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

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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

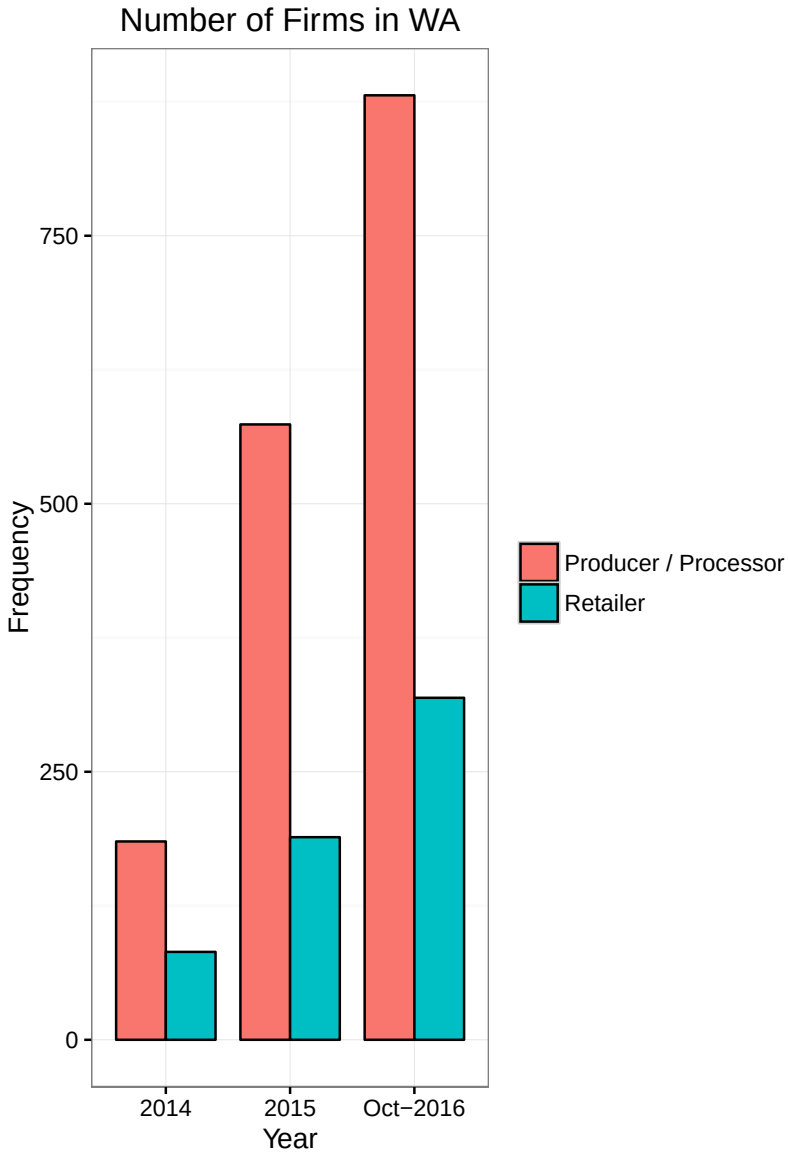
- ***Does legalization of cannabis lead to an increase in crime?***
- We look at different levels of crime (Alcohol, Burglary/Theft, Marijuana Usage, Other Drug Usage, Property Crime, and Violent Crime)
- Due to data constraints we focused on Seattle instead of WA

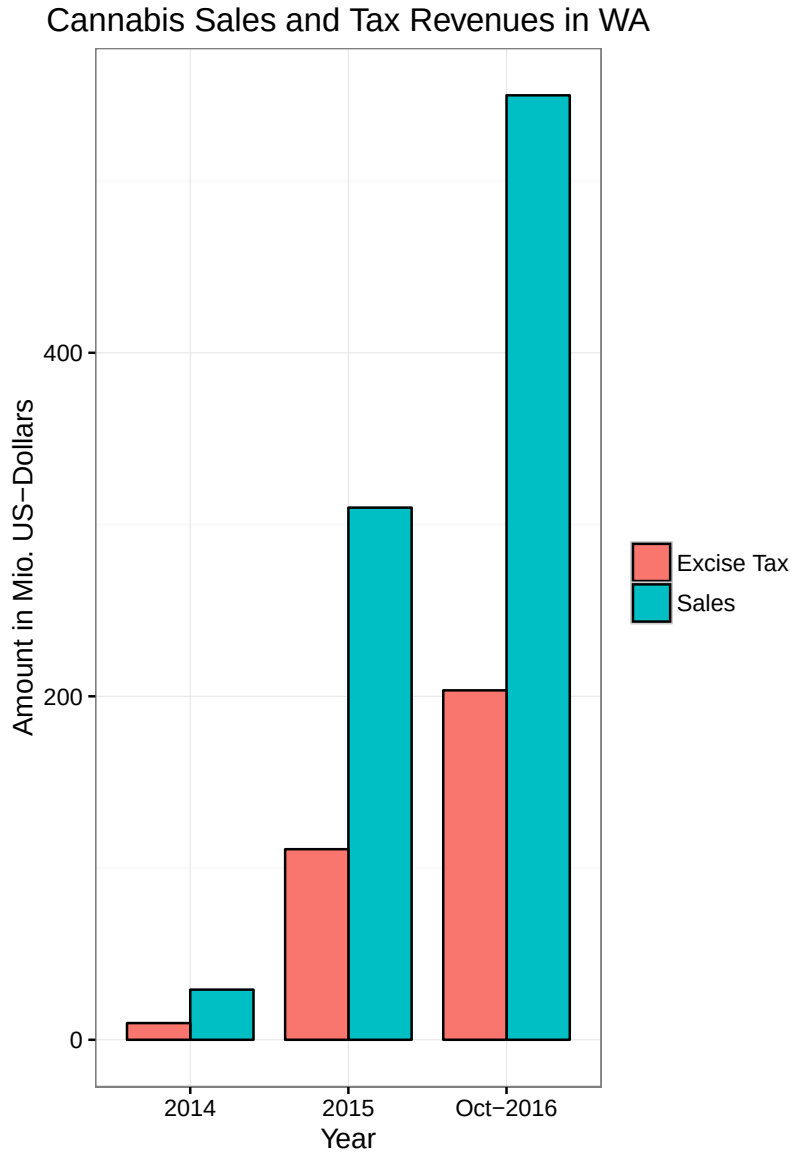
Policy Relevance

- 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)

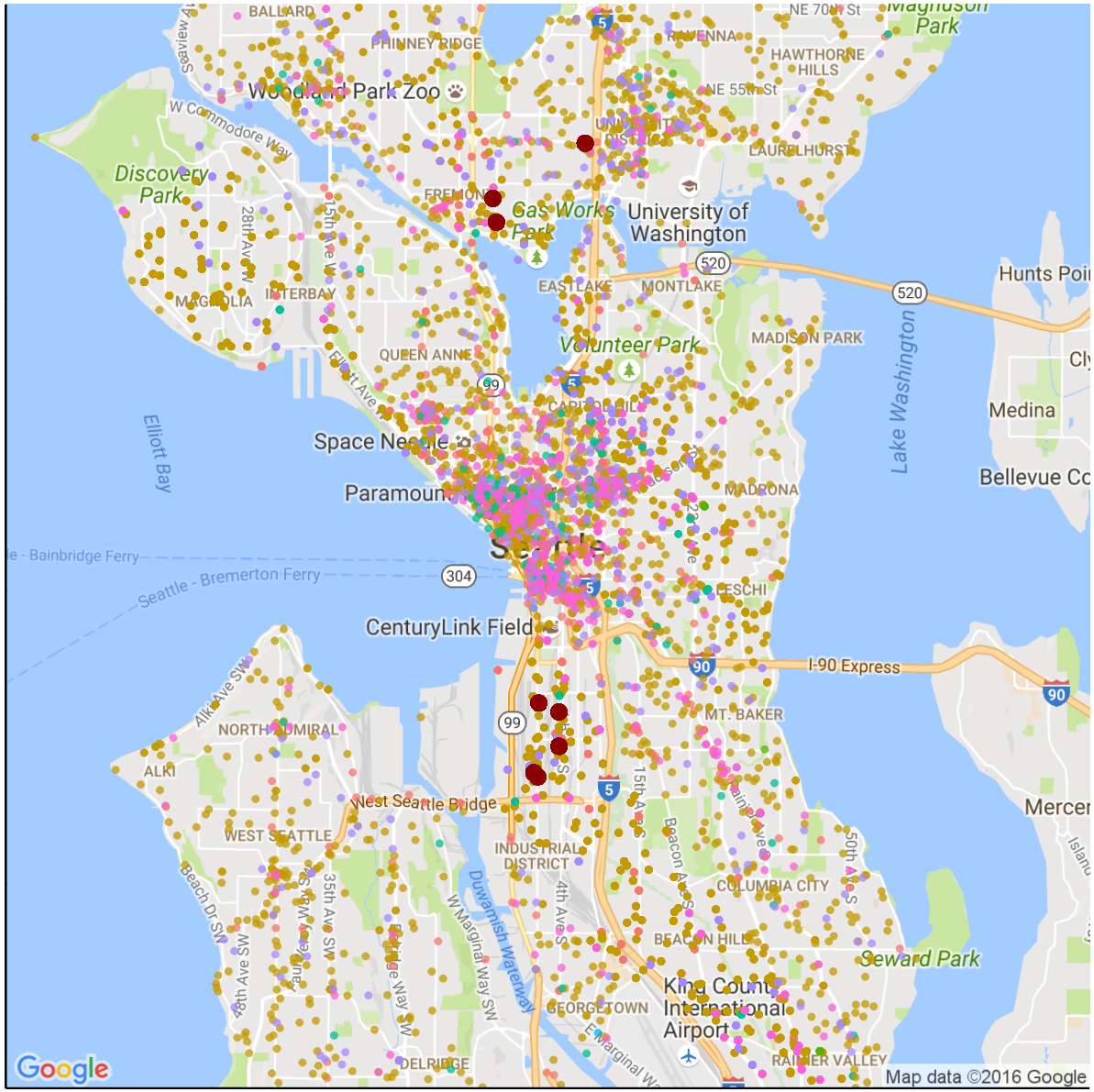
- Business is booming in WA and Sales and Tax Revenues are increasing





Analysis - Descriptive Statistics (II)

- Crime concentrates in central Seattle. Retailers seem not to be within the vicinty

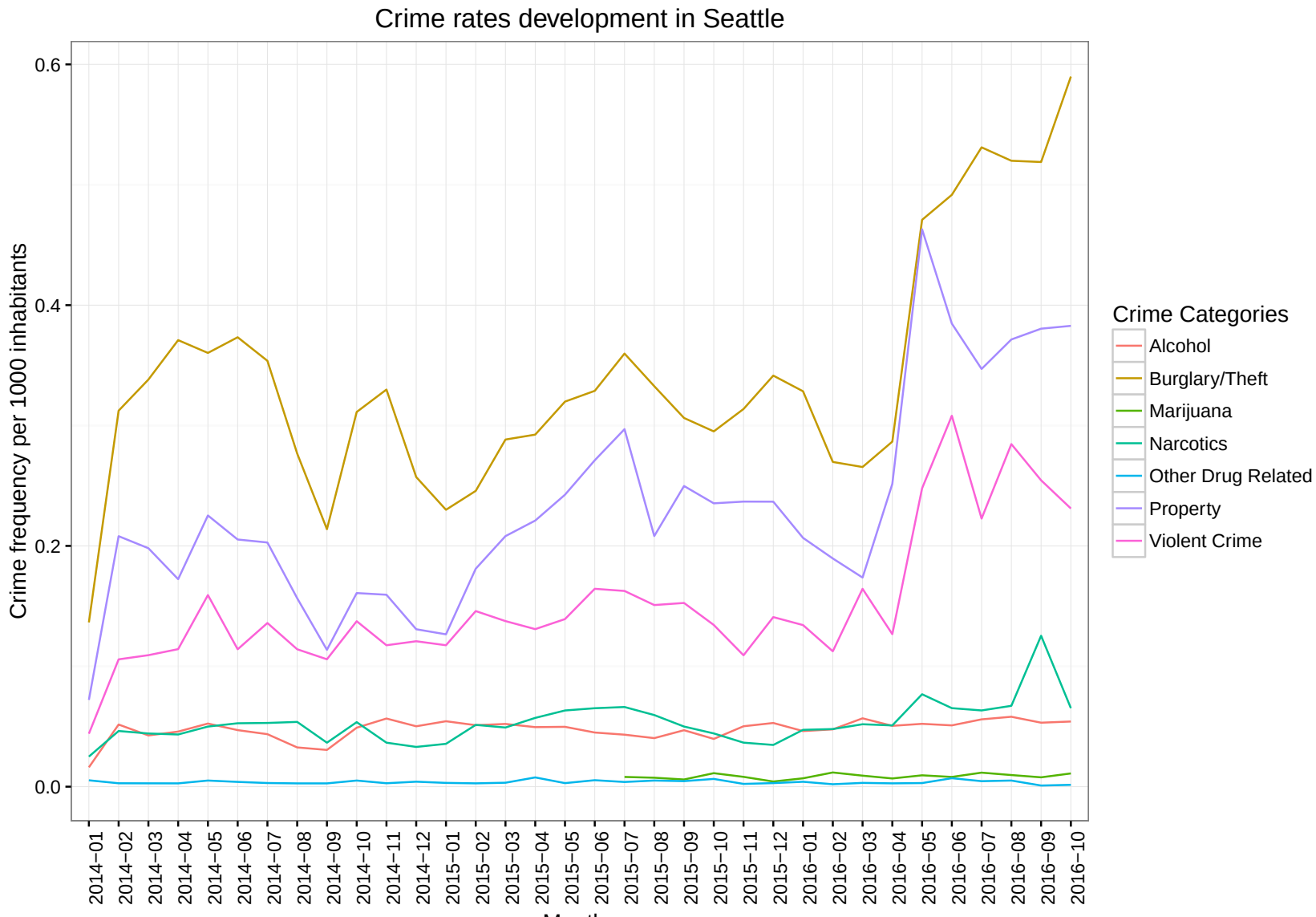


Crime Categories Oct 2016

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

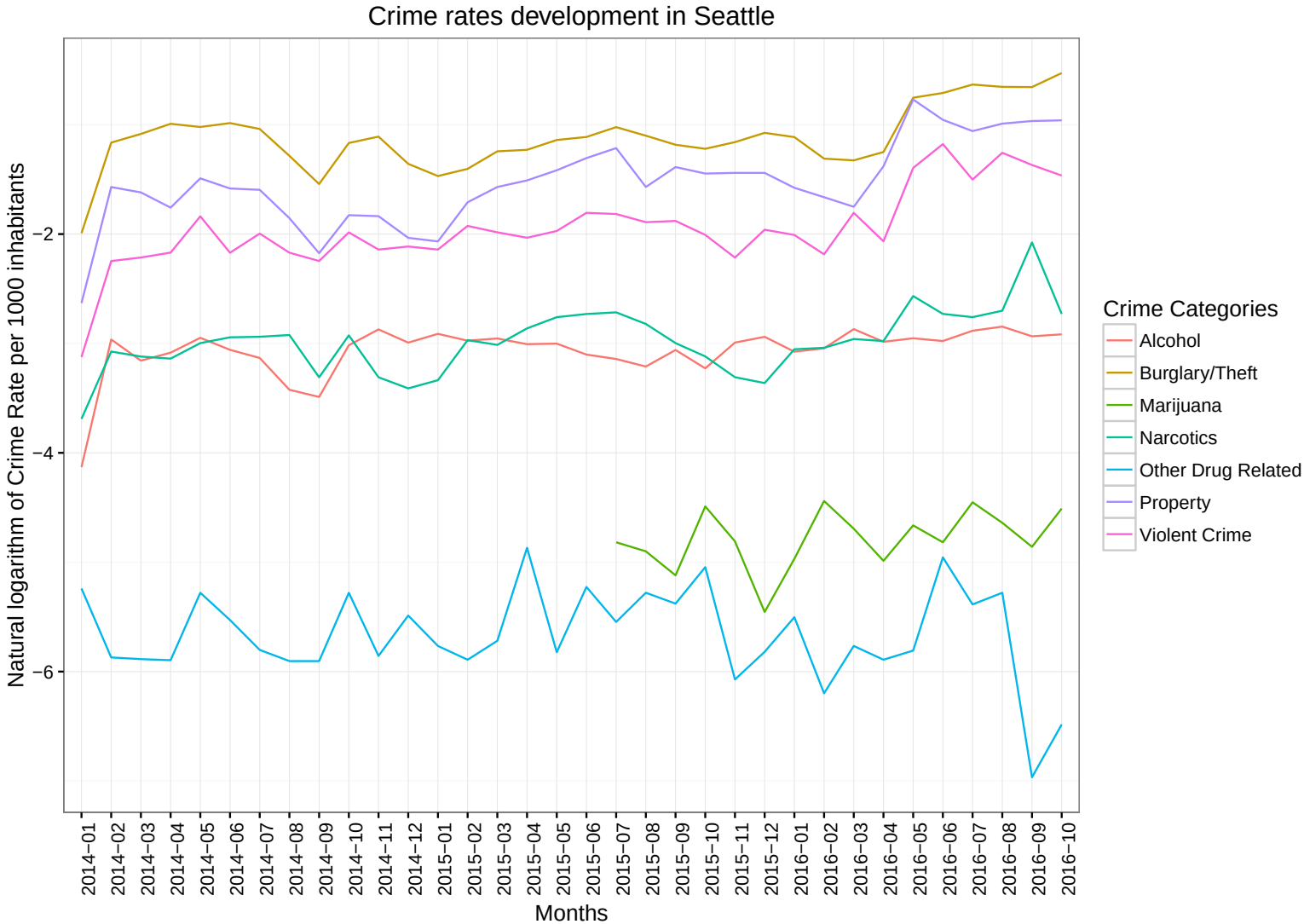
Analysis - Descriptive Statistics (III)

- Jump in February 2014 could mean that there is a reporting error that flaws our result (not the case)
- Next slide will show the development in log-scale



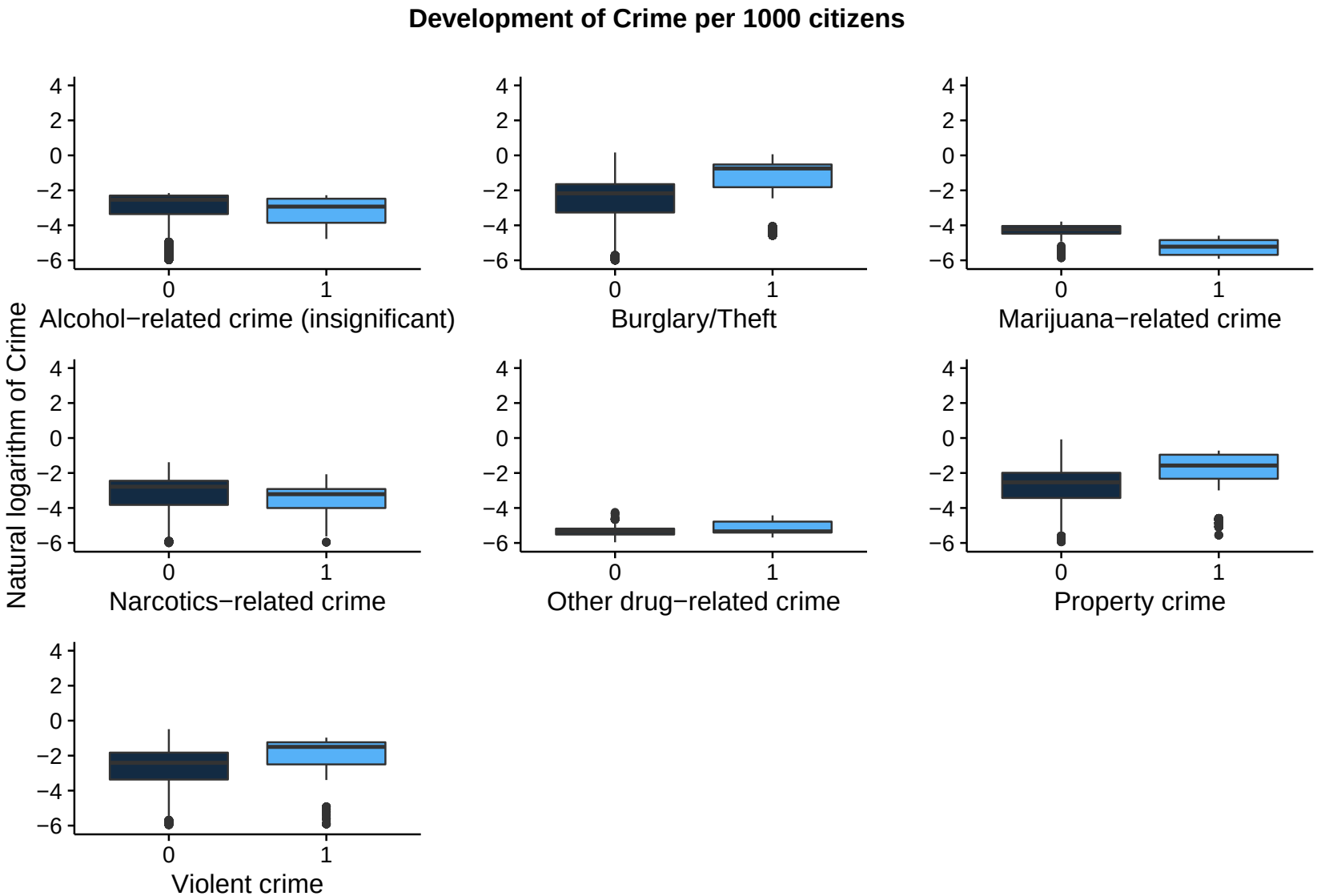
Analysis - Descriptive Statistics (IV)

- Crimes in Property, Burglary/Theft, and Other Drugs seem to have changed most



Analysis - Inferential Statistics (I)

- t-test shows that *treatment* differs with crime category



Analysis - Inferential Statistics (II)

Table 1: Analysis of Crime

	Dependent variable:	
	ln(Crime Rate Per Thousand)	
	(1)	(2)
Established	1.14^{***} (1.13, 1.15)	0.59^{***} (0.58, 0.61)
Constant	-2.71^{***} (-2.71, -2.70)	-2.86^{***} (-2.86, -2.85)
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:	
	ln(Crime Rate Per Thousand)	
	(1)	(2)
Established	1.47^{***} (1.45, 1.48)	0.31^{***} (0.29, 0.33)
Poverty Rate	0.01^{***} (0.01, 0.01)	0.03^{***} (0.03, 0.03)
$>$ Average Adults	0.16^{***} (0.15, 0.17)	-0.04^{***} (-0.05, -0.02)
$>$ Average Whites	1.00^{***} (0.98, 1.02)	0.76^{***} (0.74, 0.78)
Constant	-3.54^{***} (-3.56, -3.52)	-4.08^{***} (-4.10, -4.06)
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
- There is a significant association between Retailers and crime development overall in Seattle.
- Once we match similar districts, this becomes negligible though (CI + R^2)

Conclusion (II)

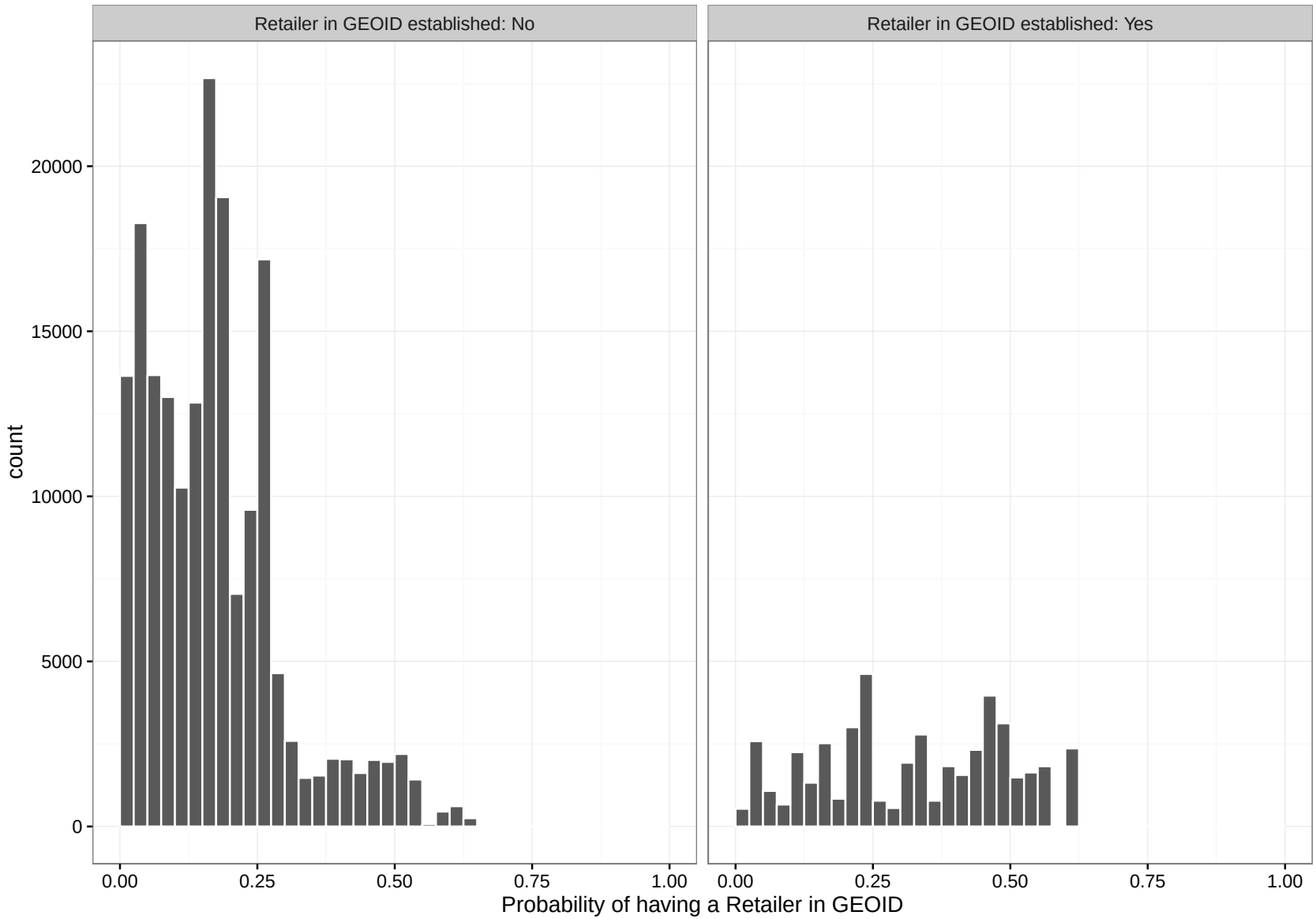
- Qualification I: self-selection bias
- Qualification II: This analysis is for all crimes without using spatial or temporal dummies
- Once we account for Month: Point estimates increase
- Once we account for GEOID: Point estimates decrease
- Qualification III: Not with propensity score matching (computational restrictions)

Conclusion (III)

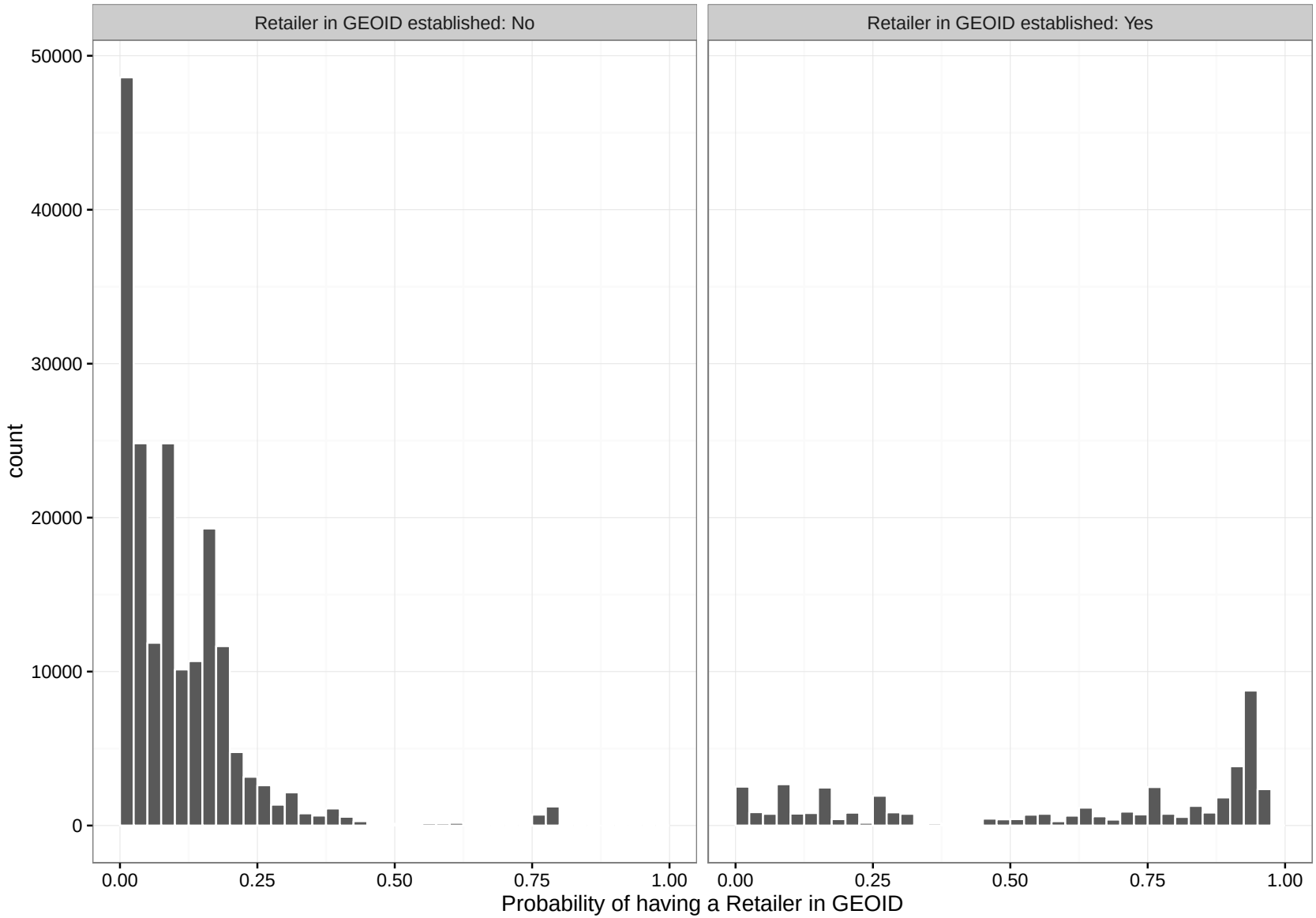
Thank you for your attention.

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