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

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

Critics claim that **legalization** leads to an **increase in marijuana and other drug use**, "*increases crime, diminishes traffic safety, harms public health, and lowers teen educational achievement*."

Table of Contents

Introduction

- Explain our way to the topic and how we coped with it

Research Question

- Does legalization of cannabis lead to an increase in crime?
- we look at different levels of crime (Alcohol, Burglary/Theft, Marijuana, Narcotics, Other Drug Related, Property, and Violent Crime)
- due to data restraints we have focused on Seattle instead of WA
- H0: X -> Y as an equation

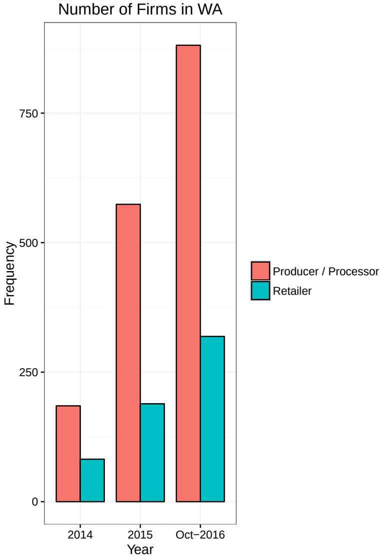
Policy Relevance

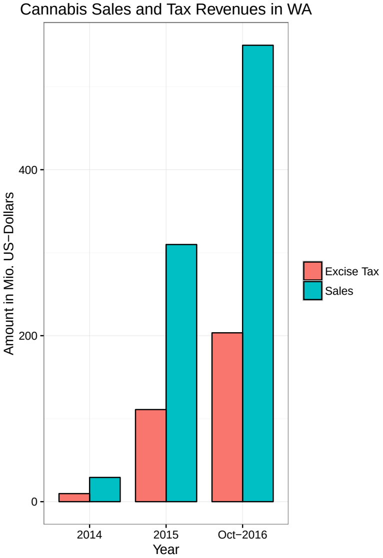
- Cato paper

- elections
- Rand paper
- cost of drug on war / change of perceptions (cultural shift)

Analysis - Descriptive Statistics (I)

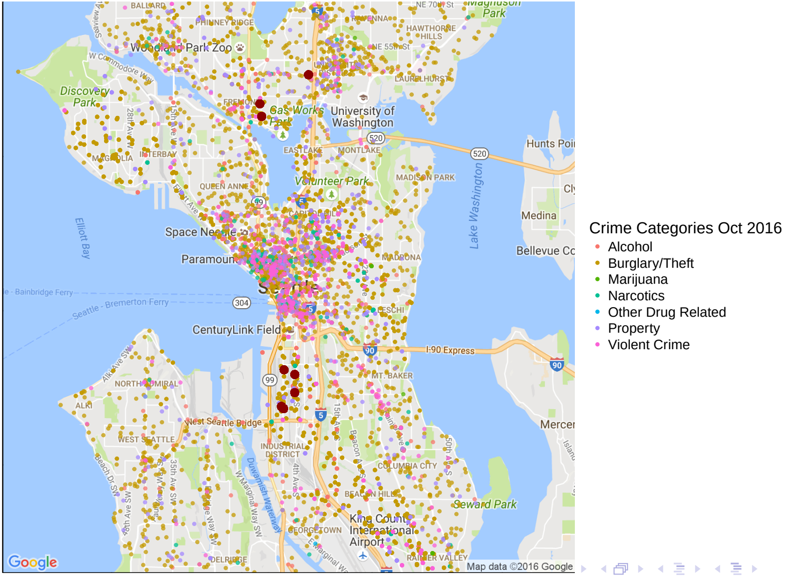
- business is booming in WA and Sales and Tax Revenues are increasing (in “Analysis.R” you can find the growth pattern)





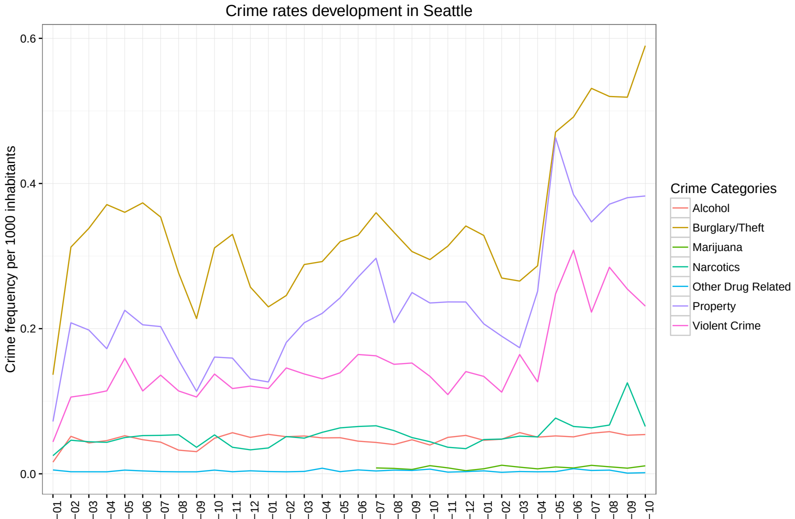
Analysis - Descriptive Statistics (II)

- explain the map -> concentration of crime in one area. it seems that retailers not associated with crime



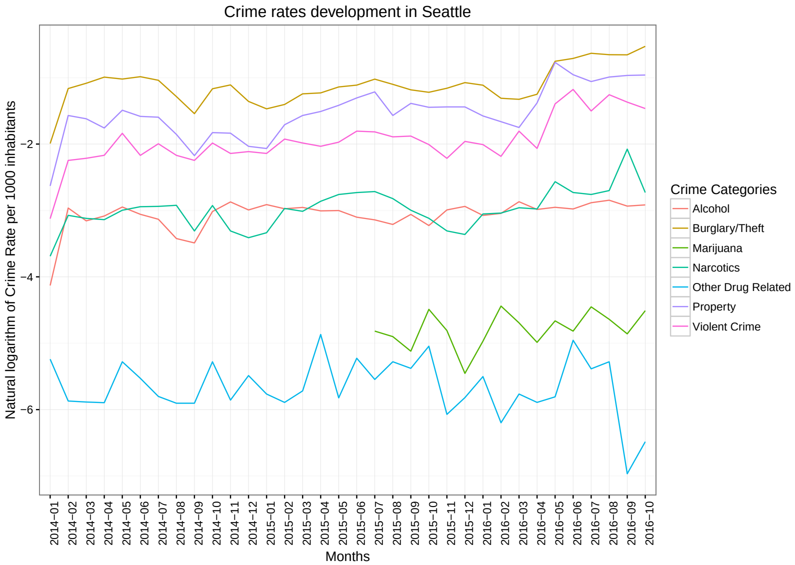
Analysis - Descriptive Statistics (III)

- January 2014 -> looks like coding has been different -> but later no statistically significant difference
- Development varies for each category -> thus natural logarithm (i.e. percentage change month-to-month) -> see next slide



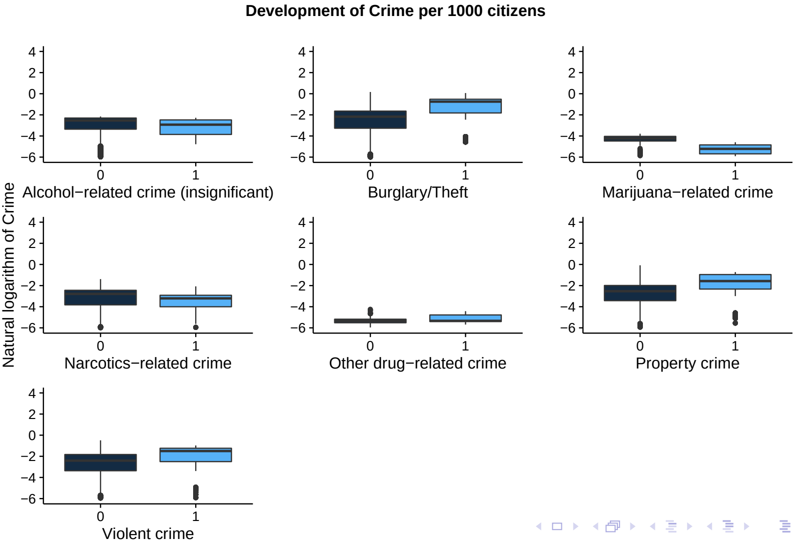
Analysis - Descriptive Statistics (IV)

- we can see property, burglary and other drug relate crime to change substantially



Analysis - Inferential Statistics (I)

- t-test = differences in mean -> significant for all but alcohol related crime
- different picture depending on the crime rate



Analysis - Inferential Statistics (II)

Table 1: Analysis of Crime

	Dependent variable:	
	log(CrimePerThousand)	
	(1)	(2)
Established	1.14^{***} (0.01)	0.59^{***} (0.01)
Constant	-2.71^{***} (0.003)	-2.86^{***} (0.003)
Observations	228,574	198,674
R^2	0.11	0.03
Adjusted R^2	0.11	0.03
Note:		*p$<$0.1; **p$<$0.05; ***p$<$0.01

Analysis - Inferential Statistics (III)

Table 2: Analysis of Crime

	Dependent variable:	
	log(CrimePerThousand)	
	(1)	(2)
Established	1.47*** (0.01)	0.31*** (0.01)
share_poverty	0.01*** (0.0004)	0.03*** (0.0004)
AgeCatMore than average Adults	0.16*** (0.01)	−0.04*** (0.01)
RaceCatMore than average Whites	1.00*** (0.01)	0.76*** (0.01)
Constant	−3.54*** (0.01)	−4.08*** (0.01)
Observations	228,574	132,958
R^2	0.19	0.05
Adjusted R^2	0.19	0.05
Note:		*p<0.1; **p<0.05; ***p<0.01

Conclusion (I)

- Model 1 and 3 are non-matched regressions
- Model 2 and 4 are matched regressions

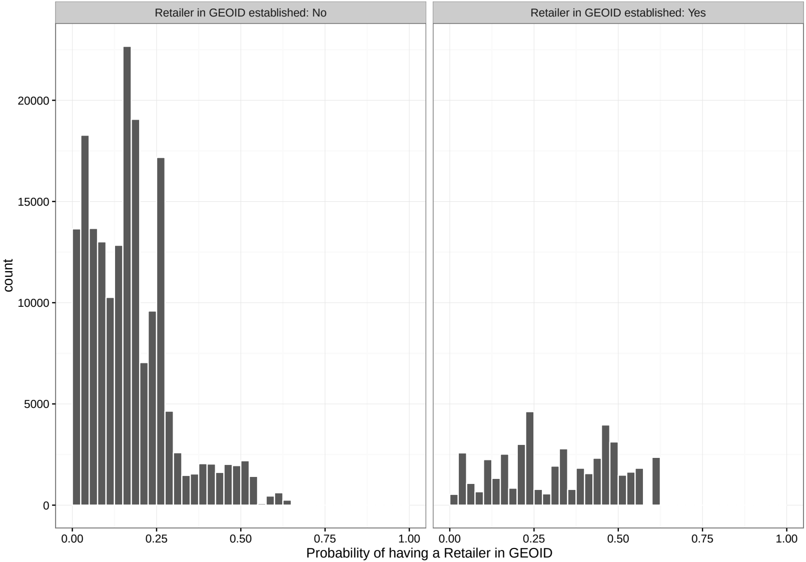
- We can see that there is a significant relationship between the establishment and the crime development but once we match similar districts, this drops substantially
- additionally, the R^2 becomes much lower also highlighting that the variance explained by the establishment is rather low
- an explanation for this could be that crime is spatially concentrated and auto-correlated with previous crime levels
- Retailers might choose not to start up near crime areas (i.e. self-selection bias)

Conclusion (II)

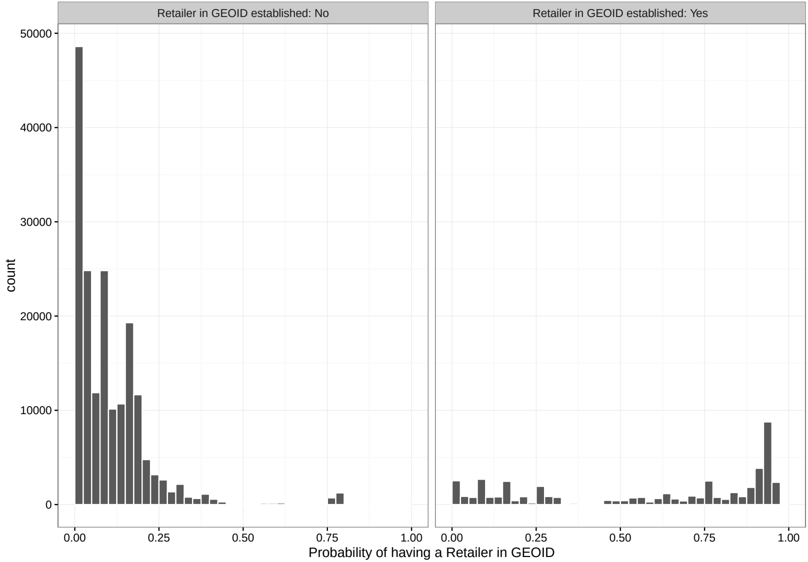
- Once accounted for GEOID: the point estimation are smaller -> GEOID important
- Once accounted for Month: the point estimation are higher -> maybe due to the geoid issue (time-trend not as important than spatial?)
- Will not do propensity score matching -> too computationally powerful

Annex (I)

- common support problem with the univariate regression



Annex (II)


Retailer in GEOID established: No
Retailer in GEOID established: Yes
50000
40000
30000
20000
10000
0
count
0.00
0.25
0.50
0.75
1.00
0.00
0.25
0.50
0.75
1.00
Probability of having a Retailer in GEOID