2014; Markowitz, 2005; Morris et al., 2014; Gavrilova et al., 2017; Chu and Townsend, 2018). Focusing on marijuana prohibition makes sense, since it is the drug which is most commonly detected among arrestees (Chu and Townsend, 2018). However, the results of these studies have been inconclusive. Both Huber et al.

[1] See page 4 of the "National Drug Control Strategy" (NDCS) published by the Executive Office of the President of the United States in 2016.

(2014) and Markowitz (2005) find evidence that states in the U.S. that decriminalize marijuana experience higher crime rates. On the other hand, Adda et al. (2014) finds evidence that decriminalization in a London borough led to reductions in crime. Still, decriminalization is not the same as legalization.

Accordingly, other studies take advantage of a recent trend of medical marijuana laws (MMLs) in the U.S., where individual states have rejected federal laws to permit the prescription of marijuana to patients. California was the first state to enact an MML in 1996 (ProCon.org 2019b). Currently, thirty-three states and the District of Columbia permit the sale of marijuana for medical purposes (see figure 1 or table 1). These laws effectively put an end to marijuana prohibition, as evidenced by the rise in usage (Chu, 2014). By exploiting variation in MMLs across states and over time, these studies explore the link between marijuana prohibition and crime. Still, while Gavrilova et al. (2017) and Huber et al. (2014) find evidence that the end of marijuana prohibition led to significant reductions in crime, Morris et al. (2014) and Chu and Townsend (2018) find no robust evidence of a link between MMLs and crime. However, these studies vary in their units of observation (city, county, or state), aggregation of crime (e.g., all violent crime versus robbery or assault), time periods, and control variables. Moreover, with the exception of Gavrilova et al. (2017) who compare the effect of MMLs on crime between Mexican border states and others, no study controls for possible observable heterogeneity in the effect of MMLs on crime. Given these discrepancies, it should not be surprising that these studies have not produced consistent results.

Unfortunately, the uniform crime report has serious issues with measurement error. Reporting to the uniform crime report is voluntary, and more rural law enforcement agencies are less consistent in reporting crime statistics to the FBI. As such, county level aggregates will lead to biased estimates since the mechanism causing missing data is causally linked to jurisdictional population, which contributes significantly to criminal behavior.

We extend this literature in two ways. First, we develop a simple imputation procedure for agency level crime data to reduce the measurement error endemic in county level crime data. Second, we apply these imputed data to explore whether there are heterogenous effects of MMLs on different types of crime between urban and rural communities in border and non-border states. Using the Federal Bureau of Investigation Uniform Crime Report (UCR) data from 1994 to 2016, along with control variables from the U.S. Census and the U.S. Bureau of Labor Statistics, we construct two panel data sets where the unit of observation is a county. The first follows the procedure of Gavrilova et al. (2017) using county level data not corrected for measurement error. The second analysis uses the same model applied to a county level panel in which the county level estimates are aggregated from the imputed agency crime dataset. By conducting the analysis using both the raw and impute dataset, we explore the effects of ignoring the measurement error problem, as well as attempt to replicate the results of previous studies. All of our empirical specifications control for county fixed-effects, year fixed-effects, time-varying socio-economic demographics, as well as state-specific linear time trends, in addition to clustering the standard errors at the state level to account for unobserved heterogeneity.

We find robust evidence that MML reduces both violent and property crime. While we find evidence of heterogeneity in the effect of MMLs on motor vehicle theft rates, once measurement error is accounted for, heterogeneity in most of the other crime rates disappears. Combined, these results demonstrate the importance of correcting the measurement error problem in estimating the effect of MMLs on different types of crimes in different types of communities.

2. LITERATURE REVIEW

This paper fits into a broad area of economic literature that examines the effects of medical marijuana laws and marijuana decriminalization on crime.[2] Our analysis is most closely related to five papers summarized in table 2. Like them, we use both the Uniform Crime Reporting (UCR) Program Data and a difference-in-differences (DD) empirical strategy that exploits both state and temporal heterogeneity. Despite those similarities, the papers summarized in table 2 have arrived at different conclusions about the effect of MML on crime. Other differences among those papers include the time periods analyzed, geographic jurisdiction considered, and the empirical model used.

Most importantly, table 2 reports that previous literature fails to find that MML leads to an increase in crime. This generalized robust result is surprising given the rationale supporting historical marijuana policy in the United States (Executive Office of the President of the U.S. 2016). The size of the non-positive effect varied among the five studies summarized in table 2, and is in part dependent on which violent and property crimes were analyzed. For example, Alford (2014) examined property crimes and murder, but not other violent crimes like aggravated assault. Furthermore, unlike other papers summarized in table 2, Alford (2014) accounts for the effect of various attributes of MML including the existence of dispensaries and the ability for home cultivation. Her results illustrate how treating heterogeneous laws as equal can lead to confounding conclusions. In particular, she finds that dispensaries are correlated with an increase in robbery rates and home cultivation is correlated with a decrease in robbery rates. Morris, TenEyck, Barnes,

[2] See Model 1993; Williams 2004; Damrongplasit, Hsiao, Zhao 2010; Anderson, Hansen, and Rees 2013; Adda, McConnell, and Rasul 2014; Alford 2014; Braakman and Jones 2014; Morris, TenEyck, Barnes, and Kovandzic 2014; Chu 2014; Pacula, Powell, Heaton, and Sevigny 2015; Huber, Newman, and LaFave 2016; Gavrilova, Kamada, and Zoutman 2017; Chu and Townsend 2018; and Powell, Pacula, and Jacobson 2018.

and Kovandzic (2014) conducts a similar state-level analysis on all violent and property crimes tracked in the UCR. Their analysis, however, uses a different time period and ignore heterogeneous attributes of MML. Like Alford (2014), they estimate that MML has a non-positive effect on crime.

The analyses of Alford (2014) and Huber, Newman, and LaFave (2016) were also similar, but yield different conclusions. Both papers examine the effects of both MML and depenalization, but employ different empirical specifications to estimate the effect of MML on crime. Specifically, Alford (2014) use ordinary least squares and Huber et al. (2016) employs weighted least squares. In addition, Huber et al. (2016) extended their data from 1995 to 1970. Their results suggested that MML has a negative effect on both property and violent crime.

Gavrilova, Kamada, and Zoutman (2017) extend the Alford (2014) analysis in two important ways. First, they consider another dimension of heterogeneity in MML policy to create a difference-in-difference-in-differences (DDD) estimation. Their analysis shows that the effect of MML on crime depends on whether or not an MML state shars a border with Mexico. In particular, the effect of MML is strongest in counties close to the border and for crimes associated with drug trafficking organizations (DTOs). Second, the extension of the analysis from the state-level to the county level is another important distinction that contributes to their overall result and contribution. Past papers have treated all counties in a state equally, which may have prevented the identification of a negative effect of MML on crime.

Like Gavrilova et al. (2017), and relative to Alford (2014), Chu and Townsend (2018) employ a DD empirical approach and examines the effects of crime at a more local level. Their analysis focuses on city-level effects for urban areas in counties, but does not account for local specific differences like distance to the Mexican border. Interestingly, they found no evidence that MML effects violent or property crime. This result, however, must be considered in the context in which it is derived. The lack of an effect of MML on crime in urban areas does not preclude crime effects in non-urban areas within counties. It is possible that the effect of MML depends on whether an area is urban or rural, and its proximity to the Mexican border.

3. EMPIRICAL MODEL

We use two primary approaches to estimate the effect of MML on violent and property crime. Equation 1 below describes our difference-in-difference-in-difference (DDD) approach. Like Gavrilova et al. (2017) we exploit the time-dependent MML status, and whether a state shares a border with Mexico. We extend this framework for a third difference based on whether a county contains an urban area.

On the left hand side of equation 1 is the natural log of the crime rate in county *c*, in state *s*, at time *t*. We add one to the crime rate so that the natural log is not undefined. Crime is a function of a constant term, county fixed-effects, time fixed effects, county-specific control variables, and state-linear time trends. The coefficients of interest are the betas ($\beta_{\square}$), which estimate the spatially heterogeneous effect of MML in urban and rural counties in states both inland and sharing a border with Mexico. The variable MML is a dummy variable for medical marijuana laws passed in state *s* at time *t*. We use the dummy variable MB to flag states that border Mexico and URBAN to identify counties with cities that have populations of more than 50,000. Equation 1 also includes a county-specific error term.

$$\begin{aligned}
&\square\square\square(\square_{\square\square\square} + 1) = \square_0 + \square_{\square} + \square_{\square} + (\square\square_{\square\square\square}) + \square_{\square\square} + \\
&(\beta_1 \times \square\square\square_{\square\square} \times \square\square_{\square} \times \square\square\square\square\square_{\square\square}) + \\
&(\beta_2 \times \square\square\square_{\square\square} \times (1 - \square\square_{\square}) \times \square\square\square\square\square_{\square\square}) + \\
&\text{Equation 1} \\
&\big(\beta_3 \times \square\square\square_{\square\square} \times \square\square_{\square} \times (1 - \square\square\square\square\square_{\square\square})\big) + \\
&\big(\beta_4 \times \square\square\square_{\square\square} \times (1 - \square\square_{\square}) \times (1 - \square\square\square\square\square_{\square\square})\big) +
\end{aligned}$$

$\varepsilon_{\square\square\square}$

4. DATA

Data on crime rates are obtained directly from the U.S. Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCR) Program. These data contain agency level annual crime totals for the following categories; violent crime, murder, rape, robbery, aggravated assault, property crime, burglary, motor vehicle theft, larceny and arson. We independently aggregate our own measure of violent crime (murder, robbery, and aggravated assault) and property crime (burglary, motor vehicle theft, and larceny).[3] It is important to note that the UCR Program is voluntary. Consequently, the sample is not guaranteed to be representative of the population. If a law enforcement jurisdiction does not submit records to the FBI, then that observation is missing, a problem discussed in depth by Maltz and Targonski (2002). Regardless, this imperfect data is the best that there is for analyzing the effect of MML on crime (Alford (2014); Chu (2014); Morris et al. (2014); Huber et al. (2014); Gavrilova et al. (2017); and Chu and Townsend (2018)).

To resolve these issues, we implement a regression imputation strategy at the agency level, in order to reduce measurement error in the county level aggregates. Using intercensal municipality level population data obtained from the US Census, we estimate the total number of crimes annually at the agency level using a Poisson regression model with county indicators, year indicators and state specific time trends. Due to computational constraints, each model is estimated at the state level. Values of the time trends, agency level population and fixed effects are plugged into the estimated Poisson regression equation to obtain predicted values of the missing crime

[3] We exclude rape from our measure of violent crime due to inconsistencies in measurement due to a change in the definition of rape in 20XX (CITE). We independently aggregate property crime for consistency.

rates. Certain agencies which only reported crime rates in one or two years lacked the degrees of freedom necessary to estimate the agency identifying dummy coefficient. For these agencies, the imputed coefficients were extreme outliers. To remove them, we delete all observations for agencies in which the imputed value in any time period exceeds the maximum number of observed violent crimes in a given year.

Unfortunately, since true zeros and missing observations are both coded as missing, they cannot be distinguished empirically. We assume that if any crime data are reported in a given year, then the remaining blanks for that agency are equal to zero. We make this assumption in order to treat the missing data process as missing at random. In so doing we assume that the propensity for an observation to be missing is based on agency level population, which itself is not missing.

The time series begins in 1994, the year the federal Crime Control Bill was implemented into law, which represents a significant policy regime change in federal law enforcement efforts. Demographic data for the period from 1994 to 2016 come from the Decennial Census and the Bureau of Labor Statistics. We use urban population estimates from the 2010 Census to identify urban counties; those which contain areas with populations above 50,000. Our covariates are the percentage of the population that is male, black, hispanic, between the ages of 10 and 19, between the ages of 20 and 24, the unemployment rate and the log of population.

Finally, we collect information about MML passage. MML is a binary variable coded as 1 in the year MML legislation goes into effect. MML is also interacted with other indicators, namely urban status and border state status to ascertain if the effect of MML varies based on these factors.

5. RESULTS

Empirical results are reported in tables 5 through 11. In each table, results for crime regressions with county aggregation of the raw data, in line with the prior literature are reported in the top half of the table. Results based on the county aggregates of the imputed data are reported in the bottom of each table. In each case, we conduct four estimations. The first tests for the effect of legalizing medical marijuana on crime rates as a point of comparison. The second set of estimations tests the border state hypothesis set forth by Gavrilova et al. (2017). The third set tests for differences in the affect of MML on crime rates between urban and rural counties. The fourth set tests for urban differences and border state differences in the same model.

Table 5 contains estimates for the effect of MML on violent crime rates. Using the raw data, MML has a negative and statistically significant impact on violent crime rates in each regression. When only border state MML is included, there is a border effect. When urban county MML is included, there is an additional reduction in violent crimes in urban counties. But when urban MML and border state MML are included in the same model, these effects disappear.

Contrast these results to results for the imputed data. In these estimations, there is a robust decrease in violent crime rates in response MML, with no added effect in urban areas or border states. When we use our imputation strategy to reduce measurement error, the border state theory no longer explains violent crime rates as a whole. Results suggest that violent crime rates were reduced approximately by between 3.9 and 5.8 percent in response to MML.

Regressions on murder rates are shown in table 6. In this case, our replication of Gavriolova et al. (2017) results in coefficients that have an unclear story and don’t fit their border state hypothesis. Once measurement error is reduced using imputed data, MML lacks statistical significance in all cases.

Results for rates of robbery are reported in table 7. In the Gavrilova et a. (2017) extension, we find evidence supporting their border state hypothesis when the urban county interactions are not included. When they are included, urban areas in general account for the reduction in crime rates rather than the presence of the county in a border state.

When we correct for measurement error, there is a general reduction in robbery rates, with the estimated reduction being between 9.2 and 10.7 percent. Further, we do find evidence of a further reduction in Mexican border states that is robust when urban MML counties are controlled for, confirming the Mexican border theory for robbery rates. The further reduction in robbery rates for border state counties is estimated to be between 13.9 and 17.6 percent.

Table 8 reports results for aggravated assault. It is worth noting that the causal story for aggravated assault rates is quite different from the more serious categories of violent crime. Excessive alcohol consumption can lead to violent behavior such as aggravated assault, while marijuana consumption generally does not. If legal marijuana is a substitute for alcohol, then there should be a general reduction in aggravated assaults. The results bear this out. While the Gavrilova et al (2017) extension finds some evidence for a reduction in aggravated assaults in general and in border states, our results once measurement error is accounted for find a robust, general reduction in rates of aggravated assault ranging from 3.6 to 5.4 percent, regardless of the urban or border state classification of the county.

Property crime results are presented in table 9. If legalizing marijuana reduces the price of marijuana, then we should expect property crime rates in general to decrease if a subset of marijuana users commit property crimes in order to pay for their drugs. With the raw county aggregated data, there is a general decrease in property crimes in response to MML, with this effect being muted in non-border state urban areas and enhanced in urban counties within border states. With the imputed county level data, when MML is accounted for, there is a modest reduction in property crime rates of approximately 3.5%. However, this effect disappears when controlling for urban MML and both urban and border state MML.

Table 10 reports results for burglary rates and table 11 reports results for larceny rates. These results are nearly identical to property crime rates as a whole. When MML is the only policy variable included, burglary rates decrease by 2.7 percent and larceny rates decrease by 3.6 percent when urban or border state MML are not included. When they are, this effect disappears.

Table 11 reports motor vehicle theft rates. Motor vehicle thefts differ from other property crimes, in that Mexican drug cartels may steal vehicles in border states specifically for smuggling purposes. When using the imputed data and including MML policy variables such as urban and border state MML, results suggest a 14 percent reduction in motor vehicle thefts in border states, with no effect of MML on motor vehicle thefts in urban areas or non-border states.

6. CONCLUSION

This paper demonstrates the significant effect that measurement error has on criminology studies utilizing county level aggregates of the Uniform Crime Report. Due to the importance of using demographic and socio-economic control variables in explaining crime rates, which are only available at the county level for the first half of the time series, agency level analysis in the spirit of Chu and Townsend (2018) can lead to bias if MML is correlated with unobserved demographic and socioeconomic characteristics which is almost certainly the case. Likewise, if there is a heterogeneous effect of MML on crime rates in urban areas versus rural areas, the Chu and Townsend (2018) approach of deleting rural agencies provides and incomplete analysis for a large proportion of the country. Imputing missing observations at the agency level and aggregating these data to the county level reduces measurement error by ensuring that crime rates changes are not driven by significant agencies being omitted.

Our empirical analysis, which mimics Gavrilova et al (2017) in spirit, demonstrates that using imputation procedures to mitigate measurement error has a dramatic effect on estimates of the effect of MML on crime rates. When using the imputed data and allowing for urban MML to have an interactive effect on crime rates, evidence of the Mexican drug smuggling hypothesis largely disappears.

Our imputation procedure should be thought of as a first pass at attempting to rectify the shortcomings of using county aggregate estimates of the Uniform Crime Report. In the presented results, basic regression imputation using a Poisson model is utilized. Further work should focus on using other imputation strategies to assess if the results from imputed data are robust. Such methods include stochastic and multiple imputation among others.

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8. TABLES

Table 1 Medical marijuana jurisdictions

	Jurisdiction	**Effective date**		**Jurisdiction**	**Effective date**
1	California	11/6/1996	**18**	Connecticut	10/1/2012
2	Alaska	3/4/1998	**19**	District of Columbia	7/27/2010
3	Oregon	12/3/1998	**20**	Illinois	1/1/2014
4	Washington	11/3/1998	**21**	New Hampshire	7/23/2013
5	Maine	12/22/1999	**22**	Maryland	6/1/2014
6	Colorado	6/1/2001	**23**	Minnesota	5/30/2014
7	Hawai'i	12/28/2000	**24**	New York	7/5/2014
8	Nevada	10/1/2001	**25**	Louisiana	5/19/2016
9	Montana	11/2/2004	**26**	Arkansas	11/9/2016
10	Vermont	7/1/2004	**27**	Florida	1/3/2017
11	Rhode Island	1/3/2006	**28**	North Dakota	4/18/2017
12	New Mexico	7/1/2007	**29**	Ohio	9/8/2016
13	Massachusetts	1/1/2013	**30**	Pennsylvania	4/17/2016
14	Michigan	12/4/2008	**31**	West Virginia	7/1/2019
15	Arizona	4/14/2010	**32**	Missouri	12/6/2018
16	New Jersey	6/1/2010	**33**	Oklahoma	6/26/2018*
17	Delaware	7/1/2011	**34**	Utah	12/12018

This is an update of Chu and Townsend's (2018) table 1. Our version contains six additional states (Louisiana, Arkansas, West Virginia, Missouri, Oklahoma, and Utah) and is based on ProCon.org (2019b). Oklahoma's MML was effective within 30 days of the passages of the ballot initiative (June 26, 2018).

Table 2 *Summary of previous literature*

	Alford (2014)	**Morris et al. (2014)**	**Huber et al. (2016)**	**Gavrilova et al. (2017)**	**Chu and Townsend (2018)**
UCR data	✔	✔	✔	✔	✔
DD	✔	✔	✔	✔	✔
DDD				✔	
3rd Diff.				B/NB states	
Time period	1995-2012	1990-2006	1970-2012	1994-2012	1988-2013
Jurisdiction	State	State	State	County	City
Model	OLS	OLS	WLS	WLS	OLS
MML on Violent	<= 0 (murder)	<= 0	< 0	< 0*	0
MML on Property	<= 0; > 0	<= 0	< 0		0
Notes	Examines effects of different aspects of the laws, as well as marijuana depenalization; estimated effects depend on whether time trends are included		Authors estimate the effects of both MML <u>and</u> depenalization, include lots of controls	MML reduces crime in border states	

Table 3 *Summary Statistics for raw data.*					
Variable	N	Min	Max	Mean	STD
Violent	63,079.00	0.00	7,726.47	269.86	271.00
Murder	63,079.00	0.00	248.45	3.79	7.36
Robbery	63,079.00	0.00	2,432.43	44.26	76.53
Agg_Assault	63,079.00	0.00	7,726.47	221.81	225.41
Property	63,079.00	3.43	66,688.52	2,440.93	1,613.66
Burglary	63,079.00	0.00	16,786.89	596.17	419.18
Larceny	63,079.00	0.00	47,868.85	1,687.02	1,180.96
MV_Theft	63,079.00	0.00	33,593.92	157.74	214.87
MML	63,079.00	0.00	1.00	0.12	0.33
Unemployment Rate	63,079.00	0.70	38.10	6.21	2.80
Population	63,079.00	55.00	10,057,155.00	101,114.71	312,010.10
Male	63,079.00	37.36	78.49	49.72	2.10
Age 10-19	63,079.00	3.95	33.38	14.25	1.95
Age 20-24	63,079.00	0.00	37.69	6.29	2.59
Black	63,079.00	0.00	86.26	9.40	14.64
Hispanic	63,079.00	0.00	98.96	7.86	13.02

Table 4 *Summary statistics for imputed data.*					
Variable	N	Min	Max	Mean	STD
Violent	62,569.00	0.00	334,285.71	535.69	2,904.77
MML	62,569.00	0.00	19,694.16	8.77	109.24
unemploymentrate	62,569.00	0.00	102,857.14	105.79	707.80
pop	62,569.00	0.00	225,714.29	421.13	2,232.07
property	62,569.00	4.00	3,071,666.67	5,180.73	32,883.99
robbery	62,569.00	0.00	595,000.00	1,127.91	5,878.02
male	62,569.00	0.00	2,300,000.00	3,718.61	24,783.05
murder	62,569.00	0.00	282,857.14	334.21	2,468.60
mv_theft	62,569.00	0.00	1.00	0.11	0.31
Unemployment Rate	62,569.00	0.70	38.10	6.23	2.81
Population	62,569.00	35.00	10,150,558.00	81,702.82	281,626.13
Male	62,569.00	37.36	78.49	49.72	2.11
Age 10-19	62,569.00	3.90	33.38	14.30	1.94
Age 20-24	62,569.00	0.00	37.69	6.22	2.56
Black	62,569.00	0.00	86.90	9.25	14.83
Hispanic	62,569.00	0.00	98.96	7.51	12.86

Table 5 *Estimation results for the violent crime rate regressions. Violent crime rates exclude rape. *,**,*** denote statistical significance at the 1%,5% and 10% levels, respectively.*

Variables	Violent	Violent	Violent	Violent
MML	-0.057***	-0.044**	-0.041*	-0.033
	(0.018)	(0.020)	(0.023)	(0.024)
Border MML		-0.115**		-0.085
		(0.047)		(0.079)
Urban MML			-0.056**	-0.043
			(0.028)	(0.030)
Urban Border MML				-0.035
				(0.096)
Constant	8.291***	8.293***	8.236***	8.241***
	(0.927)	(0.927)	(0.928)	(0.927)
Observations	63,079	63,079	63,079	63,079
R2	0.056	0.056	0.056	0.056
Number of Counties	3,091	3,091	3,091	3,091
Time Trends	Linear	Linear	Linear	Linear
Data	Raw	Raw	Raw	Raw
Variables	Violent	Violent	Violent	Violent
MML	-0.058***	-0.055***	-0.039**	-0.039**
	(0.015)	(0.017)	(0.017)	(0.018)
Border MML		-0.022		-0.004
		(0.037)		(0.061)
Urban MML			-0.071	-0.073
			(0.064)	(0.079)
Urban Border MML				0.012
				(0.114)
Constant	6.459***	6.458***	6.457***	6.457***
	(0.248)	(0.248)	(0.248)	(0.248)
Observations	62,569	62,569	62,569	62,569
R2	0.422	0.422	0.422	0.422
Number of Counties	2,721	2,721	2,721	2,721
Time Trends	Linear	Linear	Linear	Linear
Data	Imputed	Imputed	Imputed	Imputed

Table 6 *Estimation results for the murder rate regressions. *,**,*** denote statistical significance at the 1%,5% and 10% levels, respectively.*

Variables	Murder	Murder	Murder	Murder
MML	0.001	-0.012	0.031	0.012
	(0.023)	(0.024)	(0.027)	(0.027)
Border MML		0.108		0.218**
		(0.080)		(0.103)
Urban MML			-0.108***	-0.093***
			(0.027)	(0.029)
Urban Border MML				-0.163*
				(0.084)
Constant	2.207***	2.205***	2.100**	2.068**
	(0.855)	(0.855)	(0.856)	(0.857)
Observations	63,079	63,079	63,079	63,079
R2	0.013	0.013	0.013	0.013
Number of Counties	3,091	3,091	3,091	3,091
Time Trends	Linear	Linear	Linear	Linear
Data	Raw	Raw	Raw	Raw
Variables	Murder	Murder	Murder	Murder
MML	-0.003	-0.009	0.007	-0.001
	(0.014)	(0.015)	(0.017)	(0.017)
Border MML		0.057		0.098
		(0.045)		(0.060)
Urban MML			-0.037	-0.036
			(0.031)	(0.036)
Urban Border MML				-0.051
				(0.072)
Constant	2.451***	2.453***	2.450***	2.452***
	(0.334)	(0.334)	(0.334)	(0.334)
Observations	62,569	62,569	62,569	62,569
R2	0.184	0.184	0.184	0.184
Number of Counties	2,721	2,721	2,721	2,721
Time Trends	Linear	Linear	Linear	Linear
Data	Imputed	Imputed	Imputed	Imputed

Table 7 *Estimation results for the robbery rate regressions. *,**,*** denote statistical significance at the 1%,5% and 10% levels, respectively.*

Variables	Robbery	Robbery	Robbery	Robbery
MML	-0.038	-0.019	0.019	0.026
	(0.025)	(0.027)	(0.031)	(0.032)
Border MML		-0.165**		-0.062
		(0.074)		(0.125)
Urban MML			-0.206***	-0.182***
			(0.035)	(0.035)
Urban Border MML				-0.104
				(0.133)
Constant	2.355**	2.358**	2.150**	2.148**
	(1.045)	(1.045)	(1.046)	(1.045)
Observations	63,079	63,079	63,079	63,079
R2	0.017	0.017	0.017	0.017
Number of Counties	3,091	3,091	3,091	3,091
Time Trends	Linear	Linear	Linear	Linear
Data	Raw	Raw	Raw	Raw
Variables	Robbery	Robbery	Robbery	Robbery
MML	-0.107***	-0.092***	-0.098***	-0.084***
	(0.020)	(0.022)	(0.023)	(0.024)
Border MML		-0.139**		-0.176*
		(0.056)		(0.094)
Urban MML			-0.036	-0.037
			(0.062)	(0.075)
Urban Border MML				0.088
				(0.127)
Constant	3.972***	3.967***	3.970***	3.965***
	(0.399)	(0.399)	(0.399)	(0.399)
Observations	62,569	62,569	62,569	62,569
R2	0.221	0.221	0.221	0.221
Number of Counties	2,721	2,721	2,721	2,721
Time Trends	Linear	Linear	Linear	Linear
Data	Imputed	Imputed	Imputed	Imputed

Table 8 *Estimation results for the aggravated assault rate regressions. *,**,*** denote statistical significance at the 1%,5% and 10% levels, respectively.*

Variables	Agg. Assault	Agg. Assault	Agg. Assault	Agg. Assault
MML	-0.059***	-0.046**	-0.049*	-0.041
	(0.021)	(0.023)	(0.026)	(0.027)
Border MML		-0.110**		-0.084
		(0.050)		(0.082)
Urban MML			-0.035	-0.022
			(0.032)	(0.034)
Urban Border MML				-0.040
				(0.099)
Constant	8.098***	8.100***	8.063***	8.068***
	(1.097)	(1.097)	(1.098)	(1.098)
Observations	63,079	63,079	63,079	63,079
R2	0.048	0.048	0.048	0.048
Number of Counties	3,091	3,091	3,091	3,091
Time Trends	Linear	Linear	Linear	Linear
Data	Raw	Raw	Raw	Raw
Variables	Agg. Assault	Agg. Assault	Agg. Assault	Agg. Assault
MML	-0.054***	-0.053***	-0.036**	-0.037**
	(0.016)	(0.017)	(0.018)	(0.018)
Border MML		-0.009		0.012
		(0.039)		(0.063)
Urban MML			-0.069	-0.072
			(0.066)	(0.081)
Urban Border MML				0.006
				(0.117)
Constant	6.375***	6.374***	6.372***	6.373***
	(0.249)	(0.249)	(0.248)	(0.248)
Observations	62,569	62,569	62,569	62,569
R2	0.416	0.416	0.416	0.416
Number of Counties	2,721	2,721	2,721	2,721
Time Trends	Linear	Linear	Linear	Linear
Data	Imputed	Imputed	Imputed	Imputed

Table 9 *Estimation results for the property crime rate regressions. *,**,*** denote statistical significance at the 1%,5% and 10% levels, respectively.*

Variables	Property	Property	Property	Property
MML	-0.040***	-0.034***	-0.044***	-0.044***
	(0.012)	(0.013)	(0.015)	(0.015)
Border MML		-0.052		0.012
		(0.043)		(0.067)
Urban MML			0.012	0.038*
			(0.019)	(0.019)
Urban Border MML				-0.144**
				(0.068)
Constant	10.605***	10.606***	10.617***	10.605***
	(0.684)	(0.684)	(0.685)	(0.685)
Observations	63,079	63,079	63,079	63,079
R2	0.150	0.150	0.150	0.150
Number of Counties	3,091	3,091	3,091	3,091
Time Trends	Linear	Linear	Linear	Linear
Data	Raw	Raw	Raw	Raw
Variables	Property	Property	Property	Property
MML	-0.035***	-0.030**	-0.019	-0.017
	(0.013)	(0.014)	(0.013)	(0.013)
Border MML		-0.052		-0.028
		(0.040)		(0.058)
Urban MML			-0.062	-0.058
			(0.055)	(0.068)
Urban Border MML				-0.007
				(0.096)
Constant	8.747***	8.745***	8.744***	8.743***
	(0.195)	(0.195)	(0.194)	(0.194)
Observations	62,569	62,569	62,569	62,569
R2	0.524	0.524	0.524	0.524
Number of Counties	2,721	2,721	2,721	2,721
Time Trends	Linear	Linear	Linear	Linear
Data	Imputed	Imputed	Imputed	Imputed

Table 10 *Estimation results for the burglary rate regressions. *,**,*** denote statistical significance at the 1%,5% and 10% levels, respectively.*

Variables	Burglary	Burglary	Burglary	Burglary
MML	-0.085***	-0.081***	-0.086***	-0.093***
	(0.018)	(0.019)	(0.021)	(0.022)
Border MML		-0.035		0.099
		(0.053)		(0.070)
Urban MML			0.002	0.048**
			(0.025)	(0.025)
Urban Border MML				-0.283***
				(0.089)
Constant	10.212***	10.213***	10.215***	10.185***
	(0.881)	(0.881)	(0.881)	(0.878)
Observations	63,079	63,079	63,079	63,079
R2	0.090	0.090	0.090	0.090
Number of Counties	3,091	3,091	3,091	3,091
Time Trends	Linear	Linear	Linear	Linear
Data	Raw	Raw	Raw	Raw
Variables	Burglary	Burglary	Burglary	Burglary
MML	-0.027**	-0.022	-0.011	-0.011
	(0.014)	(0.015)	(0.014)	(0.014)
Border MML		-0.047		0.010
		(0.041)		(0.058)
Urban MML			-0.064	-0.051
			(0.056)	(0.069)
Urban Border MML				-0.071
				(0.098)
Constant	7.129***	7.127***	7.127***	7.127***
	(0.203)	(0.203)	(0.202)	(0.202)
Observations	62,569	62,569	62,569	62,569
R2	0.489	0.489	0.489	0.489
Number of Counties	2,721	2,721	2,721	2,721
Time Trends	Linear	Linear	Linear	Linear
Data	Imputed	Imputed	Imputed	Imputed

Table 11 *Estimation results for the larceny rate regressions. *,**,*** denote statistical significance at the 1%,5% and 10% levels, respectively.*

Variables	Larceny	Larceny	Larceny	Larceny
MML	-0.026*	-0.026*	-0.032*	-0.038**
	(0.015)	(0.015)	(0.018)	(0.018)
Border MML		-0.001		0.066
		(0.053)		(0.090)
Urban MML			0.024	0.047**
			(0.022)	(0.022)
Urban Border MML				-0.153*
				(0.092)
Constant	8.800***	8.800***	8.824***	8.807***
	(0.923)	(0.923)	(0.925)	(0.924)
Observations	63,079	63,079	63,079	63,079
R2	0.091	0.091	0.091	0.091
Number of Counties	3,091	3,091	3,091	3,091
Time Trends	Linear	Linear	Linear	Linear
Data	Raw	Raw	Raw	Raw
Variables	Larceny	Larceny	Larceny	Larceny
MML	-0.036***	-0.032**	-0.020	-0.018
	(0.013)	(0.014)	(0.014)	(0.014)
Border MML		-0.043		-0.035
		(0.042)		(0.060)
Urban MML			-0.062	-0.063
			(0.055)	(0.069)
Urban Border MML				0.024
				(0.097)
Constant	8.476***	8.474***	8.474***	8.473***
	(0.209)	(0.209)	(0.208)	(0.208)
Observations	62,569	62,569	62,569	62,569
R2	0.481	0.481	0.482	0.482
Number of Counties	2,721	2,721	2,721	2,721
Time Trends	Linear	Linear	Linear	Linear
Data	Imputed	Imputed	Imputed	Imputed

Table 11 *Estimation results for the motor vehicle theft rate regressions. *,**,*** denote statistical significance at the 1%,5% and 10% levels, respectively.*

Variables	MV Theft	MV Theft	MV Theft	MV Theft
MML	-0.051**	-0.020	-0.028	-0.015
	(0.023)	(0.025)	(0.027)	(0.029)
Border MML		-0.268***		-0.110
		(0.065)		(0.093)
Urban MML			-0.082**	-0.020
			(0.034)	(0.034)
Urban Border MML				-0.292**
				(0.119)
Constant	5.614***	5.619***	5.532***	5.521***
	(1.163)	(1.162)	(1.164)	(1.163)
Observations	63,079	63,079	63,079	63,079
R2	0.083	0.083	0.083	0.083
Number of Counties	3,091	3,091	3,091	3,091
Time Trends	Linear	Linear	Linear	Linear
Data	Raw	Raw	Raw	Raw
Variables	MV Theft	MV Theft	MV Theft	MV Theft
MML	-0.045**	-0.023	-0.038*	-0.025
	(0.018)	(0.019)	(0.020)	(0.021)
Border MML		-0.205***		-0.144**
		(0.045)		(0.062)
Urban MML			-0.030	0.005
			(0.060)	(0.074)
Urban Border MML				-0.112
				(0.102)
Constant	5.799***	5.792***	5.798***	5.793***
	(0.310)	(0.310)	(0.310)	(0.310)
Observations	62,569	62,569	62,569	62,569
R2	0.532	0.532	0.532	0.532
Number of Counties	2,721	2,721	2,721	2,721
Time Trends	Linear	Linear	Linear	Linear
Data	Imputed	Imputed	Imputed	Imputed

9. FIGURES

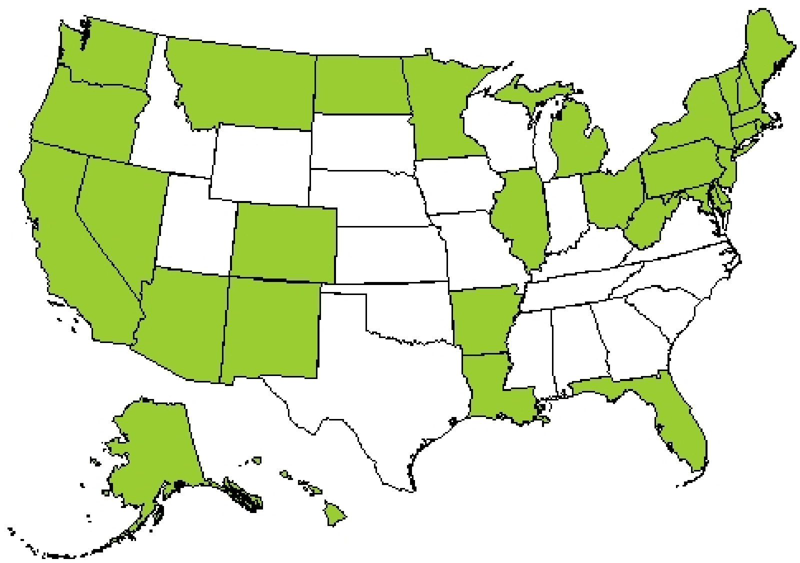

Figure 1 *Medical marijuana law states: 1996-2017*

10. Old outline

General outline:

- Marijuana and crime
    - Highlight general schools of thought (Anderson et al. 2013)
        - Proponents of MML say MML is efficacious and safe
        - Opponents of MML focus on social issues like crime
            - of course marijuana and crime are linked, the former is illegal
    - Discuss empirical connections from research, high level
        - Anderson et al. (2013) show that
            - MML leads to a decrease in traffic fatalities
            - MML and alcohol are substitutes
            - MML affect on illegal marijuana markets depends on the class of marijuana (high vs low grade)
        - Braakman and Jones (2014) also look at 2004 cannabis decriminalization in UK on crime
            - no increase in crime, data is only 2003-2006
    - MML and marijuana use
        - Chu 2014 looks at the effect of MML on marijuana use among non-patients → arrests increase
        - Pacula et al. (2015) discuss
            - how MML effects recreational marijuana use and
            - not all MML are equal
- Summarize the status of the literature on MML and crime
    - There is no consensus on the effect
        - Conflicting results
        - Not surprising, particularly when considering how different many of the existing MML laws are (Alford 2014; Pacula et al. 2015; Huber et al. 2016)
            - Can argue that Huber et al. 2016 are able to find effects of MML on crime at the state level (relative to Morris et al. 2014) by
                - including a related policy, depenalization
                - including 6 additional years of data
- We contribute to the literature by providing an explanation for conflicting results in the previous literature
    - Two primary sources of conflict:
        - First, spatial heterogeneity and spatial measurement
            - Different researchers have used different units of measurement
                - Alford (2014) → state DD
                - Morris et al. (2014) → state DD

        - Huber et al. (2016) → DD
        - Gavrilova et al. (2017) → county DD and DDD
        - Chu and Townsend (2018) → city DD
    - The result of Chu and Townsend (2018) doesn't mean that MML doesn't affect crime, there is simply no effect in cities. It is plausible that the crime effects take place outside of the city limits.
    - Furthermore, the aggregation used by Morris et al. (2014) may confound detection of crime in smaller jurisdictions
        - Gavrilova et al. (2017) extend Morris et al. (2014) and demonstrate that MML affects crime in border states differently than non-border states
- Second, the effect of MML on crime is lagged. This is particularly evident considering there is a lag between passing MML and when the MML goes into effect.
    - Explore how past researchers have coded MML
    - With current data
        - we show MML decreases both property and violent crime at the national level, and violent crime in urban areas
            - these effects are not evident in the data when excluding years after 2013 (consistent with the Chu and Townsend (2018) story)
                - Furthermore, while a national effect is not detected, Chu and Townsend (2018) find an effect of MML on crime in California, the first state to enact such laws. Indicative of a potentially long lag.
                - Also, it is possible that MML causes DTOs or gangs to substitute illicit markets for rent collection using violence, causing rebound effects. Decreases in crime associated with marijuana may be nullified by increases in crime associated with human/sex trafficking or other drugs like cocaine or heroin.
                    - Given the lag we can think about BCA with respect to MML and discounting. What is the social rate of time preference for crime? What is the value to society of less crime in the near and distant futures?

            - furthermore we show that the effect of MML on violent and property crime is stronger in border states than inland states and the effect on violent crime holds when we restrict our sample to exclude years after 2012 (consistent with Gavrilova et al. (2017))
        - Third, other empirical issues such as model specification (OLS, WLS, clustering, etc.) may also impact results. We leave those issues for another time.
    - In addition, we extend the analysis of Gavrilova et al. (2017) and illustrate another area of heterogeneity in the effects of MML on crime
        - We show not only are effects different in border and non-border states, but the effects depends on county population. Generally speaking MML doesn't appear to have much of an effect on violent crime in rural counties of non-border states. It does appear, however, to decrease property crime, which may be indicative of an opioid epidemic story
        - Our results, however, are not robust to time periods included in the model. The effects of MML are different for the whole sample relative to the restricted sample (excluding data after 2012).
- Our results suggest that legislatively and administratively complex policies may need time to work before their effects are observed. Don't salt the earth in anger the day after planting, it takes a while for the tree to grow. Previous results showing no effect should given time to be disproven.

11. Old literature review outline

First, identification, and time and spatial heterogeneity literature

Second, our paper is most closely related to: (see table 2)

- Alford (2014)
    - MML and depenalization
- Morris et al. (2014)
- Huber et al. (2016)
    - MML versus depenalization
- Gavrilova et al. (2017)
    - Border versus non-border
- Chu and Townsend (2018)

Major differences between these papers are

- time period
- jurisdictional aggregation (city, county, state)
- empirical strategy (OLS versus WLS)
- coding of MML in terms of passage or effective dates?
- degree of distangling of MML attributes, and MML from related policy

Third,