
Robert G. Morris*, Michael TenEyck, J. C. Barnes, Tomislav V. Kovandzic
Program in Criminology, University of Texas at Dallas, Richardson, Texas, United States of America

Abstract

Background: Debate has surrounded the legalization of marijuana for medical purposes for decades. Some have argued medical marijuana legalization (MML) poses a threat to public health and safety, perhaps also affecting crime rates. In recent years, some U.S. states have legalized marijuana for medical purposes, reigniting political and public interest in the impact of marijuana legalization on a range of outcomes.

Methods: Relying on U.S. state panel data, we analyzed the association between state MML and state crime rates for all Part I offenses collected by the FBI.

Findings: Results did not indicate a crime exacerbating effect of MML on any of the Part I offenses. Alternatively, state MML may be correlated with a reduction in homicide and assault rates, net of other covariates.

Conclusions: These findings run counter to arguments suggesting the legalization of marijuana for medical purposes poses a danger to public health in terms of exposure to violent crime and property crimes.


Editor: Joseph A. Koating, Tulane University School of Public Health and Tropical Medicine, United States of America

Received November 22, 2013; Accepted February 25, 2014; Published March 26, 2014

Copyright: © 2014 Morris et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Funding: The authors have no funding or support to report.

Competing Interests: The authors have declared that no competing interests exist.

* E-mail: morris@utdallas.edu

Introduction

The social ramifications of marijuana legalization have been hotly debated for at least four decades [1]. Despite a long history of marijuana use for medical purposes, policymakers and in some instances, the scientific community, have been quick to note the potential problematic social outcomes of marijuana legalization [2]. In spite of these political discussions, medical marijuana legalization (MML) has occurred in 20 states and the District of Columbia (between 1996 and the writing of this paper) and its recreational use has now been legalized in Colorado and Washington [3]. An interest in the ramifications of these laws has led to an increase in scholarly activity on the topic [4], [5]. The issue addressed in this article is whether MML has the effect of increasing crime. While there are many mechanisms by which MML might affect crime rates, the most obvious is by increasing the number of marijuana users, which may lead to a broader social acceptance of drug using behaviors and drug users [6]. To the extent that marijuana use serves as a “gateway” to harder drugs such as cocaine and heroin, MML could lead to long-term increases in crime as an ever-growing number of illicit drug users engage in serious predatory crimes to support their habits (but see [7]). But even if MML does not lead to a rise in marijuana use (especially among youths), the laws could still stimulate crime as newly opened medical marijuana dispensaries provide criminals with a highly attractive target with their repository of high quality marijuana and customers carrying large amounts of cash (but see [8]). As a member of the California Chiefs of Police Association stated, “A disturbing and continuing trend is the increasing number of home invasion robberies and associated violence resulting in the victimization of those cultivating and possessing marijuana ... [D]ispersaries also continue to be targeted based upon the availability of larger quantities of drugs and cash” (see http://californiapolicchiefs.org/wp-content/uploads/2012/02/July_Security_report_2010_Final.pdf). Though anecdotal evidence abounds to support both theses, and a few single-jurisdiction and cross-sectional studies have examined the MML-crime link (e.g., [9]), no single analysis has assessed the overall consequences of medical marijuana laws on crime rates across the United States. This study seeks to inform the debate by providing a comprehensive evaluation of the effects of state MML on state crime rates.

The Positive Correlation between Marijuana Use and Criminal Behavior

Though the gateway hypothesis applies to the progression of drug-using behaviors, there remains the possibility that marijuana use leads to delinquent or criminal behavior via a similar mechanism. A number of studies have specifically examined the relationship between marijuana use and crime [10], [11], [12], [13], [14]. Early studies compared the amount of crimes committed by juveniles whose urine tested positive for marijuana upon entering a detention center and those committed by individuals who tested negative for marijuana. Dembo and associates [15], [16], for instance, found that youths who tested positive for marijuana had a significantly higher number of
It has been argued that medicinal marijuana laws may increase crime because the dispensaries and grow houses provide an opportunity for property crime and violent crime to occur, such as burglary and robbery. Kephel and Frechtl [9] examined the relationship between medical marijuana dispensaries and crime and their results suggested that after controlling for a host of ecological variables, no relationship existed between medical marijuana dispensaries and property or violent crime. Additional research has shown that medicinal marijuana dispensaries may actually reduce crime within the immediate vicinity of the dispensaries [8]. This may be due to the security measures implemented by dispensary owners (i.e., having security cameras, having a doorman, and having signs requiring identification). Importantly, medical marijuana dispensaries do not appear to increase crime in their surrounding areas.

In sum, research on the relationship between medicinal marijuana and crime is mixed. Studies have shown that states allowing the use of medical marijuana have higher prevalence rates of marijuana use [13, 14], yet other studies have found that legalized medicinal marijuana does not lead to an increase in its overall use [21, 22]. Research has also suggested that marijuana use is associated with an increase in illicit drug use [23, 19] and an increase in crime [17, 19, 16]. Others, however, have revealed that marijuana is not related to additional illicit drug use [22, 7, 17] or crime [8], [9], [21]. Thus, the available evidence is equivocal and in need of a rigorous evaluation of the MML-crime relationship.

Methods

Data & Measures

Dependent Variables. Data on all seven Part I offenses—homicide, rape, robbery, assaults, burglary, larceny, and auto theft—for each state between 1990 and 2006 were obtained from the Federal Bureau of Investigation’s Uniform Crime Reporting (UCR) Program, published as Crime in the United States. The data were obtained using the “data for analysis” tool on the Bureau of Justice Statistics Web site (http://www.ojp.usdoj.gov/bjs/did.htm). All data were gathered for each of the 50 U.S. states across the 17 year time span for a total N = 850. Values reflect the rate of each crime per 100,000 residents.

Medical Marijuana Legalization (MML). To determine if and when MML occurred within a state, we searched the official legislative website of each U.S. state. Between 1990 and 2006, the following 11 states legalized marijuana for medicinal use, with the year the law was passed in parentheses: Alaska (1998), California (1996), Colorado (2000), Hawaii (2000), Maine (1999), Montana (2004), Nevada (2000), Oregon (1998), Rhode Island (2006), Vermont (2004), and Washington (1998). We also ran models based on MML “legislation-effective year” rather than “legislation-passed year” and found no substantive differences in the results. The MML effective dates were also gathered from each state’s official legislative website. Only 2 states (Connecticut and Colorado) had an MML effective year different than “passed” year, both being only a 1-year difference. While there are many options in modeling the effects of MML adoption on crime, we opted to use a post-law trend variable. The trend variable represents the number of years the law has been in effect with a value of zero for all years before the law was passed, a value of 1 for the year the law was passed, and a value of 1 + k, where k = number of years after the initial passage of the law, for all subsequent years. Unlike the traditional “dummy variable” approach (i.e., 0 = no MML law, 1 = MML law), which posits a once-and-for-all impact on crime, the post-law trend variable
captures any changes in the linear trend of crime that may be observed over time. If opponents of MML are correct that the laws lead to increased marijuana use by teenagers, many of whom are likely to continue illicit hard drug use throughout their adulthood, one might expect a gradual increase in crime over time. Such an effect would be best captured by the post-law trend variable.

Sociodemographic Control Variables. Sociodemographic variables were included in the analysis to aid in controlling for a vast array of other time-varying influences that might be potential confounding factors over the study period. These variables, and their sources, have been described previously [24]. Specifically, they include each state’s percent of the civilian labor force unemployed; the total employment rate; percent of the population living below the poverty line; real per-capita income (divided by the Consumer Price Index); the proportion of residents aged 15-24; the proportion of residents aged 25-34; the proportion of residents aged 35-44 years; the per-capita rate of beer consumption [23]; the proportion of residents with at least a bachelor’s degree; and the percent of the state’s population that lived in a metropolitan area. State-level unemployment data were obtained from the Bureau of Labor Statistics website (www.bls.gov/sae/home). Data on poverty were acquired via the Bureau of the Census website (www.census.gov/hhes/www/poverty). Personal income and real welfare payments data were taken from the Bureau of Economic Analysis website (www.bea.doc.gov/bea/regional/real). The age variables were obtained directly from the U.S. Bureau of the Census. Data on beer consumption were taken from the Beer Institute website (www.beerinstitute.org). The percent of the population with college degrees or higher and the percent of the population living in a metropolitan area are linear interpolations of decennial census data, as reported in various editions of the Statistical Abstracts of the United States.

Additional measures included the number of prison inmates per 100,000 residents and the number of police officers per 100,000 residents. The number of prisoners was measured as the number of prisoners sentenced to more than a year in custody as of December 31 per 100,000 residents and was obtained from the Bureau of Justice Statistics’s website (www.bjs.gov/). Data on the number of police, including civilians, were taken from the Public Employment series prepared by the Bureau of the Census. Louisiana and Mississippi were missing information on that variable for the year 2006, therefore reducing the usable case count by two units. Substantive results were identical when values for this year were imputed with values from the previous year. Summary statistics for these explanatory variables are presented in Table 1.

Analysis Plan
To identify the effect of MML on crime, we used a fixed-effects panel design, exploiting the within-state variation introduced by the passage of MML in 11 states over the 17-year observation period. The design allows for the assessment of whether states adopting MML experienced changes in the trend of crime by analyzing within state changes in crime rates over time and comparing those changes to the crime rate trends among states that did not pass an MML law. To carry out this analysis, we estimate fixed-effects ordinary least squares regression models, where the natural log of each crime rate variable (i.e., homicide, rape, robbery, assault, burglary, larceny, and auto theft) is the dependent variable. This model directly accounts for dynamic factors that cause crime to vary from state to state, as well as those stable unmeasured factors that differ between states [26], [27]. In addition, we also include “year fixed-effects,” which capture any national influences on crime that are not captured in any of the time-varying explanatory variables. Robust standard errors are clustered at the state level to avoid biased standard errors due to the non-independence of data points over time [28]. Thus, the fixed effects models can be expressed algebraically following the convention set forth by Wooldridge [27] as:

$$\log (y_{ijt}) = b_0 + b_1 MML_j t + \ldots + b_k x_{ijt} + \epsilon_{ijt}$$

where:
- the subscripts i, j, and t are used to identify the crime rate variable being used as the dependent variable, the 50 states, and time (1990–2006), respectively;
- \(\log (y_{ijt}) = \) the time-demeaned (see [27]) logged crime rate outcome variable;
- \(b_0 = \) the crime-specific constant term;
- \(b_1 MML_j t = \) the time-demeaned crime-specific average impact of MML on crime rates;
- \(\ldots + b_k x_{ijt} = \) the time-demeaned crime-specific effect of the various control variables, including year dummies, a linear trend variable, and state fixed effects;
- and, \(\epsilon_{ijt} = \) the time-demeaned crime-specific error term.

It is important to note that fixed-effects models are not without limitations. While they are well suited to address the issue at hand and account for unobserved time-varying factors, they are always
vulnerable to time-varying factors that are not accounted for that differ between states with MML and those without. However, we have accounted for the bulk of factors that have been shown associated with state crime rates and our models explain a considerable amount of variation in each outcome. It is also important to acknowledge that fixed-effects models do not account for temporal ordering for time-varying predictors within a given observation period. For example, it is unknown whether states adopted MML after experiencing lower crime rates in a given year(s), however, this is unlikely to be an issue here since policy response to crime rates tend to take time and we account for this via operationalization of MML as an additive effect.

Results

Primary Findings

Before consulting the results from the fixed effects regression models, a series of unconditioned crime rates for each offense type were generated and are presented in Figure 1. Note that two crime rate trends are presented in each panel. One trend—the solid line—shows the crime rate, by year, for states that had not passed an MML law. Thus, states that eventually did pass an MML law contribute to the solid line up until the year that they passed the MML law. As expected from the overall crime trend during this time period, the solid line reveals that all states experienced a reduction in each of the seven crimes from 1990 to 2006. Important to note is the trend revealed by the dashed line, which shows the crime rate trends for states after passing an MML law. With one exception—forcible rape—states passing MML laws experienced reductions in crime and the rate of reduction appears to be steeper for states passing MML laws as compared to others for several crimes such as homicide, robbery, and aggravated assault. The raw number of homicides, robberies, and aggravated assaults also appear to be lower for states passing MML as compared to other states, especially from 1998-2006. These preliminary results suggest MML may have a crime-reducing effect, but recall that these are unconditional averages, meaning that the impact of the covariates and other factors related to time series trends have not been accounted for in these figures.

The results of the fixed effects analyses are presented in Table 2. It is important to note that a Hausman test was carried out to determine whether the fixed effects model was preferable over the random effects model; the latter model is more parsimonious and, thus, should be preferred when results do not systematically differ across the two approaches. The results of the Hausman tests (with year fixed effects omitted for both equations because they are inestimable in the random effects model) suggested that the fixed effects model was preferred in each of the seven analyses. For reference, the Hausman χ² values were 302.61, 23.64, 102.50, 414.94, 58.87, 34.18, and 31.26 for homicide, rape, robbery, assault, burglary, larceny, and auto theft, respectively.

The key results gleaned from the fixed effects analyses are presented in row 1 of Table 2, which reveals the impact of the MML trend variable on crime rates, while controlling for the other time-varying explanatory variables. Two findings worth noting emerged from the different fixed effects regression analyses. First, the impact of MML on crime was negative or not statistically significant in all but one of the models, suggesting the passage of MML may have a dampening effect on certain crimes. The second key finding was that the coefficients capturing the impact of MML on homicide and assault were the only two that emerged as statistically significant. Specifically, the results indicate approximately a 2.4 percent reduction in homicide and assault, respectively, for each additional year the law is in effect. Because log-linear models were estimated, the coefficient must be transformed according to the following formula to generate percentage changes in crime for a one-unit increase in MML: 

\[ b \times 10^{10} \]  

However, it is important to note that the finding for homicide was less variable (i.e., a lower standard error) as compared to assault. One might argue a Bonferroni correction is necessary given the exploratory nature of the study and the multiple models that were analyzed. Once a Bonferroni correction was carried out (i.e., α/7), only the effect of MML on homicide remained statistically significant (.05/7 = .007). Perhaps the most important finding in Table 2 is the lack of evidence of any increase in robbery or burglary, which are the type of crimes one might expect to gradually increase over time if the MML-crime thesis was correct. Thus, in the end, MML was not found to have a crime enhancing effect for any of the crime types analyzed.

Sensitivity Analyses

The fixed effects models presented above were subjected to a range of sensitivity tests to determine whether the findings were robust to alternative model specifications. First, and as previously noted, data for the two missing cases were imputed using matched case replacement for Louisiana and Mississippi. Importantly, substantive results were identical when this strategy was carried out. A second sensitivity analysis explored the possibility that the effect of MML on crime rates was non-linear. No evidence emerged to support the hypothesis that MML has a non-linear effect on crime rate trends. Third, a related issue concerns whether the MML effect has both a trend effect (shown above) and a one-time shock effect. We considered this issue by including the MML trend variable (discussed above) along with a dummy variable coded 0 for years when no MML law was present (by state) and coded 1 in years when an MML law had been passed. The findings were practically identical to those shown above: the MML trend variable was negatively related to homicide (b = -.02, p<.10) and assault (b = -.02, p<.10). A fourth sensitivity analysis re-estimated the original models (shown above), by weighting each state proportional to its population size. When these weighted fixed effects models were estimated, the substantive findings were somewhat different than those presented above. Specifically, the effect of MML on homicide rates was no longer statistically significant (b = -.01, p=.30), MML negatively predicted robbery rates (b = -.02, p<.10), MML negatively predicted assault rates (b = -.03, p<.10), and MML positively predicted auto theft rates (b = .03, p<.05). While it is common in the crime policy literature to weight observations by resident population to correct for possible heteroskedasticity, this will be the efficient feasible GLS (generalized least squares) procedure only if the heteroskedasticity takes a particular form, i.e. variance proportional to the square of the population. In the present study, the unweighted results produce findings that are substantively consistent with the weighted results, although they differ slightly quantitatively. The most likely explanation for this discrepancy is that the weighted results are driven by a few large population states. For this reason, we present the unweighted results as the main results and the weighted results as part of our numerous robustness checks.

Discussion and Conclusion

The effects of legalized medical marijuana have been passionately debated in recent years. Empirical research on the direct relationship between medical marijuana laws and crime, however, is scant and the consequences of marijuana use on crime remain unknown. Studies have shown that marijuana use was associated with higher prevalence of subsequent illicit drug use [19] and an
Attachment K

The Effect of Medical Marijuana Laws on Crime
increased risk of violence [17]. Yet, other studies have found that increased risk of violence [17]. Yet, other studies have found that once additional factors were controlled for, there was no relationship between marijuana use and later serious drug use [7]. Research has also shown that marijuana use is not related to violent crime when measured at the individual-level [20]. Once drug charges are controlled for, Pedersen and Skardhamar [21] reported that the relationship between marijuana and crime was not significantly different from zero. Unfortunately, no study has examined the effect of legalized medical marijuana on state crime rates across the United States. The current study sought to fill this gap by assessing the effect of legalized medicinal marijuana on the seven Part I UCR offenses. The analysis was the first to look at multiple offenses across multiple states and time periods to explore whether MML impacts state crime rates.

The central finding gleaned from the present study was that MML is not predictive of higher crime rates and may be related to reductions in rates of homicide and assault. Interestingly, robbery and burglary rates were unaffected by medicinal marijuana legislation, which runs counter to the claim that dispensaries and grow houses lead to an increase in victimization due to the opportunity structures linked to the amount of drugs and cash that are present. Although, this is in line with prior research suggesting that medical marijuana dispensaries may actually reduce crime in the immediate vicinity [9].

In sum, these findings run counter to arguments suggesting the legalization of marijuana for medical purposes poses a danger to public health in terms of exposure to violent crime and property crimes. To be sure, medical marijuana laws were not found to have a crime exacerbating effect on any of the seven crime types. On the contrary, our findings indicated that MML predicts a reduction in homicide and assault. While it is important to remain cautious when interpreting these findings as evidence that MML reduces crime, these results do fall in line with recent evidence [29] and they conform to the longstanding notion that marijuana

### Table 2. The Impact of Medical Marijuana Laws on Crime Rates.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Homicide</th>
<th>Rape</th>
<th>Robbery</th>
<th>Assault</th>
<th>Burglary</th>
<th>Larceny</th>
<th>Auto Theft</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medical Marijuana Law (MML)</td>
<td>-0.024**</td>
<td>-0.005</td>
<td>-0.018</td>
<td>-0.024*</td>
<td>-0.004</td>
<td>-0.002</td>
<td>0.026</td>
</tr>
<tr>
<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.013)</td>
<td>(0.007)</td>
<td>(0.004)</td>
<td>(0.016)</td>
<td></td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>0.031**</td>
<td>-0.001</td>
<td>0.039**</td>
<td>-0.021</td>
<td>0.022**</td>
<td>0.005</td>
<td>0.035**</td>
</tr>
<tr>
<td>(0.012)</td>
<td>(0.014)</td>
<td>(0.015)</td>
<td>(0.022)</td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.017)</td>
<td></td>
</tr>
<tr>
<td>Employment rate</td>
<td>1.325***</td>
<td>3.672***</td>
<td>3.63***</td>
<td>4.249***</td>
<td>0.420</td>
<td>-0.584</td>
<td>-0.069</td>
</tr>
<tr>
<td>(1.277)</td>
<td>(1.56)</td>
<td>(1.55)</td>
<td>(1.53)</td>
<td>(1.38)</td>
<td>(0.94)</td>
<td>(0.74)</td>
<td>(1.715)</td>
</tr>
<tr>
<td>Poverty rate</td>
<td>-0.008**</td>
<td>0.006</td>
<td>0.001</td>
<td>-0.004</td>
<td>-0.002</td>
<td>-0.607</td>
<td>-0.607**</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Per-capita income</td>
<td>-0.013</td>
<td>-0.229***</td>
<td>-0.146*</td>
<td>-0.173*</td>
<td>-0.194***</td>
<td>-0.095***</td>
<td>-0.137</td>
</tr>
<tr>
<td>(0.057)</td>
<td>(0.067)</td>
<td>(0.072)</td>
<td>(0.100)</td>
<td>(0.048)</td>
<td>(0.036)</td>
<td>(0.102)</td>
<td></td>
</tr>
<tr>
<td>Proportion aged 15 to 24</td>
<td>3.358</td>
<td>0.279</td>
<td>3.591</td>
<td>3.245</td>
<td>0.676</td>
<td>-0.206</td>
<td>5.279</td>
</tr>
<tr>
<td>(2.447)</td>
<td>(1.681)</td>
<td>(3.37)</td>
<td>(2.96)</td>
<td>(1.69)</td>
<td>(1.42)</td>
<td>(3.50)</td>
<td></td>
</tr>
<tr>
<td>(1.846)</td>
<td>(2.638)</td>
<td>(2.320)</td>
<td>(3.13)</td>
<td>(1.09)</td>
<td>(1.71)</td>
<td>(2.60)</td>
<td></td>
</tr>
<tr>
<td>Proportion aged 35 to 44</td>
<td>-1.393</td>
<td>-3.083</td>
<td>-4.004</td>
<td>-13.77***</td>
<td>-1.940</td>
<td>0.193</td>
<td>-3.558</td>
</tr>
<tr>
<td>(2.041)</td>
<td>(2.319)</td>
<td>(3.365)</td>
<td>(4.654)</td>
<td>(1.928)</td>
<td>(1.48)</td>
<td>(4.07)</td>
<td></td>
</tr>
<tr>
<td>Beer consumption</td>
<td>0.003**</td>
<td>0.004*</td>
<td>1.26***</td>
<td>0.436</td>
<td>0.857**</td>
<td>0.762**</td>
<td>1.375**</td>
</tr>
<tr>
<td>(0.099)</td>
<td>(0.203)</td>
<td>(0.442)</td>
<td>(0.570)</td>
<td>(0.29)</td>
<td>(0.28)</td>
<td>(0.580)</td>
<td></td>
</tr>
<tr>
<td>Percent college degree</td>
<td>-0.004</td>
<td>0.016</td>
<td>-0.032**</td>
<td>-0.012</td>
<td>-0.001</td>
<td>0.005</td>
<td>-0.018</td>
</tr>
<tr>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.012)</td>
<td>(0.017)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>Percent metropolitan</td>
<td>0.015**</td>
<td>0.022**</td>
<td>0.004</td>
<td>0.004</td>
<td>-0.005</td>
<td>-0.005</td>
<td>-0.009</td>
</tr>
<tr>
<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.015)</td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td>Prisoners per 100k</td>
<td>-45575</td>
<td>-20410</td>
<td>-33918</td>
<td>41979</td>
<td>-7186</td>
<td>9724</td>
<td>-56412</td>
</tr>
<tr>
<td>(33664)</td>
<td>(22442)</td>
<td>(35013)</td>
<td>(30046)</td>
<td>(26127)</td>
<td>(18575)</td>
<td>(48726)</td>
<td></td>
</tr>
<tr>
<td>Police officers per 100k</td>
<td>-0.001</td>
<td>0.000</td>
<td>-0.002</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>$^2$</td>
<td>.50</td>
<td>.46</td>
<td>.58</td>
<td>.44</td>
<td>.83</td>
<td>.75</td>
<td>.44</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses.

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

Note: State fixed effects and year fixed effects are included in all estimates but are not shown in the table. The following variables were divided by 100000 in order to produce coefficients that did not require scientific notation to interpret: Employment rate, Beer consumption, and Prisoners per 100k.

doi:10.1371/journal.pone.0092816.g001
legalization may lead to a reduction in alcohol use due to individuals substituting marijuana for alcohol [see generally 29, 30]. Given the relationship between alcohol and violent crime [31], it may turn out that substituting marijuana for alcohol leads to minor reductions in violent crimes that can be detected at the state level. That said, it also remains possible that these associations are statistical artifacts (recall that only the homicide effect holds up when a Bonferroni correction is made).

Given that the current results failed to uncover a crime exacerbating effect attributable to MML, it is important to examine the findings with a critical eye. While we report no positive association between MML and any crime type, this does not mean that MML has no effect on crime (or even that it reduces crime). It may be the case that an omitted variable, or set of variables, has confounded the associations and masked the true positive effect of MML on crime. If this were the case, such a variable would need to be something that was restricted to the states that have passed MML, if it would need to have emerged in close temporal proximity to the passage of MML in all of those states (all of which had different dates of passage for the marijuana law), and it would need to be something that decreased crime to such an extent that it "masked" the true positive effect of MML (i.e., it must be something that has an opposite sign effect to MML, e.g., a positive correlation) and crime (e.g., a negative correlation). Perhaps the more likely explanation of the current findings is that MML laws reflect behaviors and attitudes that have been established in the local communities. If these attitudes and behaviors reflect a more tolerant approach to one another’s personal rights, we are unlikely to expect an increase in crime and might even anticipate a slight reduction in personal crimes.

Moreover, the present findings should also be taken in context with the nature of the data at hand. They are based on official arrest records (URC), which do not account for crimes not reported to the police and do not account for all charges that may underlie an arrest. In any case, this longitudinal assessment of medical marijuana laws on state crime rates suggests that these laws do not appear to have any negative (i.e., crime exacerbating) impact on officially reported criminality during the years in which the laws are in effect, at least when it comes to the types of offending explored here. It is also important to keep in mind that the UCR data used here did not account for juvenile offending, which may or may not be empirically tethered to MML in some form or another; an assessment of which is beyond the scope of this study.

Author Contributions

Analyzed the data: RM JGB. Contributed reagents/materials/analysis tools: TK. Wrote the paper: RM MT JGB TK.

References

Exploring the Ecological Association Between Crime and Medical Marijuana Dispensaries

NANCY J. KEPPLE, M.S.W., a, * AND BRIDGET FREISTHLER, PH.D., a, b

aDepartment of Social Welfare, University of California, Los Angeles, Luskin School of Public Affairs, Los Angeles, California
bLewis Center Faculty Fellow, University of California, Los Angeles, Luskin School of Public Affairs, Los Angeles, California

ABSTRACT. Objective: Routine activities theory purports that crime occurs in places with a suitable target, motivated offender, and lack of guardianship. Medical marijuana dispensaries may be places that satisfy these conditions, but this has not yet been studied. The current study examined whether the density of medical marijuana dispensaries is associated with crime. Method: An ecological, cross-sectional design was used to explore the spatial relationship between density of medical marijuana dispensaries and two types of crime rates (violent crime and property crime) in 95 census tracts in Sacramento, CA, during 2009. Multivariate regression models were used to determine associations between crime rates and density of medical marijuana dispensaries, controlling for neighborhood characteristics associated with routine activities. Results: Violent and property crime rates were positively associated with percentage of commercially zoned areas, percentage of one-person households, and unemployment rate. Higher violent crime rates were associated with concentrated disadvantage. Property crime rates were positively associated with the percentage of population 15–24 years of age. Density of medical marijuana dispensaries was not associated with violent or property crime rates. Conclusions: Consistent with previous work, variables measuring routine activities at the ecological level were related to crime. There were no observed cross-sectional associations between the density of medical marijuana dispensaries and either violent or property crime rates in this study. These results suggest that the density of medical marijuana dispensaries may not be associated with crime rates or that other factors, such as measures of dispensary take to reduce crime (i.e., doormen, video cameras), may increase guardianship such that it deters possible motivated offenders. (J. Stud. Alcohol Drugs, 73, 523–530, 2012)

Within the past 15 years, a new type of drug outlet has developed in the United States that combines place-based distribution with an illicit substance—medical marijuana dispensaries. At present, 17 states and the District of Columbia have passed legislation legitimizing the use of medical marijuana and its distribution (National Organization for the Reform of Marijuana Laws, 2012). Thus, marijuana distribution in the United States is for the purpose of medical use and only recognized by state-level policies.

Internationally, similar place-based dispensaries have been present since the late 1970s as “coffee houses” or “hash clubs.” They are perceived to be a breeding ground for criminal networks, attracting individuals prone to crime and increasing potential for crime around these locations (Asmussen, 2007, 2008; Ministry of Health, Welfare, and Sport, 1995; Möller, 2008). In the United States, the increase in medical marijuana outlets (often referred to as dispensaries or collectives) during the mid to late 2000s has created perceptions that dispensaries support conditions that encourage crime in and around their locations (California Police Chief’s Association, 2009). Although the concerns of place-based related crime are consistent across geographic contexts, little is known empirically about medical marijuana dispensaries (Penick, 2006; Reiman, 2007). In fact, only one study has assessed the ecological effects of dispensaries: Jacobson et al. (2011) observed that crime was higher around medical marijuana dispensaries 10 days after their mandated closures compared with 10 days before the closure. Although contrary to previously discussed perceptions, the results cannot be fully evaluated because this technical report was withdrawn after the authors determined that a systematic review of the study’s methodology and conclusions was required.

Routine activity theory of crime

Routine activity theory provides a framework to understand how the presence of medical marijuana dispensaries may contribute to criminal activity. According to this theory, crime occurs when three necessary conditions are met: (a) the presence of a motivated offender; (b) a suitable target defined by its value, visibility, access, and/or likelihood of low resistance to crime; and (c) the absence of guardians against crime, such as place managers (i.e., owners and the agents they hire to monitor and regulate behaviors), inadequate security, and lower levels of informal social control in the surrounding environment (Clarke and Felson, 1993; Cohen and Felson, 1979; Eck and Weisburd, 1995).

Research for and preparation of this manuscript were supported by National Institute on Drug Abuse (NIDA) Grant R01-DA022715, National Institute on Alcohol Abuse and Alcoholism Center Grant P60-AA06282, NIDA Pre-Doctoral Training Grant T32-DA07272-19, and grants from the University of California, Los Angeles Graduate Division.
*Correspondence may be sent to Nancy J. Kepple at the Department of Social Welfare, University of California, Los Angeles, Luskin School of Public Affairs, 3250 Public Affairs Building, Box 951656, Los Angeles, CA 90095-1656, or via email at njwilliams@ucla.edu.
Neighborhood demographic and structural characteristics are not constant over space and thus create opportunities where these three conditions may converge in a geographic area that increase the potential for victimization and encourage crime (Brantingham and Brantingham, 1993; Clarke and Felson, 1993). First, demographic neighborhood characteristics capture the concentration of motivated offenders and potential targets. Various studies have observed that the concentration of potential offenders in neighborhood areas, measured by neighborhood economic deprivation (e.g., concentrated poverty and unemployment rate), is positively associated with neighborhood crime rates (Andresen, 2006; Miethe and McDowall, 1993). The concentration of populations identified as suitable targets has also been observed to be associated with neighborhood crime rates. Neighborhood areas with high concentrations of young males (ages 15–24 years) residing in single-adult households and/or disrupted family (or single-parent) households are likely targets because of the increased likelihood that these neighborhoods are composed of populations who socialize outside of the home and have an increased amount of goods per household (Cohen and Felson, 1979; Sampson and Woolard, 1987).

Guardianship of a place or geographic area is related to the presence of individuals or systems that can monitor and regulate behavior to protect against crime, such as place managers, formal authorities (e.g., security guards or police), and/or informal social control provided by individuals within the surrounding environment (e.g., friends or neighbors) (Clarke and Felson, 1993; Cohen and Felson, 1979). Thus, demographic factors can indicate potential guardianship of an area based on informal monitoring and the presence of individuals who may deter crime. For example, a higher percentage of vacant housing units can increase the absence of guardians, such as neighbors and place managers, and thus increase the potential for crime both in and around these vacant locations (Ronczek and Maier, 1991; Spelman, 1993). Conversely, high population density may increase the presence of guardians in an area, resulting in the often observed negative association between population density and crime (Andresen, 2006). This additional monitoring of individuals is likely to offset crime expected from the concentration of potential targets and goods within a given amount of space (Cohen et al., 1980).

In addition, structural neighborhood features can contribute to both violent and property crime. Commercially zoned areas are associated with a higher level of street activity and cash flow. These conditions tend to attract crime and/or create opportunities where the three conditions of crime accidentally converge. As a result, there is typically a positive relationship between a percentage of a neighborhood area identified as commercially zoned and crime outcomes (Brantingham and Brantingham, 1993; Cohen and Felson, 1979; Sampson and Woolard, 1987). Roadway features, such as the presence of highway ramps, may also encourage crime in the general area by easing a potential offender's ability for a quick getaway. Neighborhood areas with highway ramps, then, may be viewed as more suitable for crime through increased access (Felson, 1987). Therefore, those neighborhoods composed of demographic and structural factors associated with crime may create conditions in which both the physical location of a business and the surrounding areas are at risk for higher crime incidents (Brantingham and Brantingham, 1993).

Routine activities approach to medical marijuana dispensaries

Previous work has established the spatial relationships between crime locations and place (Eck and Weisburd, 1995; Greenbaum and Tita, 2004; Gruenewald et al., 2004; Ronczek et al., 1991). Places such as medical marijuana dispensaries provide an opportunity where the conditions for crime outlined by routine activities theory can also converge. However, there have been no peer-reviewed studies that explore whether medical marijuana dispensaries are related to crime.

Applying routine activity theory to medical marijuana dispensaries suggests that dispensaries may uniquely contribute to crime even when other contextual factors associated with crime have been controlled. They have on-site stock and sales of marijuana and are a predominantly cash-based business (California Police Chief's Association, 2009). The centralized location of the goods—marijuana and cash—within the dispensaries makes the location a suitable target for a potential offender who might be motivated to seek out ways to obtain the desirable goods, particularly where security appears to be absent.

Based on the conditions described above, dispensaries can be at risk for property crimes, such as burglary. Employees of the dispensaries can be at risk for violent crimes, such as robbery or assault, because they are gatekeepers to both the marijuana products and the cash at the site. Estimates from the western United States and other countries show that users of medical cannabis are primarily male (i.e., two thirds to three fourths of all users) and White, with a wide range of ages (i.e., late teen years to old age; median age between 30 and 50) (Aggarwal et al., 2009; O’Connell and Bou-Matar, 2007; Ogborne and Smart, 2000; Penick, 2006; Reiman, 2007; Ware et al., 2005). The typical clientele for dispensaries (i.e., older White men) are not associated with being at risk for perpetrating crime (Cottle et al., 2001; Hirschi and Gottfredson, 1983). However, they are at risk for being targets of violent crimes, such as robbery, because they are likely carrying cash on entry and some physical amount of marijuana product on exit. In addition, medical marijuana dispensaries have a diverse clientele, with some who are older, frail, and/or diagnosed with chronic, debilitating conditions (O’Connell and Bou-Matar, 2007; Reiman, 2007; Swift et al., 2005; Ware et al., 2003). These more vulnerable
clients may appear to be easier targets for a motivated offender and are at higher risk for victimization (Cohen and Pelson, 1979).

Study aims

To date, only preliminary quantitative evidence exists for the relationship between these medical marijuana dispensaries and crime. Thus, the current study investigated the relationship of crime rates in Sacramento, CA, during 2009 to medical marijuana dispensaries to better understand their ecological impact. We hypothesized that medical marijuana dispensaries would be associated with higher crime rates, controlling for other aggregate neighborhood measures of routine activities known to contribute to crime.

Method

Study design

This study used an ecological, cross-sectional design to explore the spatial relationship between the density of medical marijuana dispensaries and crime rates in the City of Sacramento. California recognized distribution of marijuana through collectives in 2004; however, Sacramento did not implement local regulatory policies until 2010. Thus, data are from 2009, a period that represents the longest time for growth before regulations of medical marijuana dispensaries in Sacramento. The sample for the study included all census tracts with centroids within Sacramento City boundaries (N = 95). All data were aggregated to 2000 U.S. Census tract boundaries. Census tracts approximate neighborhood areas with regard to size and composition: (a) average population is 4,000 residents, (b) boundaries align with visible features of the environment, and (c) homogeneous with respect to population characteristics and/or living conditions (U.S. Census Bureau, Geography Division, 2008).

Measures

The dependent variables in the study were violent crime and property crime as measured by police crime incident data obtained from the Sacramento Police Department. Crime incidents were available by crime code and location of incident. Data were recoded into violent crime and property crime categories and geocoded to greater than 99%. Violent crimes were recoded based on the Uniform Crime Reporting definitions, which included homicide, sexual assault, robbery, and aggravated assault. Sexual assaults were excluded from the analysis because address information is confidential to protect the victim; those crimes were not able to be geocoded. Property crimes also were recoded based on the Uniform Crime Reporting definitions, which included burglary, larceny-theft, motor vehicle theft, and arson. For each type of crime category, the number of crime incidents in a census tract was divided by the total population of the tract and multiplied by 1,000 to create the associated crime rate variable. Table 1 provides descriptive statistics for crime rates per census tract. Because of the right-skewed distributions of the dependent variables, violent crime rate and property crime rate were transformed by a natural log. Table 2 provides zero-order correlations between the natural log of each type of crime rate and each continuous independent variable.

The locations of medical marijuana dispensaries were determined by comparing multiple sources: (a) Sacramento City’s listing associated with Ordinance No. 2009-033, An Ordinance Establishing a Moratorium; (b) news publications; (c) discussion boards on the Internet; (d) trade publications; and (c) survey of dispensary owners/managers. Locations were verified by having at least three sources document that a dispensary was operating on or by June 16, 2009, which provided a midpoint estimate for locations opened during the year. All outlets were geocoded based on point location to 100%. A total of 40 medical marijuana dispensaries were located within 28 of the 95 census tracts (29.3%) in Sacramento. The density of medical marijuana dispensaries was measured by the number of dispensaries per roadway mile in a census tract; this measure was scaled to density per 10 roadway miles. The aggregation to census tracts provided the best variability of density for the smallest areal unit that approximates a neighborhood area. The number of dispensaries ranged from 0 to 3 outlets per tract with density per tract ranging from 0 to 4.95 dispensaries per 10 roadway miles. Figure 1 shows the location of medical marijuana dispensaries mapped onto an unweighted gradient of violent crime rates and property crime rates per 1,000 population by census tract. Those areas with the highest rate of violent or property crime are not necessarily the areas with the greatest population.

Table 1. Descriptive statistics for dependent and independent variables across census tracts in Sacramento, CA (N = 95)

<table>
<thead>
<tr>
<th>Variable</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Violent crime rate per 1,000 population</td>
<td>12.72</td>
<td>22.46</td>
</tr>
<tr>
<td>Property crime rate per 1,000 population</td>
<td>67.03</td>
<td>107.98</td>
</tr>
<tr>
<td>MMD density</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MMDs per 10 roadway miles</td>
<td>0.41</td>
<td>0.90</td>
</tr>
<tr>
<td>Routine activity theory controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total population, in 1,000</td>
<td>5.07</td>
<td>2.67</td>
</tr>
<tr>
<td>% Vacant housing units</td>
<td>6.14</td>
<td>3.97</td>
</tr>
<tr>
<td>Population density, in 1,000</td>
<td>7.97</td>
<td>3.66</td>
</tr>
<tr>
<td>Male-to-female ratio</td>
<td>0.99</td>
<td>0.23</td>
</tr>
<tr>
<td>% of population 15–24 years old</td>
<td>13.80</td>
<td>4.41</td>
</tr>
<tr>
<td>% One-person household</td>
<td>33.49</td>
<td>17.47</td>
</tr>
<tr>
<td>% Disrupted family household</td>
<td>11.94</td>
<td>6.05</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>14.84</td>
<td>13.45</td>
</tr>
<tr>
<td>Index of concentration at the extremes</td>
<td>-0.23</td>
<td>0.23</td>
</tr>
<tr>
<td>% Commercial zoning</td>
<td>12.16</td>
<td>13.71</td>
</tr>
</tbody>
</table>

Note: MMD = medical marijuana dispensary.
Table 2. Zero-order correlation coefficients of independent variables with violent crime rate and property crime rate (N = 95)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Violent crime rate (LN)</th>
<th>Property crime rate (LN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MMD per 19 RWM</td>
<td>.421***</td>
<td>.423***</td>
</tr>
<tr>
<td>1,000 population/square mile</td>
<td>-.208*</td>
<td>-.414***</td>
</tr>
<tr>
<td>% Vacant housing units</td>
<td>.599***</td>
<td>.423***</td>
</tr>
<tr>
<td>Male-to-female ratio (LN)</td>
<td>.522***</td>
<td>.470***</td>
</tr>
<tr>
<td>% Population 15–24 years old</td>
<td>-.207*</td>
<td>-.590***</td>
</tr>
<tr>
<td>% One-person household</td>
<td>.462***</td>
<td>.656***</td>
</tr>
<tr>
<td>% Disrupted family household</td>
<td>.440***</td>
<td>.137</td>
</tr>
<tr>
<td>Unemployment rate (LN)</td>
<td>.528***</td>
<td>.161</td>
</tr>
<tr>
<td>Index of concentration at the extremes</td>
<td>-.675***</td>
<td>-.367***</td>
</tr>
<tr>
<td>% Commercially zoned</td>
<td>.606***</td>
<td>.735***</td>
</tr>
</tbody>
</table>

Notes: LN = natural log; MMD = medical marijuana dispensary; RWM = roadway mile. *p < .05; ***p < .001.

To control for neighborhood population and place characteristics that routine activity theory would suggest contribute to observed crime rates, several control variables were created and included in the model. The following variables were selected to control for neighborhood contextual factors commonly associated with aggregate patterns of crime: population density (1,000 population per square mile), male-to-female ratio, percentage of population ages 15–24 years, percentage of one-person households, percentage of disrupted family (or single-parent) households, unemployment rate, and percentage of housing units that were vacant. Data for the measures were from the 2009 estimates of population and housing characteristics obtained from GeoLytics Inc. (2009). Geocoding rates for these census measures are, by definition, 100%. Table 1 provides a summary of descriptive statistics for all control variables. Male-to-female ratio and unemployment rate were transformed using the natural log to address right-skewed distributions.

In addition, neighborhood disadvantage was measured by the index of concentration at the extremes representing concentrated poverty (-1.0) to concentrated affluence (1.0) on a continuous scale. The variable was constructed by subtracting the number of poor households from the number of affluent households and dividing the result by the total number of households (Massey, 2001). Poor households were determined by using 2008 poverty guidelines. Any household composed of two or more individuals and with a combined income less than $26,400 (all dollar values are in

![Medical Marijuana Dispensary](image1.png)

Violent Crime per 1,000 Population

- **0.46 - 4.14**
- **4.15 - 6.91**
- **6.92 - 12.77**
- **12.78 - 162.00**

Property Crime per 1,000 Population

- **11.63 - 27.40**
- **27.41 - 38.03**
- **38.04 - 53.64**
- **53.65 - 753.96**

Figure 1. Medical marijuana dispensary locations and neighborhood crime rates per 1,000 population (N = 95): (a) violent crime rate by census tract, (b) property crime rate by census tract.
U.S. dollars) were considered to be below the 200% poverty level. As a result, all households with an income of less than $25,000 were included in the poor household count. Affluent households were determined by any income that was more than two standard deviations above median income, resulting in all households with an income of $100,000 or more being included in the affluent household count.

A categorical variable for the presence of highway on-ramps was created as a proxy measure for physical characteristics that allowed for quick and easy entry and exit into a census tract. We used a categorical measure because of the limited variability in the number of highway ramps per census tract (i.e., 56 of the 95 census tracts had no highway exits; less than 5 census tracts had more than one highway exit). All roadway segments with the Census Feature Class Code (CFCC) A63 (i.e., access ramp) were selected and then aggregated to the census tract; the variable was coded 0 for no highway ramp present and 1 for highway ramp present. ESRI 2008 Streets for United States and Canada (based on 2003 Tele Atlas Dynmap Transportation Version 5.2 product) was used to identify highway ramps (ESRI, 2008). The geocoding rate for highway ramps was 100%; however, the street file is based on 2003 streets and does not account for development in the 5 years between 2004 and 2009.

Finally, all areas defined as commercial zoning for the City of Sacramento (i.e., C1 = limited commercial; C2 = general commercial; C3 = central business district; SC = shopping center; HC = highway commercial; O4 = heavy commercial; ORMU = office/residential mixed use; EC = employment center; OB = office zone) were selected and were parsed into polygons that aligned with census tract boundaries so square mile area could be calculated. The percentage of commercially zoned area was calculated by dividing the aggregate square mile area of commercial zoning by the total square mile area of the census tract and then multiplying by 100. The shapefile for commercially zoned areas from 2010 was obtained from Sacramento County and the City of Sacramento, Geographic Information Systems Division. Geocoding rates for commercially zoned areas were 100% for areas within Sacramento City boundaries.

Statistical analyses

This study used geospatial methods, which have become standard practice for studying ecological relationships between place and crime (Gruenewald et al., 2006). Area units (e.g., census tracts) located next to each other often share similar characteristics that may bias results because they are highly correlated, a phenomenon called spatial autocorrelation (Cliff and Ord, 1973). Spatial techniques address this bias by accounting for the spatial autocorrelation. To test if spatial autocorrelation was an issue for these data, the Univariate Moran’s I, which is a global measure of spatial autocorrelation, was calculated for the dependent variables (Bailey and Gatrell, 1995). Moran’s I was statistically significant for violent crime rate ($I = 0.3257, p < .05$) and property crime rate ($I = 0.4625, p < .05$).

Spatial regression models were used to address spatial autocorrelation observed for the dependent variables. This study used a Rook’s connection matrix to identify adjacencies between census tracts using an n x n (in this case 95 x 95) matrix, where census tracts that shared a boundary were given a 1 and those that did not, a 0 (Bailey and Gatrell, 1995). One challenge to using this approach with smaller geographic areas, such as census tracts, is that the model assumes all areas have the same population. This assumption results in census tracts with small populations and with large populations being weighted equally. To address this, all variables were weighted by the square root of the census tract population to address issues of heteroscedasticity, providing more weight to census tracts with higher population (Greene, 1993). In addition, the condition index was used to test for collinearity in the geographically weighted regressions; any value above 30 indicates problematic collinearity issues within the model (Belsley, 1991; Wheeler, 2007). The condition index for the final models was 21.2 (Table 3), which is not indicative of severe multicollinearity. The fit of the model was examined using the likelihood ratio test, which compared the log-likelihood from the full model (i.e., medical marijuana dispensary density variable plus routine activity variables) with that of the restricted model (i.e., medical marijuana dispensary density variable) to determine if the contribution of routine activity variables improved the overall fit of the model (Greene, 1993).

Results

Table 3 shows the results of the spatial error regression models for violent and property crime rates with the associated condition index, pseudo-$R^2$, and model-fit statistics. Model I for violent crime rates indicated that medical marijuana dispensaries per 10 roadway miles were not significantly related to violent crime rates. When routine activity theory control variables were added in Model II, the density of medical marijuana dispensaries remained not significantly related to violent crime rates. Model II showed that violent crime rates had a significant positive association with percentage of one-person households, unemployment rate, and percentage of commercial zoning when controlling for other variables. As expected, lower population density was associated with higher levels of violent crime. In addition, lower levels of index of concentration at the extremes (or higher levels of concentrated disadvantage) were significantly associated with higher violent crime rates.

For property crime rates, Model I indicated that medical marijuana dispensaries per 10 roadway miles were not
Table 3. Spatial error regression of MMD density on the log of violent crime rate and log of property crime rate by census tract (N = 95)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Violent crime rate (LN)</th>
<th>Property crime rate (LN)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model I</td>
<td>Model II</td>
</tr>
<tr>
<td></td>
<td>MMD density</td>
<td>+RAT controls</td>
</tr>
<tr>
<td></td>
<td>b</td>
<td>SE</td>
</tr>
<tr>
<td>Constant</td>
<td>1.752***</td>
<td>0.167</td>
</tr>
<tr>
<td>MMD density</td>
<td>0.214</td>
<td>0.138</td>
</tr>
<tr>
<td>RAT controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1,000 population/square mile</td>
<td>-0.033*</td>
<td>0.016</td>
</tr>
<tr>
<td>% Vacant housing units</td>
<td>0.019</td>
<td>0.021</td>
</tr>
<tr>
<td>Male-to-female ratio (LN)</td>
<td>-0.973</td>
<td>0.094</td>
</tr>
<tr>
<td>% Population 15-24 years old</td>
<td>-0.023</td>
<td>0.018</td>
</tr>
<tr>
<td>% One-person household</td>
<td>0.018*</td>
<td>0.006</td>
</tr>
<tr>
<td>% Disrupted family household</td>
<td>0.003</td>
<td>0.009</td>
</tr>
<tr>
<td>Unemployment rate (LN)</td>
<td>0.291**</td>
<td>0.105</td>
</tr>
<tr>
<td>Index of concentration at the extremes</td>
<td>-1.261*</td>
<td>0.537</td>
</tr>
<tr>
<td>Highway ramp present</td>
<td>0.018*</td>
<td>0.007</td>
</tr>
<tr>
<td>% Commercially zoned</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial autocorrelation</td>
<td>0.508***</td>
<td>0.108</td>
</tr>
</tbody>
</table>

Model fit statistics

<table>
<thead>
<tr>
<th>Condition index</th>
<th>Pseudo-R²</th>
<th>Log-likelihood</th>
<th>D (Adj. p)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.6092</td>
<td>21.2602</td>
<td>-112.9175</td>
<td>92.23 (10,.001)</td>
</tr>
<tr>
<td>.2462</td>
<td>.6944</td>
<td>.1374</td>
<td>.8083</td>
</tr>
<tr>
<td>-112.9175</td>
<td>-65.8066</td>
<td>-116.1663</td>
<td>-43.6518</td>
</tr>
<tr>
<td>146.23 (10,.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: MDD = medical marijuana dispensary; LN = natural log; RAT = routine activity theory; RWM = roadway mile.

*p < .05; **p < .01; ***p < .001.

significantly related to property crime rates. In Model II, the density of medical marijuana dispensaries remained not statistically significant when routine activity control variables were added to the model. Model II showed a significant positive association with percentage of population ages 15–24 years, percentage of one-person households, unemployment rate, and percentage of commercial zoning when controlling for other variables.

Discussion

In sum, the statistically significant variables for the violent crime rate and property crime rate models were consistent with aggregate neighborhood measures reported within the routine activity theory literature (Andresen, 2006; Cohen and Felson, 1979; Sampson and Woolrdedge, 1987). Percentage of a census tract that was commercially zoned, percentage of housing units in a census tract that were one-person households, and unemployment rate were positively related to violent and property crime rates. However, no cross-sectional associations were observed between the density of medical marijuana dispensaries and violent or property crime rates, controlling for ecological variables traditionally associated with routine activity theory.

These findings suggest two possible conclusions. First, the density of medical marijuana dispensaries may not be associated with neighborhood-level crime rates. For example, dispensaries may be associated with crime but no more than any other facility in a commercially zoned area with conditions that facilitate crime. Alternatively, the relationship between density of medical marijuana dispensaries and crime rates is likely more complex than measured here. The study did not measure on-site security or guardianship at the dispensaries. If medical marijuana dispensaries have strong guardianship, such as security and monitoring systems, routine activity theory would suggest that the three necessary conditions for crime are not met. Place-specific guardianship would decrease the accessibility and increase the risk of being caught, decreasing the suitability of a target.

The findings are based on an ecological, cross-sectional study. As a result, no conclusions can be made about causation. First, the study cannot demonstrate whether increasing density of medical marijuana dispensaries is associated with an increase in crime rates over time and space. At an aggregate level, dispensaries in Sacramento are not associated with crime cross-sectionally; however, the introduction of these dispensaries in these areas may have served to increase crime rates from the prior year. This hypothesis can only be tested by examining the changes in medical marijuana dispensary locations and crime rates over time. Second, the ecological design does not allow individual-level variation to be factored into the models, specifically owners' selection of the location of a dispensary. Future studies should address the issue of endogeneity by obtaining information from dispensary owners on their decision-making
processes associated with medical marijuana dispensary locations.

The small sample size of 95 census tracts may have limited the power of the final model. Limited power may have contributed to why variables theorized to affect crime (e.g., percentage of vacant housing, percentage of population ages 15–24 for violent crime rates) were not significant. However, the power was sufficient to establish whether the density of medical marijuana dispensaries would be associated with crime in the univariate models (i.e., Model 1).

Other unmeasured ecological factors may also be influencing results. Because of sample size limitations, the current study omitted the locations of illicit drug market activity (Eck, 1995; Gorman et al., 2005; Weisburd and Mazerolle, 2000) and alcohol outlets (Gruenewald et al., 2006; Scribes et al., 1999), both of which are associated with higher crime rates. In addition, dispensaries may be located in areas that reflect the demographics of their clientele (i.e., older White men). The routine activity literature indicates that areas with these local neighborhood characteristics are not likely to have high crime rates (Cohen and Felson, 1979). Exploration of ecological factors associated with location of dispensaries is essential to better understand the role of neighborhood context related to these findings.

The focus on one mid-sized city in California limits the context to which these findings can be generalized. Future studies need to expand spatial methods of this type to other regions of California, other U.S. states, and international regions where marijuana place-based distribution occurs. In addition, the sample size did not allow for the inclusions of variables, such as interaction of place and population characteristics (e.g., Medical Marijuana Dispensary Density × Commercial Zoning) or spatial lags. Finally, measures of premise-based features and operation procedures may provide a better indication of guardianship and employee vulnerabilities that may be associated with findings.

These findings run contrary to public perceptions (California Police Chief’s Association, 2009). The cross-sectional results suggest that dispensaries are not associated with crime rates; however, current media and policy efforts have focused their attention on the place-based regulation of these dispensaries to protect the public against crime (California Police Chief’s Association, 2009; City of Los Angeles, 2010; Lopez, 2010). Based on the limited evidence presented by this study, it is unclear if place-based policies will be effective. Future studies should address previously described limitations, such as longitudinal studies, to assess the influence of medical marijuana dispensaries on existing crime rates, to gain a better understanding of the relationship between medical marijuana dispensaries and crime. In addition, future studies should explore specific elements that make dispensaries vulnerable or resistant to crime to better guide future policies.

References

Aggarwal, S. K., Carter, G. T., Sullivan, M. D., Zambruno, C., Morrill, R., 
& Meyer, J. D. (2009). Characteristics of patients with chronic pain 
suffering treatment with medical cannabis in Washington State. Journal of 

Columbia: A synthesis of social disorganization and routine activity 

A cannabis reader: Global issues and local experiences, monograph series 8, Volume 1 (pp. 157–168). Lisbon, Portugal: European Monitoring 
emcdda.europa.eu/publications/monographs/cannabis


sex, England: Addison Wesley Longman.


Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths and edges: 

California Police Chief’s Association (2009). White paper on marijuana 
procon.org/sourcemeta/CAPCWhitePaperonMarijuanaDispensaries.pdf

City of Los Angeles (2010). Ordinance No. 18106: Medical mari 
juana collectives. Los Angeles, CA: Los Angeles City Clerk’s Office. 
eclf?fa=aw.rviewrecord&c=number=08-0923


Cliff, A. D., & Ord, J. K. (1973). Spatial autocorrelation, monographs in 


Cottle, C. C., Lee, R. J., & Felton, K. (2001). The prediction of criminal 


Brunswick, NJ: GeoLytics Inc.


Mahbubani, N. Lawrence Erlbaum Associates.


