The Effects of Marijuana Legalization on Crime and Other Drug Usage in Seattle

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Contents

Introduction 2
Literature Review and Policy Relevance 2
Data Gathering and Methodology 4
Analysis 5
Discussion 11
Appendix 12
References 20

Introduction

Individuals on either side of the marijuana legalization divide often make spectacular claims regarding the expected effects of legalization. Some fear that legalization is undesirable for moral reasons, while others are concerned that legalization will lead to further abuses of illicit substances. Yet changing attitudes toward the use of cannabis and the previous stigma surrounding it undergird a larger shift in the legal and regulatory landscape concerning the drug's potential medicinal uses, and its production, distribution, and taxation. As with many policy issues, money plays an obvious role. With moral arguments falling behind more liberal views on drugs and their use, the potential for states to raise millions in tax revenues often takes preeminence over other concerns. That is not to say that public health and safety does not matter to the discussion; some legalization initiatives funnel a portion of marijuana tax revenue into research into the health effects of the drug. For the most part, in purely economic terms, the costs associated with policing neighborhoods and jailing those convicted of possession or distribution seem to far outweigh the benefits of over-policing and criminalization.

Perhaps also because more individuals know someone who has used marijuana recreationally or has been prescribed medical marijuana, more people disagree with harsh penalties that have been in place for several decades now in the United States. This again hints at changing public opinions on the drug, and says less about the actual effects that legalization has had in the states that have chosen to regulate the production and sale of recreational cannabis.

In this essay, we explore marijuana legalization by aiming to address policy implications rather than normative arguments either for or against it. We hope that by doing so we contribute to the growing research on the topic, as it continues to play a prominent role in current debates in the U.S. and abroad.

Literature Review and Policy Relevance

In 2012, Colorado and Washington legalized recreational marijuana use, and in 2014 Oregon and Alaska followed suit. In November 2016, five other states (Arizona, California, Maine, Massachusetts and Nevada) voted on legalizing the recreational use of marijuana, while four others (Arkansas, Florida, Montana and North Dakota) also decided on medical marijuana initiatives. Opponents of legalization claim legalization leads to an increase in marijuana and other drug use, "increases crime, diminishes traffic safety, harms public health, and lowers teen educational achievement," while advocates "think legalization reduces crime, raises tax revenue, lowers criminal justice expenditures, improves public health, bolsters traffic safety, and stimulates the economy."[1] As researchers have pointed out though, until now, these claims have largely gone unexamined. A recent study by the Cato Institute concludes that evidence for either side's arguments is lacking, and "the absence of significant adverse consequences is especially striking given the sometimes dire predictions made by legalization opponents" (ibid). We would like to test the hypothesis that legalization does not significantly increase crime or other drug usage. We will look more closely at the state capital of Washington State, Seattle in order to test this. Given the general dearth of reliable, empirical research on the topic in relation to Washington State, we draw on the results of the Cato Institute's report as it is both recent and highly comparative in nature. Thus, we hope to contribute to the growing body of research on marijuana legalization and policy outcomes. Most research seems to run in a more medical vein. Authors writing for the RAND Corporation argue that it is too soon to adequately address the repercussions of legalization; or more specifically, that since more data is needed, policy makers must acknowledge the need to work flexibly with issues at hand since what evidence we have is remarkably varying based on which country, state or metro region we analyze.[2]

Beginning with the Cato report, "Dose of Reality: The Effect of State Marijuana Legalizations," published September 2016, it is clear that the history of state-level marijuana legalization has a rocky past. Yet "[u]ntil 1913 marijuana was legal throughout the United States under both state and federal law."[3] Ironically, the first state to make it illegal was actually California, and because of a wide-spread, anti-immigrant sentiment.

[1] Dills, Goffard, and Miron (2016)
[2] Caulkins et al. (2015)
[3] Dills, Goffard, and Miron (2016)

Often Mexicans were depicted as outlaws and responsible for bringing marijuana to the States, creating a particularly charged atmosphere of racial prejudice and stigma. In the 1930s more restrictive laws came into place, creating prohibitive taxes on marijuana possession which essentially outlawed the substance. In the 1950s, mandatory sentences and high fines were established. As researchers explain, "[t]hose mandatory sentences were mostly repealed in the early 1970s but reinstated by the Anti-Drug Abuse Act under President Ronald Reagan. The current controlling federal legislation is the Controlled Substances Act, which classifies marijuana as Schedule I. This category is for drugs that, according to the Drug Enforcement Administration (DEA), have"no currently accepted medical use and a high potential for abuse" as well as a risk of 'potentially severe psychological or physical dependence'" (ibid).

As with many federal political systems, individual states can often pursue legislation that is at odds with national laws. In the case of Washington, marijuana laws were relaxed in the 1970s, and "[t]he state legalized medical marijuana in 1998 after a 1995 court case involving a terminal cancer patient being treated with marijuana brought extra attention to the issue and set the stage for a citizen-driven ballot initiative" (ibid). Indeed, Washington state is a prime example of how changing attitudes can affect legislative outcomes.

In the Cato report, researchers answer questions dealing with several issues related to marijuana legalization including the effects of legalization on: other drug or alcohol use; health and suicide rates; crime rates; road safety; youth outcomes and economic outcomes. Regarding legalization and other drug usage, the report finds that there were no dramatic shifts in other drug use rates after legalization. "Similarly, cocaine exhibits a mild downward trend over the time period but shows no obvious change after marijuana policy changes. Alcohol use shows a pattern similar to marijuana: a gradual upward trend but no obvious evidence of a response to marijuana policy" (ibid). Similarly, the four states the authors researched (Colorado, Washington, Oregon, Alaska) presented evidence that while there seemed to be a slight upward trend in suicide rates, the link between marijuana legalization and this uptick was weak. Perhaps most interesting for our study is the report's findings on crime.

> Before referendums in 2012, police chiefs, governors, policymakers, and concerned citizens spoke up against marijuana and its purported links to crime. They also argued that expanding drug commerce could increase marijuana commerce in violent underground markets and that legalization would make it easy to smuggle the substance across borders where it remained prohibited, thus causing negative spillover effects. Proponents are that legalization reduces crime by diverting marijuana production and sale from the black market to legal venues. This shift may be incomplete if high tax rates or significant regulation keeps some marijuana activity in gray or black markets, but this merely underscores that more legalization means less crime. At the same time, legalization may reduce the burden on law enforcement to patrol for drug offenses, thereby freeing budgets and manpower to address larger crimes. Legalization supporters also dispute the claim that marijuana increases neurological tendencies toward violence or aggression (ibid).

Despite all the exuberance on either side of the legalization divide, researchers conclude that for both violent and property crime rates in Seattle, there has been a steady decline over the past two decades with no major changes pre- or post-legalization. The study finds similar outcomes regarding road safety and traffic accidents: "[n]o spike in fatal traffic accidents or fatalities followed the liberalization of medical marijuana in 2009" (ibid). Perhaps most of the fears surrounding the marijuana debate concern the effects on youth. It is a common trope in political rhetoric for politicians to speak about making the world a better place "for our children" or "for future generations." There has been a surge in new research as well over the long-term ramifications of legislation on juvenile delinquency, school attendance, intelligence/mental development, and violence or abnormal behaviors. Research was conducted on trends in standardized test scores in Washington state, but the results show that although "some studies have found that frequent marijuana use impedes teen cognitive development, our results do not suggest a major change in use, thereby implying no major changes in testing performance." As with most legislative issues, money matters; indeed, it seems probable that legislation at any level has a better chance of success if the economic outcomes have been quantified and forecasts are promising for state revenues. For political conservatives and liberal alike, the prospect of millions of new tax dollars coming in sounds equally appealing. Yet given the huge increases seen in tax revenue in states that have begun regulating the production and distribution of marijuana and related products, this represents a small sliver of overall gross domestic product. "Data from the Bureau of Economic Analysis show little evidence of significant gross domestic product (GDP) increases after legalization in any state…no clear changes have occurred in GDP per capita" (ibid).

Data Gathering and Methodology

Data Gathering

Our project will be using three main data sets: i) cannabis data on Washington State, ii) crime data on Seattle, WA, and iii) socio-economic data on Seattle, WA. As the policy field of cannabis legalization is a rather nascent field of study, there has been limited availability of reliable data (previous data sources were clouded by the illegality of possession and consumption and thus approximated dark figures).

Our project has taken advantage of one of the provisions within the 'Washington Initiative 502', the initiative that brought about the legalization of cannabis in Washington State, that established disclosure of retailers, processors and producers as well as some general economic data online. The data has been web-scraped using the *rvest* package (Wickham 2016a). As there have been difficulties due to the 502data site being scripted in Java, we additionally needed the 'phantomjs' file to use the *RSelenium* package (Harrison 2016) to make the web-scraping possible.

As the ".exe"-file does not work on Mac products / Apple operating systems, and because scraping is time-consuming, we will provide an unaldutered ".txt"-file called "ProdProc" for all producers and processors and one called "Retailer" for retailers. This way we allow for as much reproducibility as possible. The data lists the names and locations of producers/processors in the state and of retailers including YTD sales and tax revenue. For the later analysis, we will constrain the data set to Seattle. The second set of data concerns data on crime. We scraped the data for Seattle with the *jsonlite* package (Ooms, Temple Lang, and Hilaiel 2016) and formatted it into R-readable format with the *gdata*package (Warnes et al. 2015). The initial data set is rather large (>80 MB). We have transformed it into a zipped-file called "CrimeSeattle.gz". For the analysis, we cleaned the data so to only contain information about the longitude/latitude, the type of crime and the time it has occurred. For types of crime, we have aggregated individual types into seven broad categories: i) alcohol-related crime (includes Liquor offenses and DUI offenses), ii) burglary/theft, iii) marijuana-related crime, iv) narcotics-related crime, v) other-drug related crimes, vi) property crime, and vii) violent crime (includes armed robberies, assaults, drive-by shootings, strong armed robbery and homicides).

The third set of data comes from the U.S. Census data and provides us with socio-economic factors for each district. These data are only for 2014, an issue that we address in the discussion section of this paper. Our code to obtain these data follows the concept of the blog post by zevross. One limitation is that we, however, only have this data annually and only for 2014. The variables included for this analysis are the share of poverty for each district, the average age level, the prevalence of minority races, as well as the level of education. While these are classic socio-economic factors, the lack of variation means that they will only be useful for the regular OLS regression as well as for the propensity score matching, which means that this set of data will be of limited value overall.

In order to be able to merge all three data sets, we needed to ensure that we had geospatial data in all of them. Only for the first data set did we not already have longitude and latitude data. To obtain these, we scraped the street locations for all available retailers from kushtourism.com. With this information, we were able to use a simple Google API query in combination with the *RJSONIO* package (Temple Lang 2014) to determine latitude and longitude for each observation. This left us with 15 individual retailers for Seattle for which we have data.[4] For the merger of all three data sets, we calculated the centroid of each district of the U.S. Census Data and then calculated the minimum distance of crime incidents and retailers using the *fields* package (Nychka et al. 2016). The final data set is called "SeattleCrimeAnalysis.gz". As we are not looking at the individual perpetrator but at the crime incident of a district, we feel that this is an adequate way of merging the data set.

[4] The query was conducted on 10 November 2016

Methodology

This study will employ several methods in order to analyse whether there is a discernible effect between there being a dispensary in a given district of Seattle and the logarithmic crime incident per 1,000 people in that district. We will first use descriptive statistics to show the development of the cannabis industry in Washington State and Seattle to give a feeling for the scope of the topic at hand. The descriptive statistic will be rounded up by a quick look at the differences in means between districts with and without a dispensary. Secondly, we will perform a standard ordinary least squares analysis (OLS) to analyse the main relationship of this paper. Unfortunately, normal OLS is unable to adequately identify causal effects when data is observational. It might be good for an initial understanding but not more. To account for this, we complement this analysis with a propensity score matching model. "Matching on the propensity score is essentially a weighting scheme, which determines what weights are placed on comparison units when computing the estimated treatment"[5] This means that far from looking at the average effect across all districts, we will try to identify how the establishment of a dispensary has changed crime incidents for similar districts (which should boost our confidence in causality). As propensity score matching has recently been under fire, we will also use another robustness checks: the robustness check is a simple fixed effects model, as it "avoids the ommited variable bias through controlling for [district] level heterogeneity by means of dummy variables.[6] To implement this, we will be using the *plm* package (Croissant, Millo, and Tappe 2016). A robustness check could be a difference-in-differences analysis that uses establishment as *treatment* and all other districts as *control* groups. Yet, because we have different shops opening at different times throughout the period 2014-2016, we will not adopt this additional model due to its complexity.

Analysis

Descriptive Statistics

Let us begin with with simple descriptive statistics. While the 502data is rather well documented, there is the issue, however, that the retailers are not uniquely identified by names. Thus, while we will be using the names for producers/processors to get their numbers, we will be using the URL extensions that we received from the scraping process to identify how many retailers there are.

As we can see from Figure 1, the nascent industry is already booming in Washington with both the numbers of actors and the sales/tax revenues being already higher in October 2016 than in all of 2015. The numbers are quite staggering:

1. Number of Producers and Processors: The number increased by 210% YoY in 2015 from 185 to 574 and by another 53% in the ten months leading up to October 2016 to 881.
2. Number of Retailers: The number increased by 130% YoY in 2015 from 82 to 189 and by another 69% in the ten months leading up to October 2016 to 319.
3. Increase of revenues in sales: The number increased by 960% YoY in 2015 from $29.21[7] Mill to $309.86 Mill and by another 77% in the ten months leading up to October 2016 to $549.93 Mill.
4. Increase of tax revenues: The number increased by 1040% YoY in 2015 from $9.74 Mill to $110.97 Mill and by another 83% in the ten months leading up to October 2016 to $203.47 Mill.

It is a fast growing industry, and shows increasing interest of buyers. In relation to Washington State's GDP it is, however, still relatively small with a share of 0.12 % of a GDP of $445.4 Bill.[8] Unfortunately, we do not have data on the quantities that have been sold or reliable data on the price development of the good. In either of these scenarios we could have otherwise also analysed the usage.

[5] Dehejia and Wahba (2002) 153.
[6] Möhring (2012)
[7] when did the first one open
[8] Data from the Bureau of Economic Analysis was last retrieved 15/12/2016

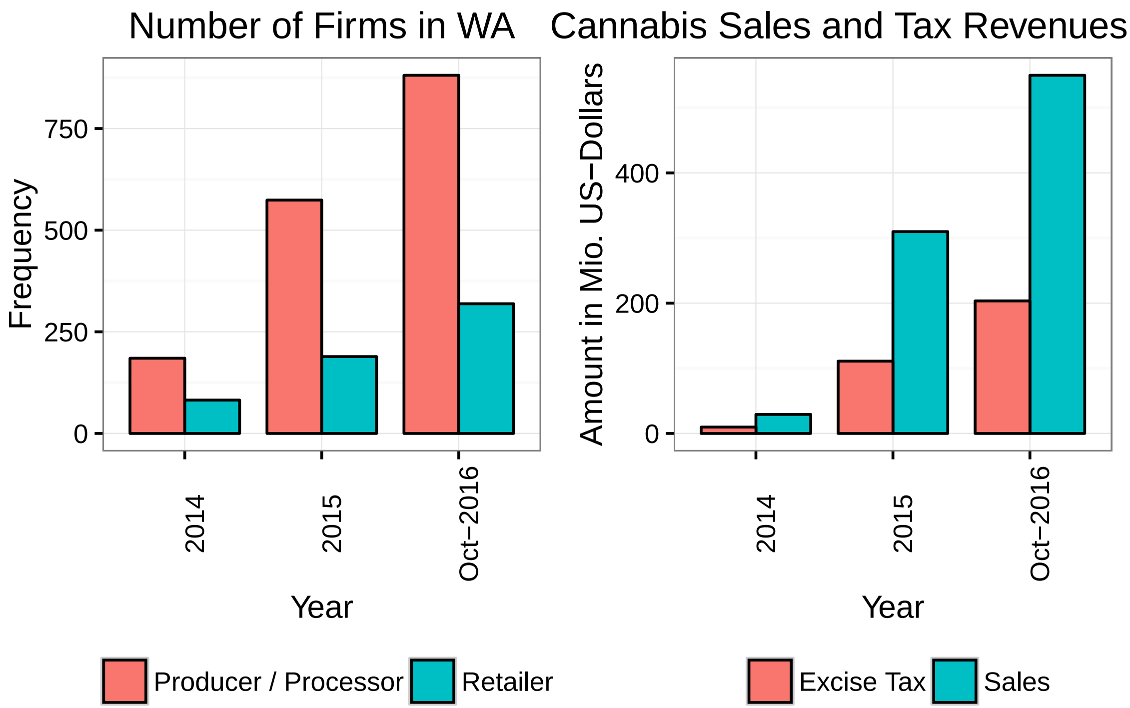

Figure 1: Business Development of Cannabis Production and Sales in Washington State

Table 0 shows the variables used in the next part of our analysis. While Seattle is divided into 132 districts by the U.S. Census, crime incidents only occured in 35 of them once accounting for other NA-related issues with our merged data set. Eight of these 35 districts have a dispensary, which is represented by the *treatment* variable "Established". The dependent variable is the natural logarithm of crime incidents per 1,000 inhabitants.[9] The poverty rate, age, diversity and education are socio-economic control variables. Table 0 also indicates how these variables have been operationalised.

Table 0: List of dependent and explanatory variables used in analysis

	Variables	Operationalisation
1	Producer/Processor	Count of Producers/Processors in WA
2	Retailer	Count of Retailers in WA
3	Excise Tax	Sum of taxes paid by retailers
4	Sales	Sum of revenue made by retailers
5	Crime Categories	Aggregates of Crime incidents from Seattle
6	Established	Treatment variable: 0 if no dispensary, 1 otherwise
7	Poverty Rate	Share of People < $15,000/year as percent of total people in district
8	Age	Shares of Adults in comparison to mean of Seattle
9	Diversity	Share of Whites in comparison to mean of Seattle
10	Education	Share of Degree holders in comparison to mean of Seattle
11	GEOID	U.S. Census District
12	Time	Months from Jan 2014 to Oct 2016

[9] As a total, as well as for each of the seven different crime categories

Crime is definitely an issue in Seattle. If we look at Figure 2, we can see the distribution of our different crime categories for October 2016. We can clearly see that crime is concentrated in central Seattle and that there is less crime around the red dots that represent the existence of a dispensary. The stark concentration of crime follows the experience of other big cities: take Boston as an example where "fewer than 5 percent of [its] street corners and block faces generated 74 percent of fatal and non-fatal shootings between 1980 and 2008."[10]

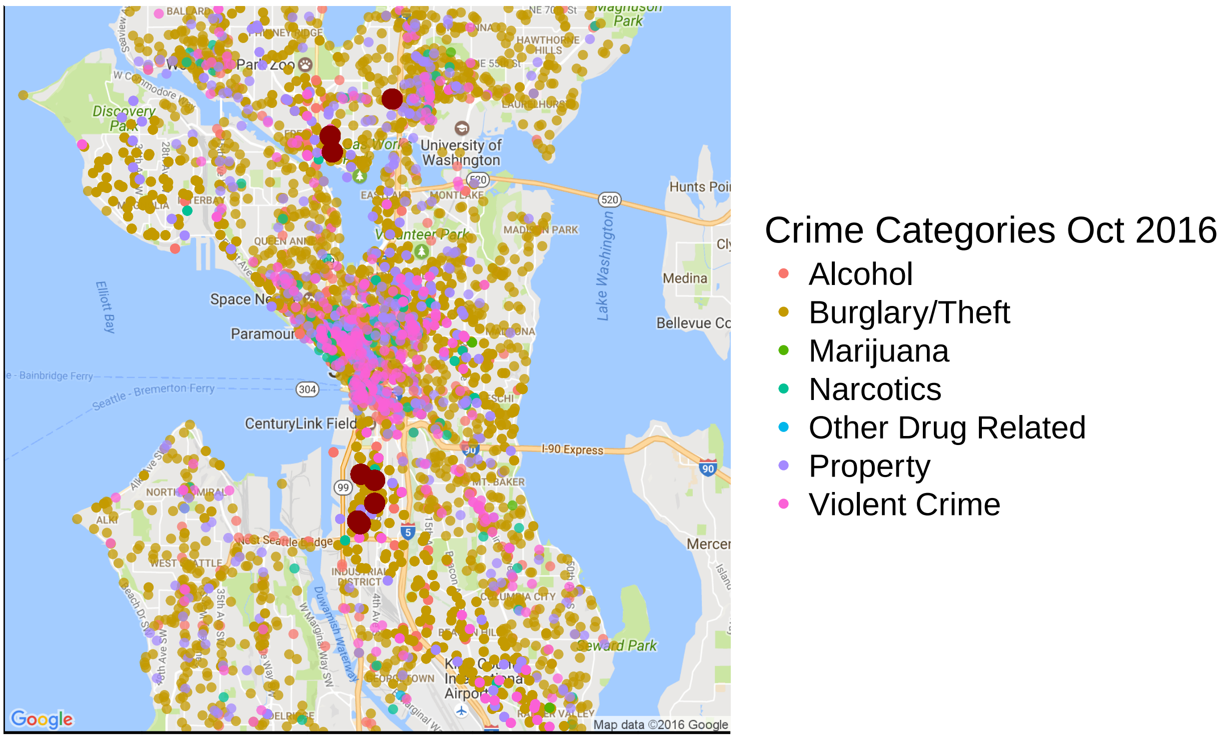

Figure 2: Map of Crime incidents in Seattle in October 2016

If we look at crime incidents per 1,000 citizens in Figure 4: A.1 in the Appendix, then we can see that the development has been different between the different categories. As you can see from Figure 5: A.2 in the Appendix, however, only looking at the distribution might be a problem due to the heavy right-tail skewedness. Thus, and in order to make interpretation easier, we will be using the natural logarithm of the crime development for this paper. The bottom line graph of Figure 4: A.1 in the Appendix now shows a slightly different picture where most of the crime follows a random walk, i.e. there is change in either direction without there being a trend. Only burglary/theft, property, and violent crime seems to have an upward trend, while other drug related crimes seem to have dropped recently.

We tested if the our analysis might be skewed due to the jumps from January 2014 to February 2014 that we can see in these two Figures in the Appendix. The jumps might be due to coding changes/errors from one year to the next. Yet, we have not found any statistical significance. You can find the results in Table 4: A3 in the Appendix.

[10] Ferguson (2016) 20-21.

Inferential Statistics

Let us now look at the actual inferential statistics. We can see from Figure 3 that the impact of the *treatment* differs for each of the crime categories differently. It seems that alcohol-related crime is not statistically affected at all by the establishment of a dispensary. Burglary/Theft, property and violent crime, however all seem to be positively impacted by the establishment, whereas marijuana-related crime is substantially smaller and narcotics-related crime somewhat smaller. Other drug-related crime seem to have changed little. Yet, this simple difference in means does our analysis and question not justice and as such, we now look at different regression models to try and identify the causal effect.

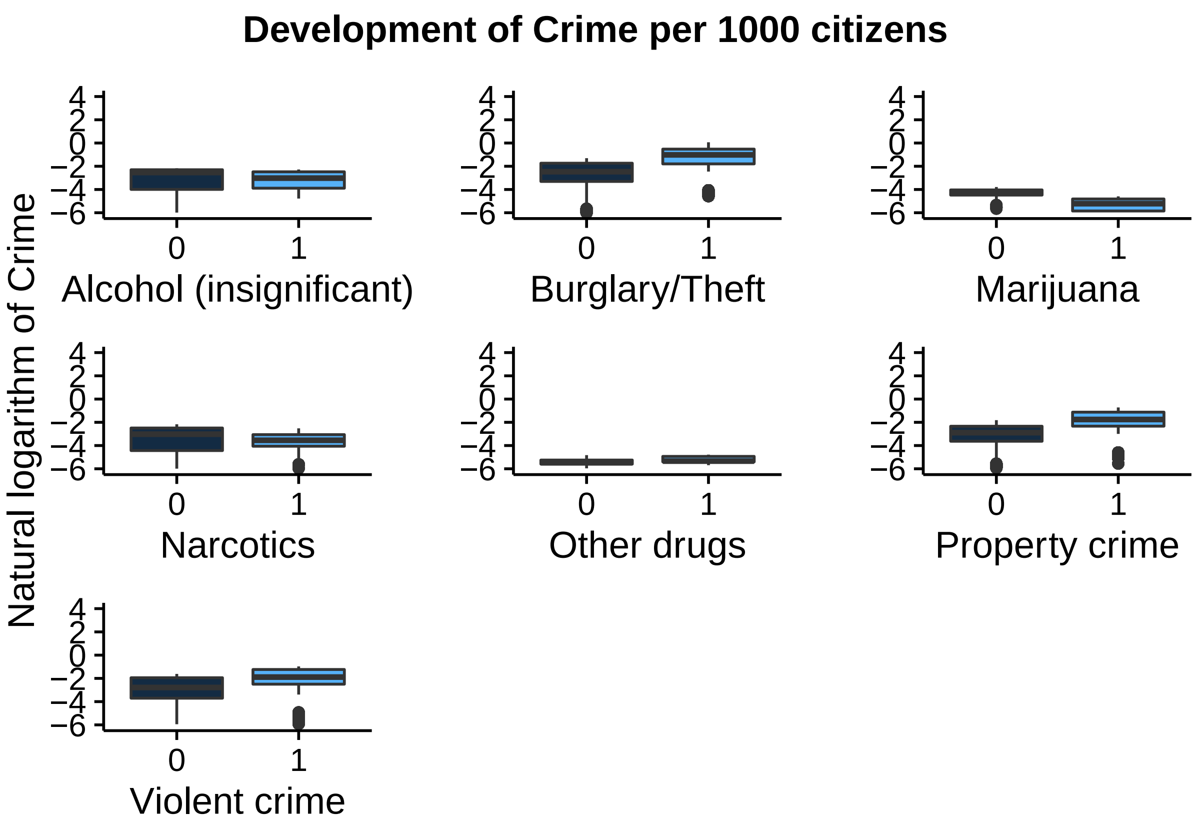

Figure 3: Impact of Dispensaries on Crime incident - Mean-difference

Table 1: Analysis of Crime

	Dependent variable:	
	ln(Crime Rate Per Thousand)	
	OLS Simple	Propensity Simple
	(1)	(2)
Established	1.34*** (1.33, 1.35)	0.55*** (0.54, 0.57)
Constant	−2.98*** (−2.98, −2.97)	−2.98*** (−2.98, −2.97)
Observations	228,574	208,172
R^2	0.17	0.02
Adjusted R^2	0.17	0.02
Residual Std. Error	1.20 (df = 228572)	1.16 (df = 208170)
F Statistic	46,214.14*** (df = 1; 228572)	5,178.47*** (df = 1; 208170)
Note:		*p<0.1; **p<0.05; ***p<0.01

A simple OLS with only our dependent and our treatment variable shows actually that there is a strong positive effect of a dispensary and the crime incident. Additionally, we include 95% confidence intervals instead of standard error. Remember that our dependent variable is in log-form which means that this equates to a 1.34 percent increase in crime. The variation explained is 17% which is not too bad for a single variable. Yet, if we apply our more rational model of propensity score matching, looking at similar units, we see that the effect drops substantially to only 0.55 percent increase in crime. Yet, still a positive and highly statistically significant effect. If we look, however at the R_squared-value now, we can see that the variation in crime is no longer explained at all by this variable, thus suggesting that there are other variables that are important.

Once we include our covariates, we are able to look at the relationship in more detail. The establishment of a dispensary is still positively related with the crime rate and is substantial in the Full OLS model and about half in the propensity score matching scenario. This time, the R_squared-value does not drop but rather increases to 53%, suggesting that the socio-economic variables chosen do explain the variation in crime quite well. After dropping the treatment variable, the variation explained remains stable (see Appendix). The drop is only 0.03%. In particular, we have seen that where there are more adults above and below the average age, i.e. when there are more retirees that could be prone to be victims or more adolescents that could be prone to become criminals, then we see more crime. A very high level of graduate degree holders in a district does also reduce the crime rate, yet so does a very low number of graduate holders, which might in this case be due to the concentration on only 35 districts.[11] For the Propensity model, it is interesting to note that almost every variable seems to have a negative effect on the crime rate, except of the share of poverty, there being less adults than on average, and there being either high or very low levels of diversity. Yet, looking at Figure 6: A.5, we must concede that our findings here might be driven for other reasons because we face the so-called common support problem, when the overlap between treated and untreated is so low that we lose confidence in our findings.

[11] in discussion

Table 2: Analysis of Crime

	Dependent variable:	
	ln(Crime Rate Per Thousand)	
	OLS Full	Propensity Full
	(1)	(2)
Established	1.40*** (1.39, 1.42)	0.66*** (0.65, 0.67)
share_poverty	0.04*** (0.04, 0.04)	0.05*** (0.05, 0.05)
Adulthood# Adults: Above average	−0.11*** (−0.13, −0.09)	−1.21*** (−1.24, −1.19)
Adulthood# Adults: Below average	1.10*** (1.08, 1.12)	0.35*** (0.34, 0.36)
Adulthood# Adults: Just above average	0.24*** (0.22, 0.26)	−0.52*** (−0.53, −0.51)
EduCat# Graduates: High	0.02 (−0.01, 0.05)	−1.33*** (−1.37, −1.29)
EduCat# Graduates: Very High	−0.79*** (−0.83, −0.76)	−2.42*** (−2.47, −2.38)
EduCat# Graduates: Very low	−1.29*** (−1.33, −1.26)	−2.42*** (−2.47, −2.38)
DiversityDiversity: High	0.17*** (0.15, 0.19)	0.11*** (0.10, 0.12)
DiversityDiversity: Very high	0.06*** (0.04, 0.08)	−0.23*** (−0.26, −0.21)
DiversityDiversity: Very Low	0.40*** (0.37, 0.43)	1.03*** (1.01, 1.05)
Constant	−3.51*** (−3.54, −3.48)	−1.22*** (−1.25, −1.18)
Observations	228,574	175,643
R^2	0.33	0.53
Adjusted R^2	0.33	0.53
Residual Std. Error	1.07 (df = 228562)	0.53 (df = 175631)
F Statistic	10,319.37*** (df = 11; 228562)	18,020.97*** (df = 11; 175631)
Note:		*p<0.1; **p<0.05; ***p<0.01

The Fixed Effects model represented in Table 3 corroborates the idea that the establishment of a dispensary has a positive effect on crime by about 0.5-0.7 percent. This is not trivial but also not as big as a simple OLS regression would have made us believe. Caution needs to be taken though with this last regression. Unfortunately, we are unable to use any control variables due to the data from the U.S. Census only being available on a yearly and not on a monthly basis. The latter would have allowed us to exploit the within-variation of our districts in a richer sense than we were able to at the moment.

Table 3: Analysis of Crime

	Dependent variable:
	ln(Crime Rate Per Thousand) Fixed Effects
Established	0.59*** (0.58, 0.61)
Observations	228,574
R^2	0.02
Adjusted R^2	0.02
F Statistic	4,178.01*** (df = 1; 228538)
Note:	*p<0.1; **p<0.05; ***p<0.01

Discussion

Consistent with our findings, we conclude that the establishment of a marijuana dispensary is positively related with an increase in the crime rate for that district. Perhaps we see this increase because our data spans a shorter time period than the data used in the Cato publication; however, were we to use longer panel data, for instance, we suspect our outcomes to be consistent with those in the Cato report. One limitation to our research outcomes depends on our chosen variables; had we looked at unemployment as a socio-economic factor affecting crime rates, we might have been able to capture a more complete picture since this data is available month-to-month. The same holds for our other variables. The problem of our U.S. Census Data being annual rather than monthly is that we cannot exploit the variation in districts over months and thus our propensity score matching as well as our fixed effects model only deals with very limited amount of data. Were we to have other variables that approximate the conceptual direction of our explanatory variables but that are available on a monthly basis, then we should use those rather than the ones presented here. Instead of Poverty Rate, we could have used a housing price index similar to the S&P Case-Shiller Home Price Index, which is the market standard in data on U.S. residential real estate prices. Another issue worth mentioning is that burglary/theft, and property and violent crimes might show an upward trend because of other omitted variables; another explanation is that the rises in crime correlate to previous drug sellers being out of a job. This does not seem to be the case, though, given the fact that the trend in the data is so late and thus happens considerably after most of the dispensaries opened. While it could be that there might be some delay between being out of business as an illegal drug seller and comitting other crimes, we do not think that several months is a plausible delay. Further research should be taken into this direction to see the economic effect on previous dealers and their likelihood to commit other crimes. Lastly, another variable to consider could have been political leaning, liberal or conservative, but the data we accessed did not specify any such variable.

An issue that we have not directly talked about and assumed to be not a problem in our analysis but that would become rather important if we were to do a difference-in-differences analysis, is the strong likelihood of dispensaries to *self-select* into one or the other district for endogeneous reasons such as accessibility, crime level and customer base. We thus will have an omitted variable bias in all of our models until we also understand how dispensaries make their choice of opening their shops in Seattle.

While the preceding analysis mainly focused on the average crime incident, we also have the data for each individual crime category.[12] There is almost no difference in the analysis, yet again supporting our estimate that the establishment of a dispensary has a slighly positive but probably negligible effect on the occurrence of crime incidents.

[12] Table 6: A.7 until Table 12: A13 represent the Full OLS models for all crime categories and Table 13: A.14 and Table 14: A.15 represent the Fixed Effects Model

Appendix

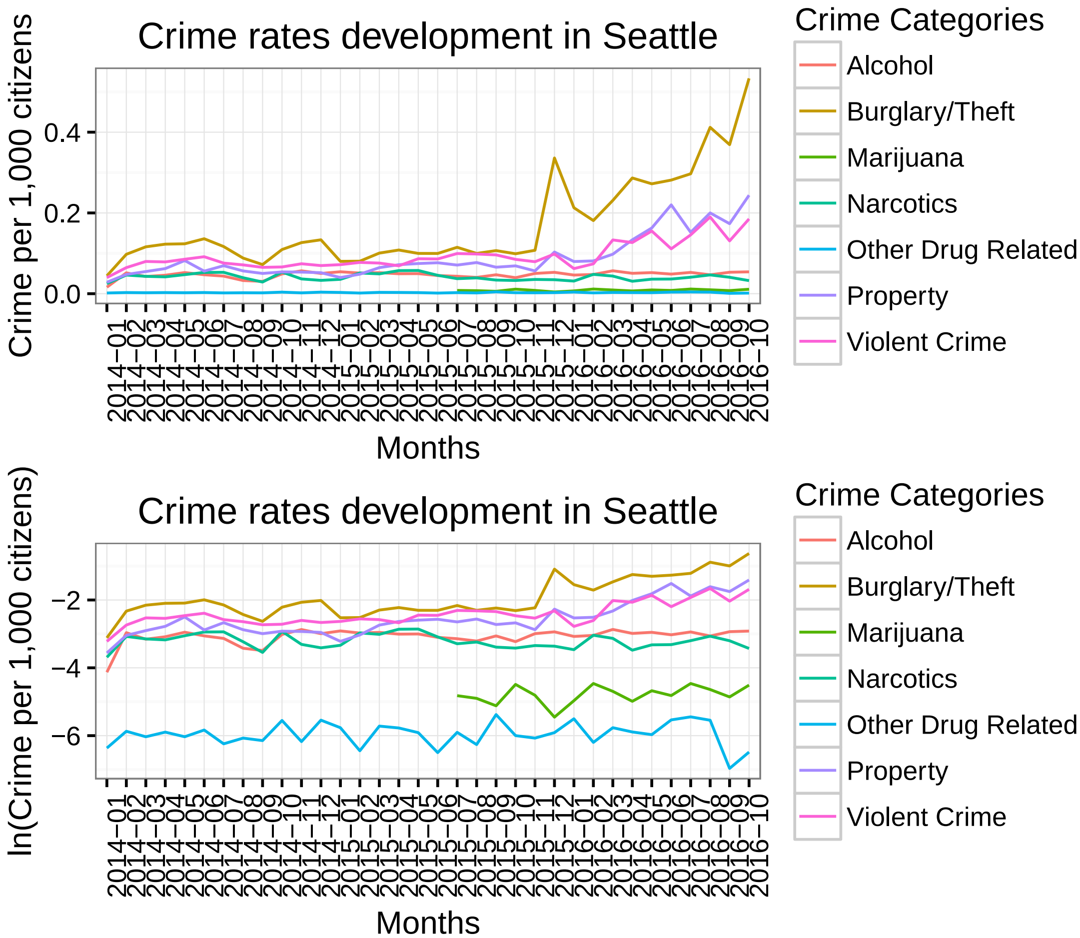

Figure 4: A.1 - Development of Crime in Seattle

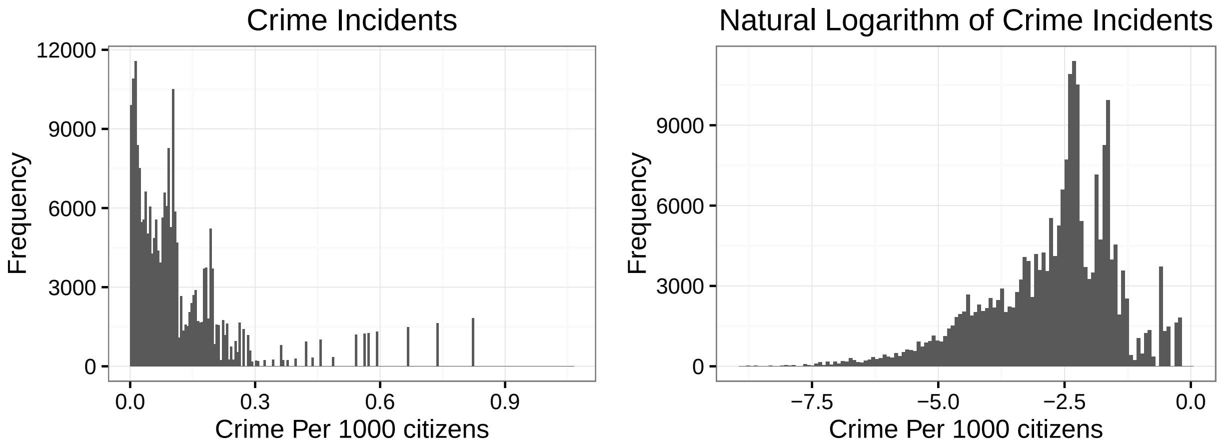

Figure 5: A.2 - Distribution of Crime across the Districts

Table 4: A.3 - t-test with and without January 2014

	Dependent variable:	
	ln(Crime Rate Per Thousand)	
	OLS Simple	OLS Simple w/o 01/2014
	(1)	(2)
Established	1.34*** (1.33, 1.35)	1.33*** (1.32, 1.34)
Constant	−2.98*** (−2.98, −2.97)	−2.97*** (−2.97, −2.96)
Observations	228,574	226,147
R^2	0.17	0.17
Adjusted R^2	0.17	0.17
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5: A.4 - Propensity w/o Treatment

	Dependent variable:
	ln(Crime Rate Per Thousand) A.4 - Propensity w/o Treatment
Share Poverty	0.06^{***} (0.05, 0.06)
Adulthood# Adults: Above average	-1.41^{***} (-1.44, -1.39)
Adulthood# Adults: Below average	0.0002 (-0.01, 0.01)
Adulthood# Adults: Just above average	-0.76^{***} (-0.77, -0.75)
EduCat# Graduates: High	-2.14^{***} (-2.18, -2.11)
EduCat# Graduates: Very High	-3.61^{***} (-3.65, -3.56)
EduCat# Graduates: Very low	-3.15^{***} (-3.19, -3.11)
DiversityDiversity: High	-0.21^{***} (-0.23, -0.20)
DiversityDiversity: Very high	-0.62^{***} (-0.64, -0.59)
DiversityDiversity: Very Low	1.28^{***} (1.25, 1.30)
Constant	-0.05^{***} (-0.09, -0.02)
Observations	175,643
R^2	0.50
Adjusted R^2	0.50
Note:	*p<0.1; **p<0.05; ***p<0.01

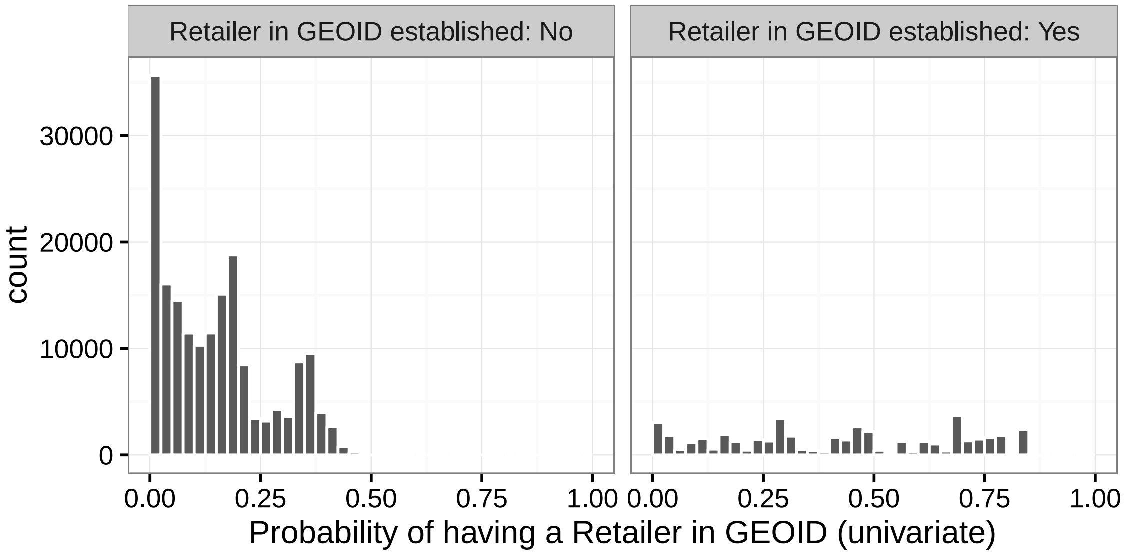

Figure 6: A.5 - Common Support Graph/Visualisation propensity score matching

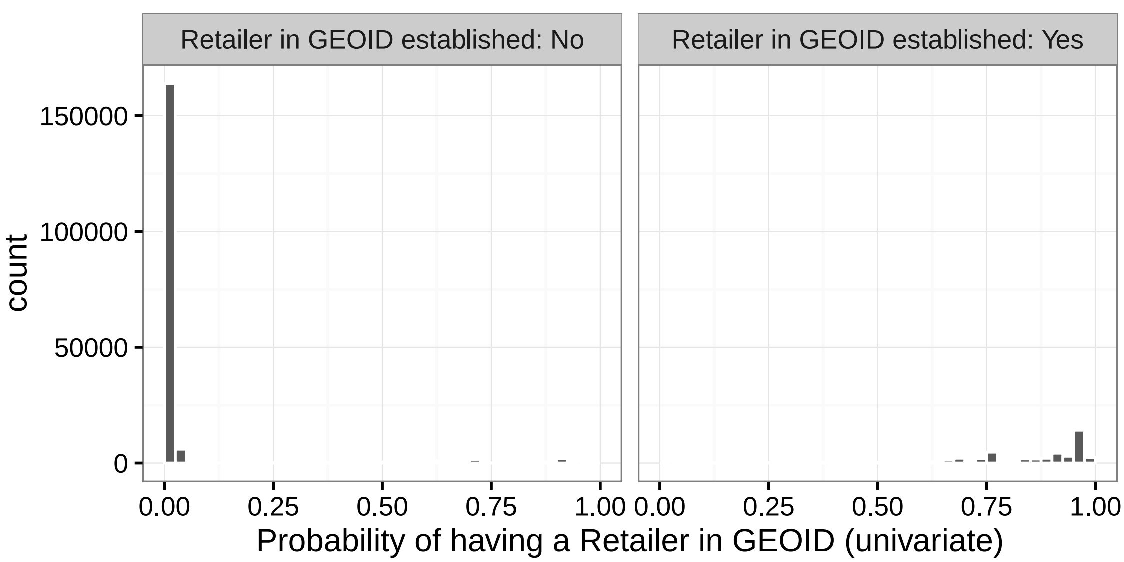

Figure 7: A.6 - Common Support Graph/Visualisation propensity score matching with covariates

Table 6: A.7 - Full OLS model Alcohol Crime

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-4.5438	0.0303	-149.96	0.0000
Established	1.7154	0.0194	88.42	0.0000
share_poverty	0.0336	0.0012	27.97	0.0000
Adulthood# Adults: Above average	1.2912	0.0236	54.72	0.0000
Adulthood# Adults: Below average	3.0391	0.0159	191.22	0.0000
Adulthood# Adults: Just above average	0.8664	0.0167	51.73	0.0000
EduCat# Graduates: High	-0.9913	0.0298	-33.28	0.0000
EduCat# Graduates: Very High	-2.4620	0.0348	-70.74	0.0000
EduCat# Graduates: Very low	-0.5537	0.0392	-14.13	0.0000
DiversityDiversity: High	-0.5729	0.0224	-25.57	0.0000
DiversityDiversity: Very high	-2.1339	0.0246	-86.66	0.0000
DiversityDiversity: Very Low	1.3581	0.0294	46.20	0.0000

Table 7: A.8 - Full OLS model Burglary Crime

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-3.0567	0.0156	-196.22	0.0000
Established	1.4325	0.0095	151.36	0.0000
share_poverty	0.0330	0.0006	52.96	0.0000
Adulthood# Adults: Above average	-0.1147	0.0102	-11.23	0.0000
Adulthood# Adults: Below average	0.8148	0.0093	87.16	0.0000
Adulthood# Adults: Just above average	0.3119	0.0094	33.22	0.0000
EduCat# Graduates: High	0.0916	0.0141	6.50	0.0000
EduCat# Graduates: Very High	-0.6911	0.0167	-41.30	0.0000
EduCat# Graduates: Very low	-1.1998	0.0174	-69.01	0.0000
DiversityDiversity: High	0.2150	0.0095	22.53	0.0000
DiversityDiversity: Very high	0.2667	0.0121	22.09	0.0000
DiversityDiversity: Very Low	0.3100	0.0163	18.98	0.0000

Table 8: A.9 - Full OLS model Marijuana Crime

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-4.4191	0.2140	-20.65	0.0000
Established	0.3815	0.1026	3.72	0.0002
share_poverty	0.1151	0.0061	18.78	0.0000
Adulthood# Adults: Above average	0.3069	0.1344	2.28	0.0226
Adulthood# Adults: Below average	2.2063	0.0932	23.66	0.0000
Adulthood# Adults: Just above average	0.2215	0.0907	2.44	0.0147
EduCat# Graduates: High	-2.4978	0.1938	-12.89	0.0000
EduCat# Graduates: Very High	-4.2183	0.2018	-20.90	0.0000
EduCat# Graduates: Very low	-3.1863	0.2392	-13.32	0.0000
DiversityDiversity: High	-0.9905	0.1233	-8.04	0.0000
DiversityDiversity: Very high	-3.0994	0.1316	-23.55	0.0000
DiversityDiversity: Very Low	0.8486	0.1441	5.89	0.0000

Table 9: A.10 - Full OLS model Narcotics Crime

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-4.4264	0.0583	-75.98	0.0000
Established	1.7270	0.0365	47.31	0.0000
share_poverty	0.0915	0.0022	42.01	0.0000
Adulthood# Adults: Above average	-0.4688	0.0371	-12.63	0.0000
Adulthood# Adults: Below average	2.7748	0.0312	88.91	0.0000
Adulthood# Adults: Just above average	0.4775	0.0310	15.42	0.0000
EduCat# Graduates: High	-1.1343	0.0538	-21.07	0.0000
EduCat# Graduates: Very High	-1.4363	0.0618	-23.25	0.0000
EduCat# Graduates: Very low	-2.3197	0.0699	-33.18	0.0000
DiversityDiversity: High	0.1625	0.0355	4.58	0.0000
DiversityDiversity: Very high	-1.8857	0.0433	-43.60	0.0000
DiversityDiversity: Very Low	0.2090	0.0510	4.09	0.0000

Table 10: A.11 - Full OLS model Other Drug-related Crime

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-6.8244	0.1528	-44.65	0.0000
Established	0.7688	0.0935	8.22	0.0000
share_poverty	0.0224	0.0058	3.84	0.0001
Adulthood# Adults: Above average	0.0711	0.0992	0.72	0.4739
Adulthood# Adults: Below average	0.8257	0.0841	9.82	0.0000
Adulthood# Adults: Just above average	0.2658	0.0817	3.25	0.0012
EduCat# Graduates: High	0.4306	0.1426	3.02	0.0026
EduCat# Graduates: Very High	-0.4326	0.1590	-2.72	0.0067
EduCat# Graduates: Very low	-0.4541	0.1720	-2.64	0.0085
DiversityDiversity: High	0.1902	0.0983	1.93	0.0535
DiversityDiversity: Very high	-0.1344	0.1216	-1.10	0.2698
DiversityDiversity: Very Low	0.4108	0.1324	3.10	0.0020

Table 11: A.12 - Full OLS model Property Crime

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-3.3997	0.0356	-95.61	0.0000
Established	1.4095	0.0205	68.89	0.0000
share_poverty	0.0375	0.0013	27.94	0.0000
Adulthood# Adults: Above average	-0.1523	0.0221	-6.89	0.0000
Adulthood# Adults: Below average	0.8988	0.0198	45.31	0.0000
Adulthood# Adults: Just above average	0.5455	0.0187	29.13	0.0000
EduCat# Graduates: High	-0.0037	0.0319	-0.12	0.9079
EduCat# Graduates: Very High	-0.7456	0.0378	-19.72	0.0000
EduCat# Graduates: Very low	-1.2286	0.0397	-30.95	0.0000
DiversityDiversity: High	-0.0837	0.0209	-4.00	0.0001
DiversityDiversity: Very high	-0.1470	0.0269	-5.47	0.0000
DiversityDiversity: Very Low	0.0152	0.0336	0.45	0.6517

Table 12: A.13 - Full OLS model Violent Crime

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-3.0448	0.0442	-68.87	0.0000
Established	1.5294	0.0263	58.21	0.0000
share_poverty	0.0528	0.0016	33.09	0.0000
Adulthood# Adults: Above average	-0.0976	0.0286	-3.42	0.0006
Adulthood# Adults: Below average	1.9970	0.0241	82.97	0.0000
Adulthood# Adults: Just above average	0.6032	0.0236	25.51	0.0000
EduCat# Graduates: High	-1.0483	0.0419	-25.03	0.0000
EduCat# Graduates: Very High	-1.7217	0.0478	-35.98	0.0000
EduCat# Graduates: Very low	-1.9203	0.0517	-37.12	0.0000
DiversityDiversity: High	0.1239	0.0274	4.53	0.0000
DiversityDiversity: Very high	-0.9696	0.0342	-28.38	0.0000
DiversityDiversity: Very Low	0.5829	0.0394	14.78	0.0000

Table 13: A.14 - Fixed effects model specific crime category

Table 6:

	Dependent variable:			
	ln(Crime Rate Per Thousand) Alcohol	log(BurCrime) Burglary	log(NarcCrime) Narcotics	log(OtherCrime) Other Drugs
	(1)	(2)	(3)	(4)
Established	0.70*** (0.68, 0.72)	0.61*** (0.60, 0.62)	0.93*** (0.87, 0.98)	0.49*** (0.29, 0.69)
Observations	46,737	126,781	10,852	569
R^2	0.07	0.11	0.09	0.04
Adjusted R^2	0.07	0.11	0.09	−0.02
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 14: A.15 - Fixed effects model specific crime category category

Table 7:

	Dependent variable:	
	ln(Crime Rate Per Thousand) Property	log(ViolCrime) Violent
	(1)	(2)
Established	0.72*** (0.69, 0.74)	0.77*** (0.74, 0.81)
Observations	24,620	17,929
R^2	0.11	0.11
Adjusted R^2	0.11	0.11
Note:		*p<0.1; **p<0.05; ***p<0.01

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