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**, that it "*increases crime, diminishes traffic safety, harms public health, and lowers teen educational achievement*."

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Introduction

- Wanted to research crime and effects of policymaking on crime
- Vox's article "Yes Weed Can" discussed upcoming legislation agenda on election day in November
- Also mentioned two studies citing the inconclusive nature of current research given limited data
- Data was indeed hard to find for a number of reasons, but decided on "Washington Initiative 502"

Research Question

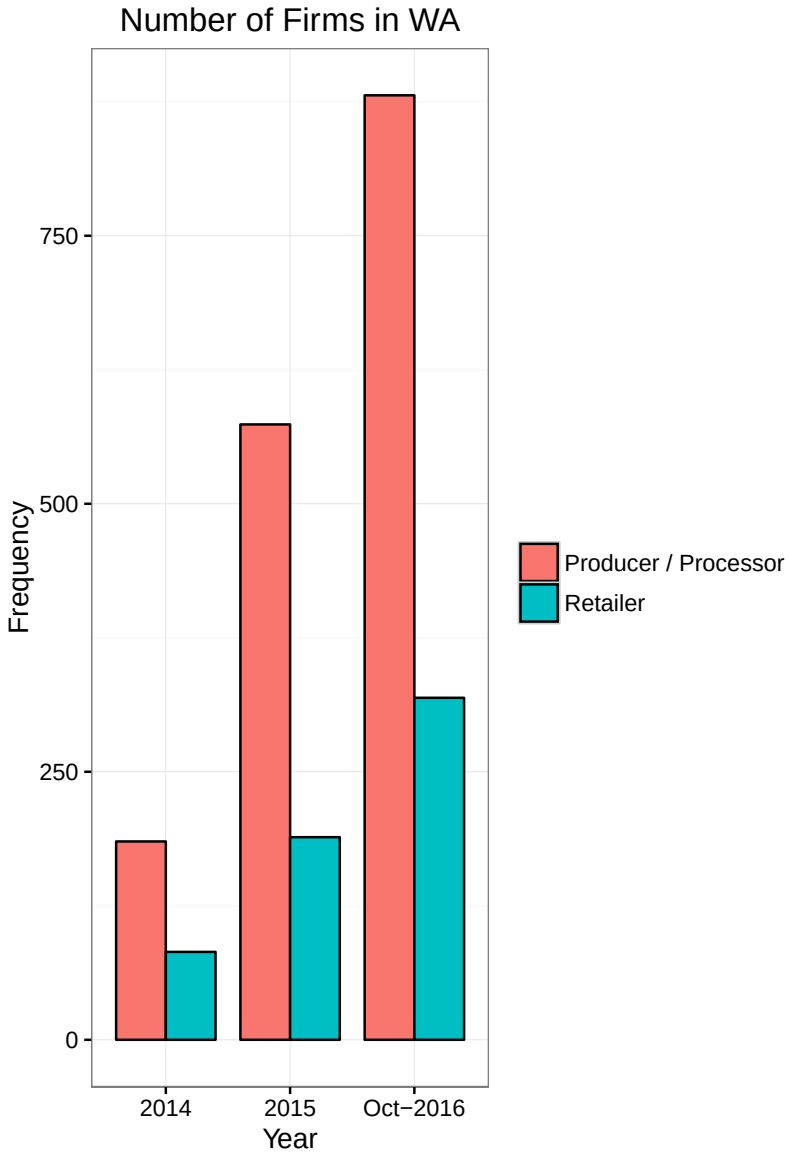
- Does legalization of cannabis lead to an increase in crime?
- We look at different levels of crime (Alcohol, Burglary/Theft, Marijuana Usage, Other Drug Usage, Property Crime, and Violent Crime)
- Due to data constraints we focused on Seattle instead of WA

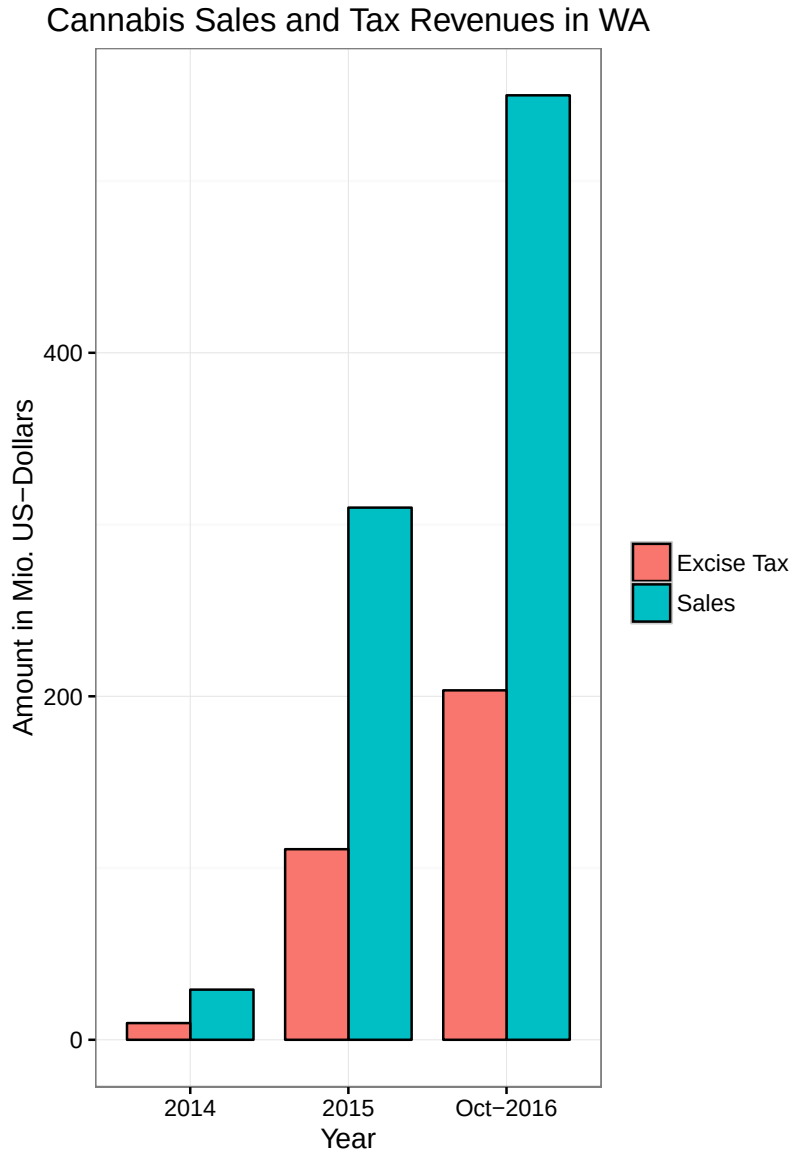
Policy Relevance

- Cato Institute policy paper, "Dose of Reality: The Effect of State Marijuana Legalizations" published in September
- Study covers Colorado, Washington, Oregon, Alaska and the effects of legalization on other drug and alcohol use, health, suicides, road safety, school expulsions
- Conclude that data provide little support for strong arguments made by either opponents or supporters
- RAND Corporation paper, "Options and Issues Regarding Marijuana Legalization" published last year
- Authors argue (1) there are other options than usual binary between prohibition and "regulate like alcohol" and (2) it is too soon to judge the repurcusions of legalization and more data needed

Analysis - Descriptive Statistics (I)

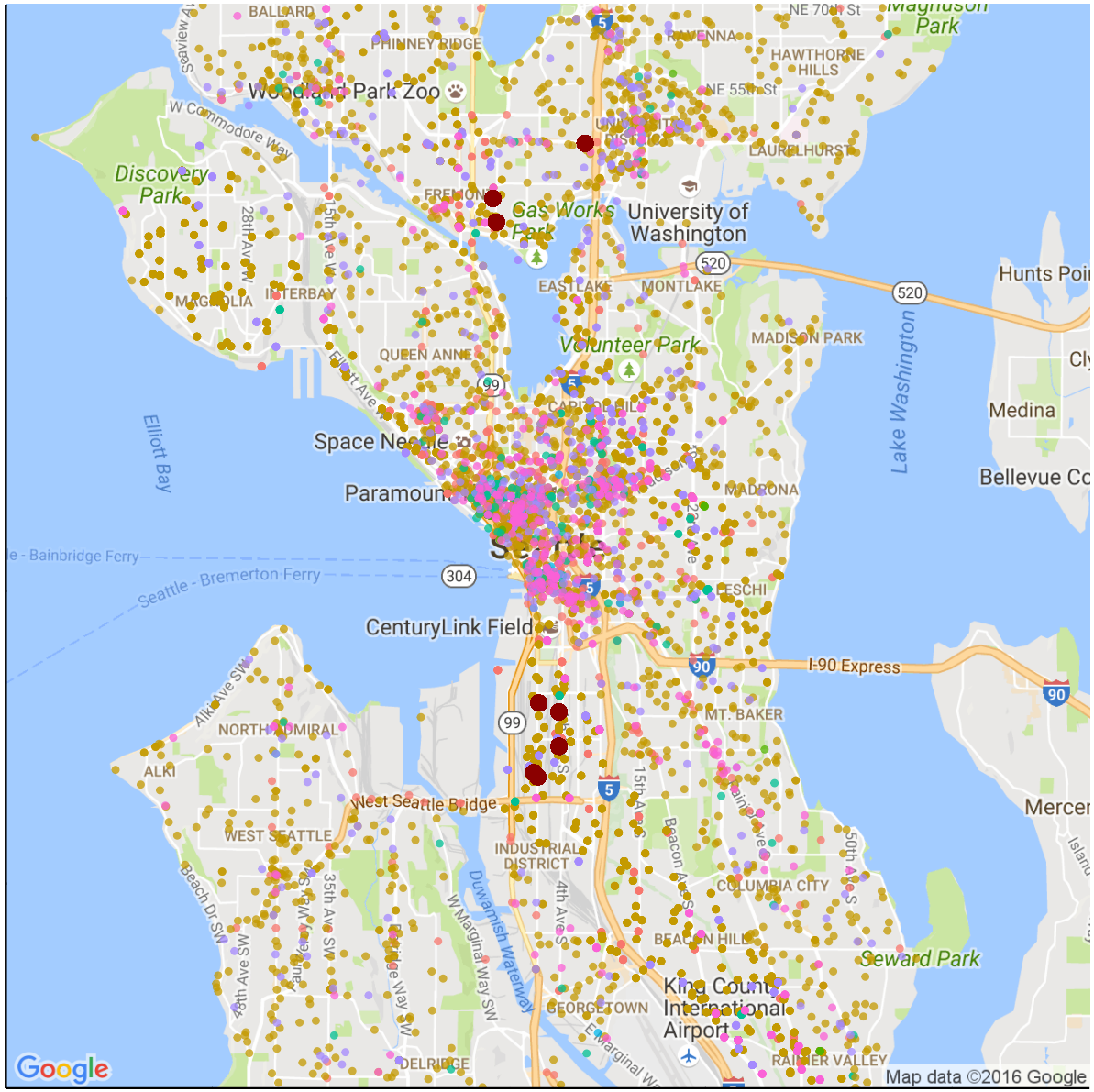
- Business is booming in WA and Sales and Tax Revenues are increasing





Analysis - Descriptive Statistics (II)

- Concentration of crime in one area. It seems that retailers not associated with crime

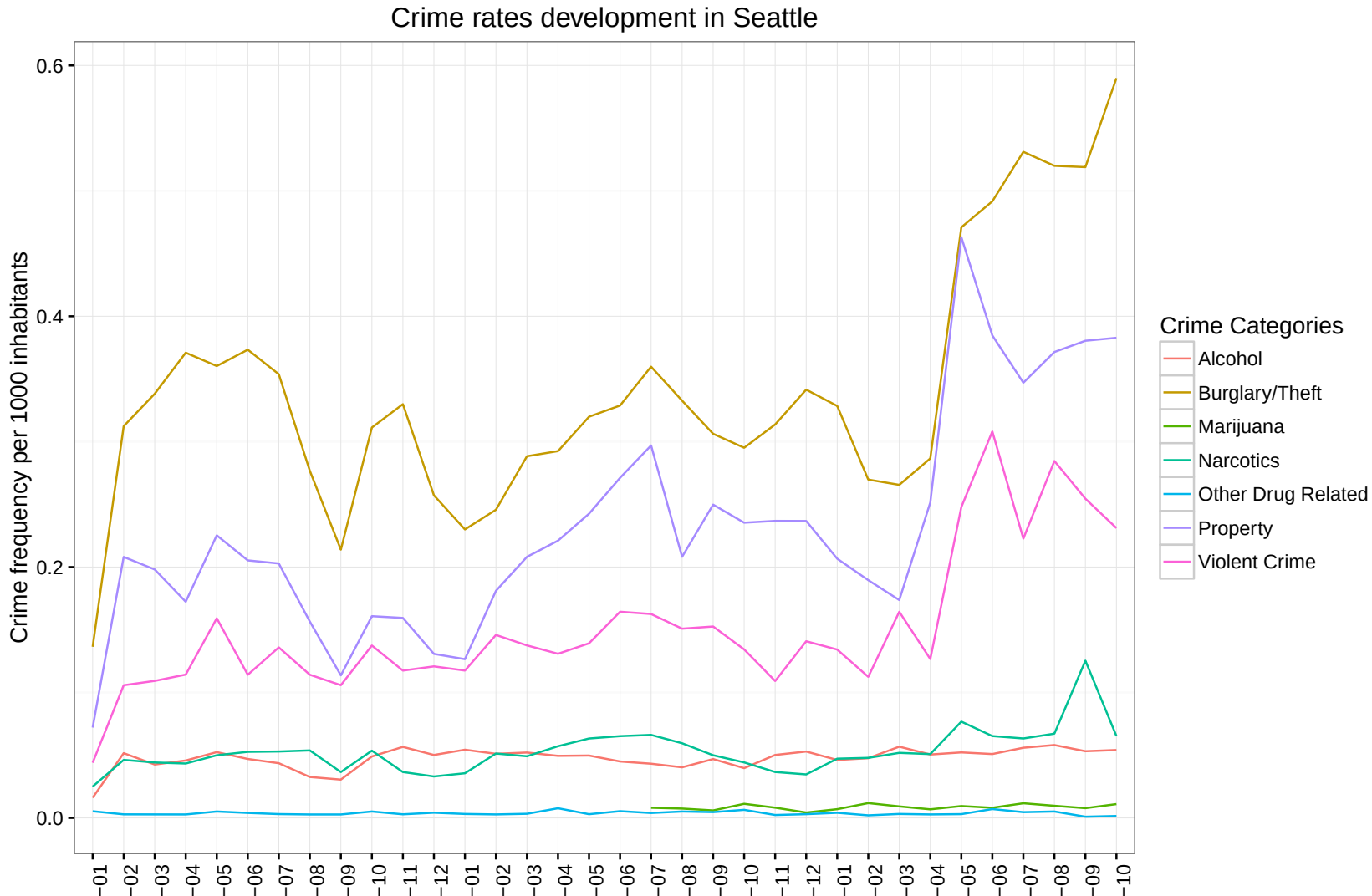


Crime Categories Oct 2016

- Alcohol
- Burglary/Theft
- Marijuana
- Narcotics
- Other Drug Related
- Property
- Violent Crime

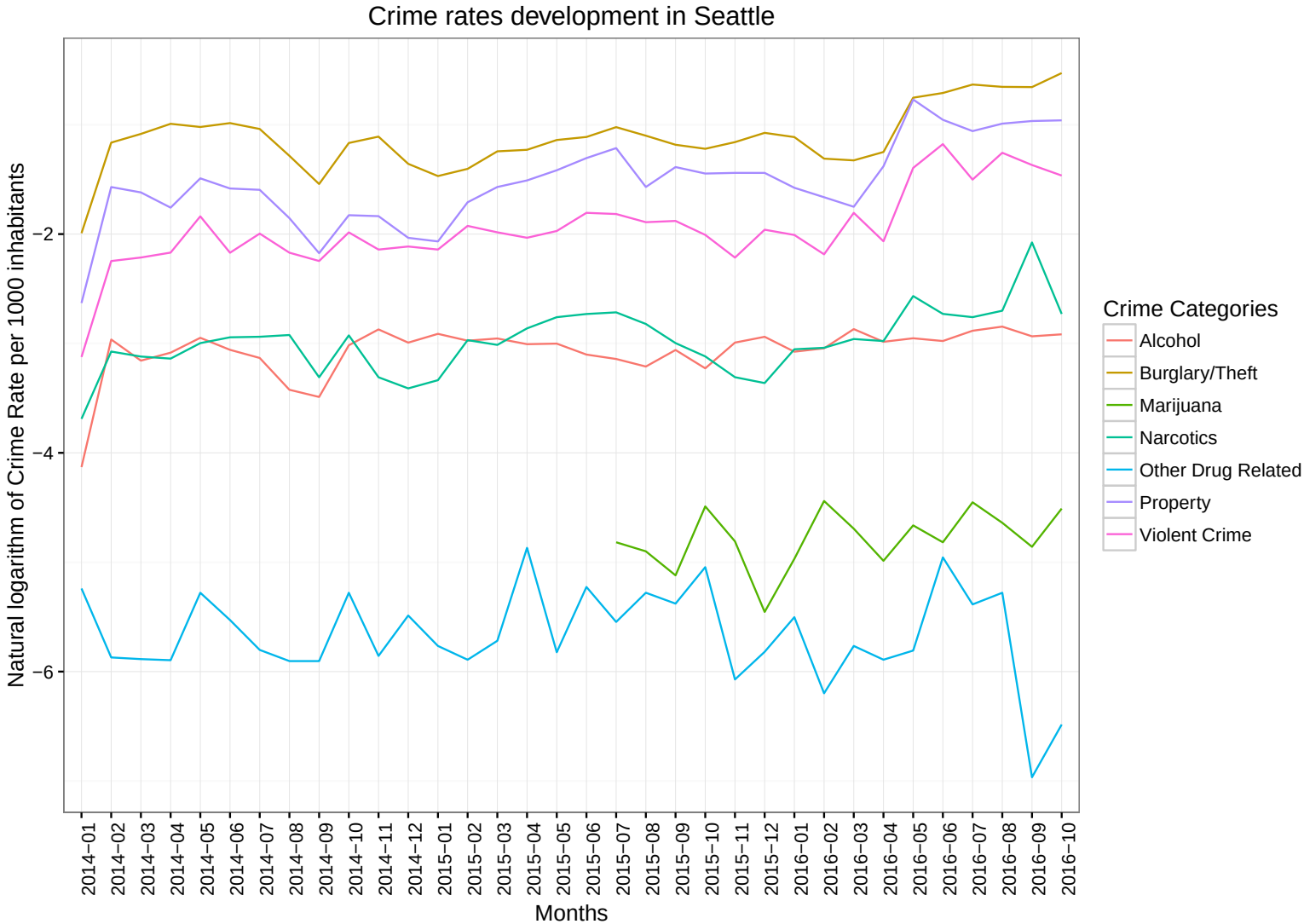
Analysis - Descriptive Statistics (III)

- Looks like coding/data processing error in January 2014, but later no statistically significant difference
- Development varies for each category -> natural logarithm (i.e. percentage change month-to-month) on next slide



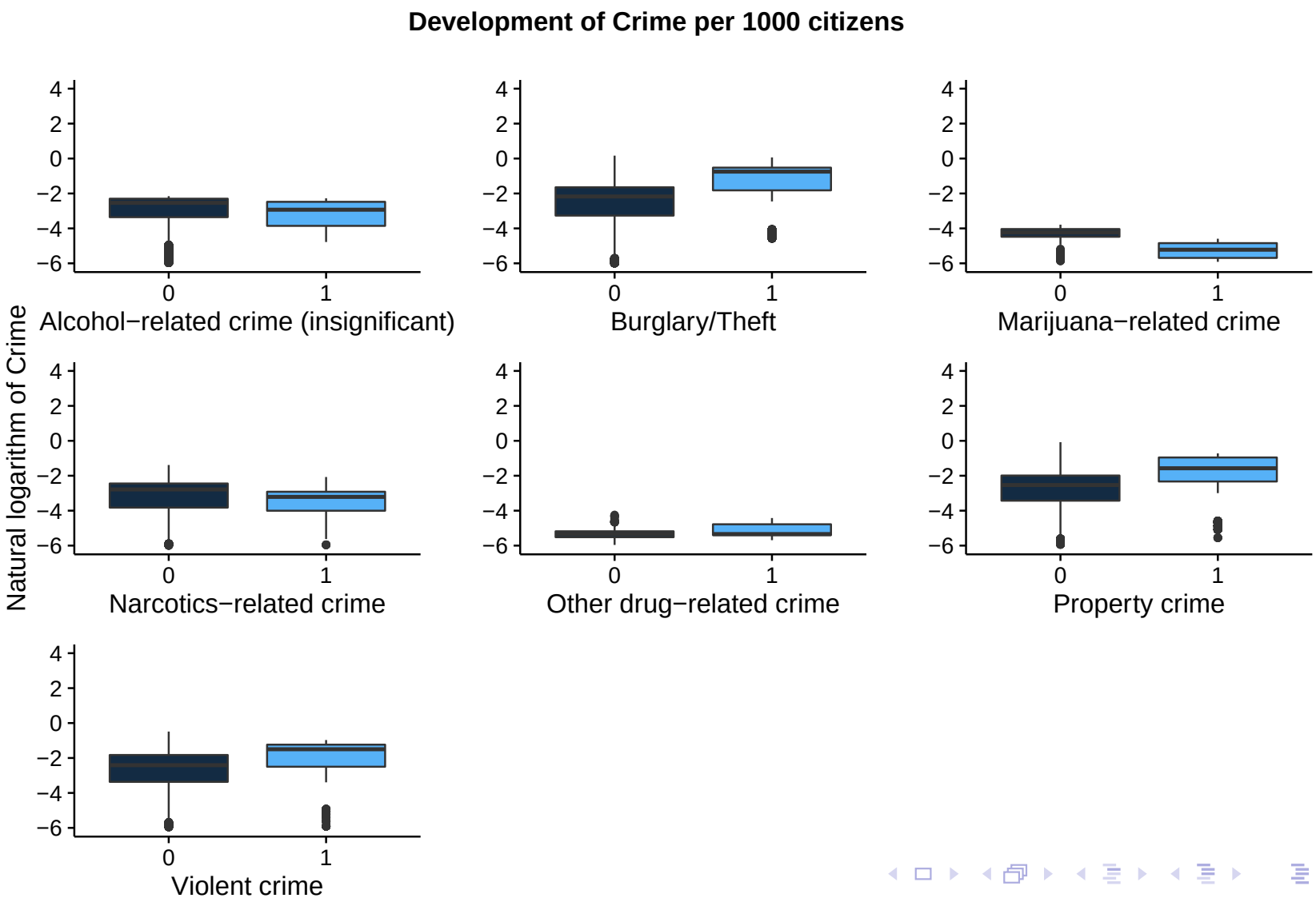
Analysis - Descriptive Statistics (IV)

- We see Property, Burglary/Theft and Other Drug Related 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)

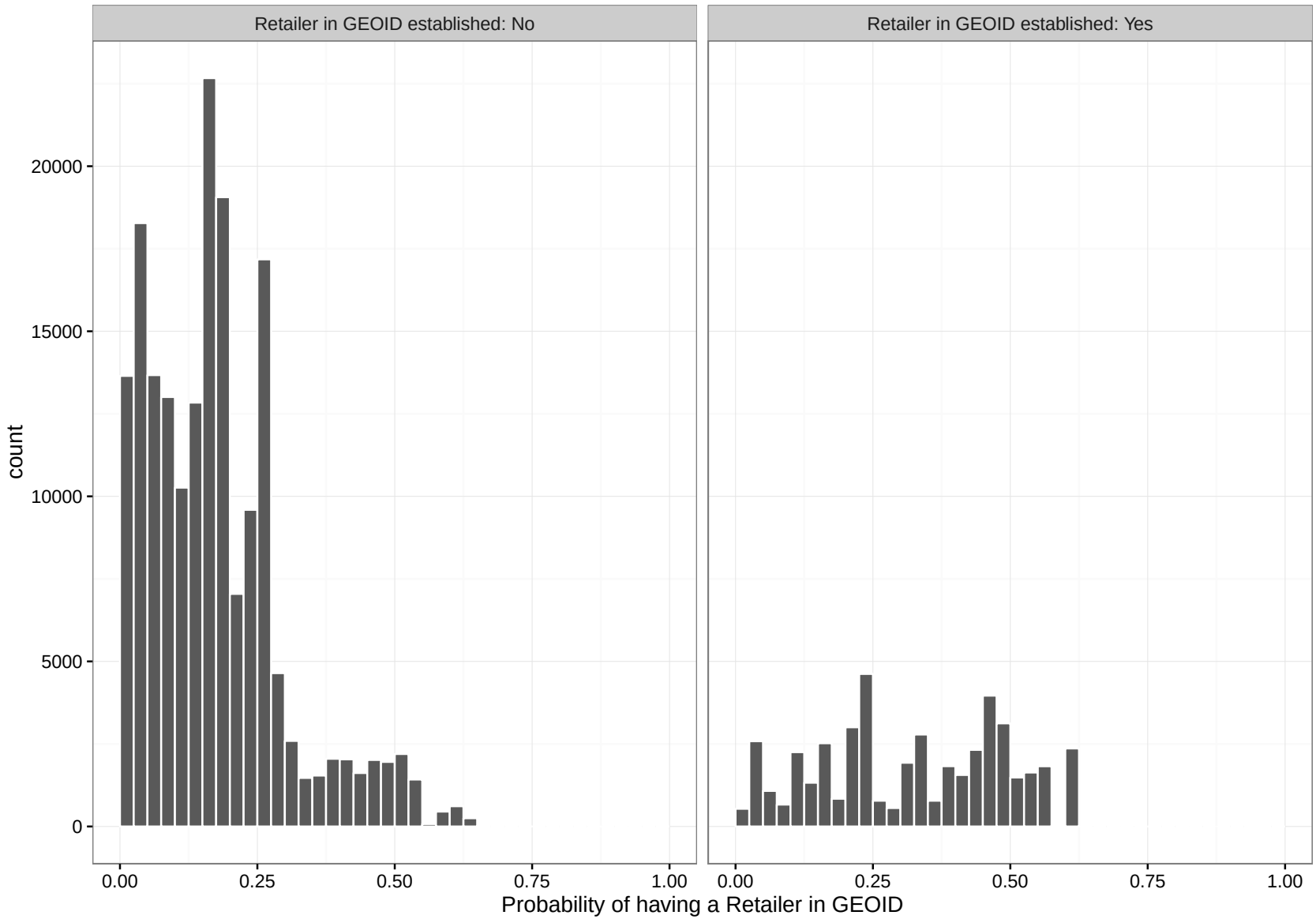
- Model 1 and 3 are non-matched regressions
- Model 2 and 4 are matched regressions
- We can see there is a significant relationship between the establishment and crime development, but once we match similar districts, this drops substantially
- Additionally, the R? becomes much lower, highlighting that 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)

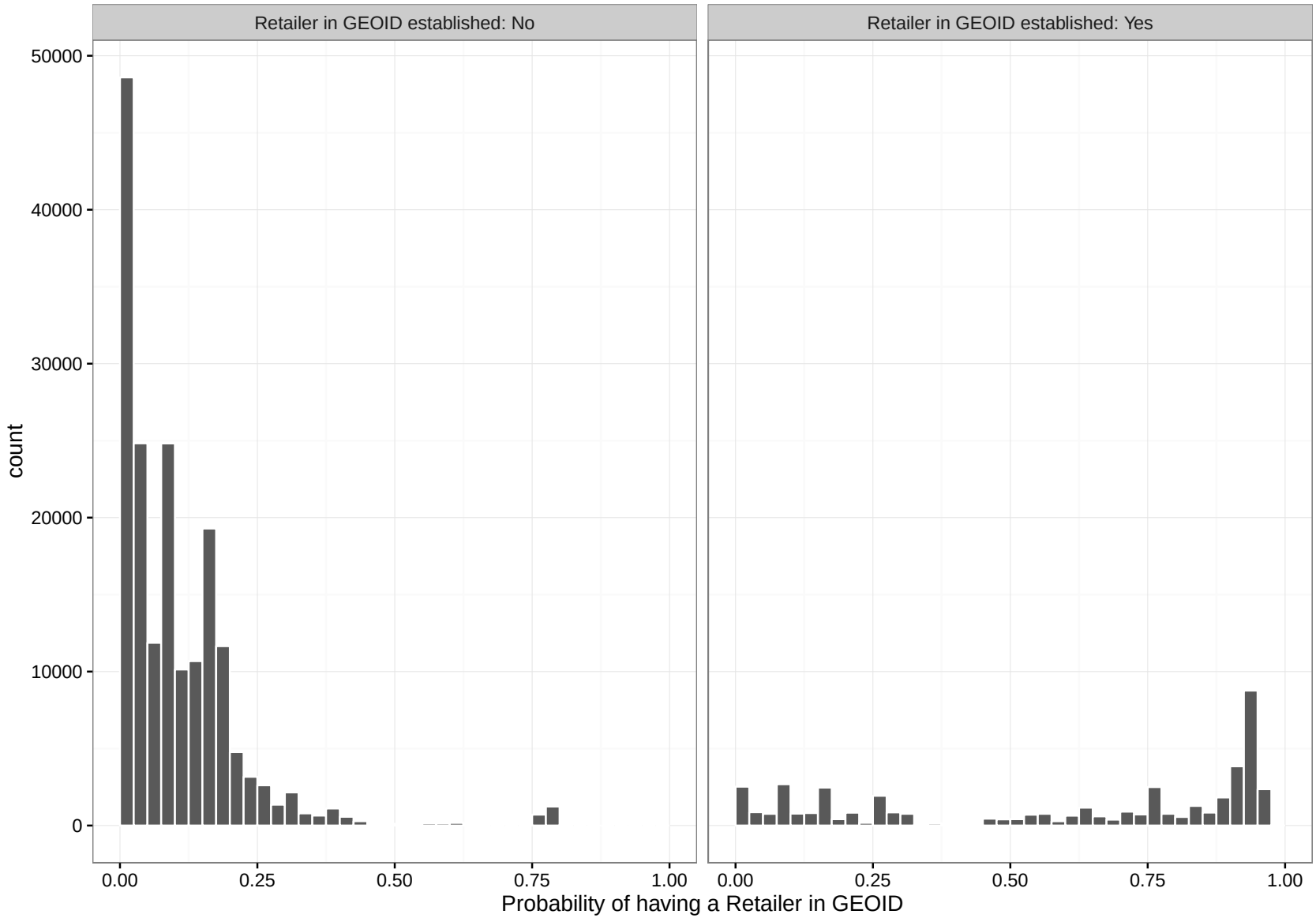
- Once accounted for GEOID: the point estimation are smaller -> GEOID important
- Once accounted for Month: the point estimation are higher -> maybe due to the geoid issue (time-trend not as important as spatial?)
- Will not do propensity score matching -> too computationally powerful

Annex (I)

- Common support problem with the univariate regression



Annex (II)


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