

Joyce Jabara
6918 E. Winterberry Circle
Wichita KS 67226

RE: In Opposition of HB 2200

My name is Joyce Jabara, I am a co-owner of a liquor store in Sedgwick County. I am also a court employee that deals with many aspects of domestic and family matters in Kansas.

I am writing today in opposition of HB 2200, not as a liquor store owner, but as an advocate of children and families in our community who sees daily the negative impact of alcohol abuse in our community. The cost of this spans many areas including increasing violent crime, traffic fatalities, under age substance use and abuse, increased domestic violence and increasing relapse rates for the recovering alcoholics.

Alcohol is a factor in 40% of all violent crimes today. Based on victim reports alcohol use by the offender was a factor:

- 37% rapes
- 15% robberies
- 27% aggravated assaults
- 25% of simple assaults.

Domestic violence affects Kansas families. The number of domestic violence cases that Kansans see will increase as the availability of alcohol increases.

- Drinking proceeds acts of family violence in 25%-50% of all domestic violence cases.
- One in four murders in Kansas are domestic violence related.
- Law enforcement receives 25,000 domestic violence calls each year

Of the families that I personally have dealt with; 30-40% allege alcohol abuse as a concern. These families vary in socio-economic status and situations; there isn't an income or moral differential here. All income brackets, races and ethnicities are negatively impacted by alcohol abuse.

Uncork Kansas would like you to believe that increasing the availability of alcohol does not contribute to an increase in crime, domestic violence and traffic fatalities. Numerous studies show a correlation between increased alcohol availability and crime.¹ In 2012 Washington State implemented privatization of liquor retailing. The number of retailers increased in the City of Seattle from 20 to 134. Reducing the distance to the nearest liquor retailer by one mile leads to a 6-8% increase in monthly crime rates.²

¹See "Reducing Alcohol-Related Harms in Los Angeles County"-December 2011

² See Andrew Chamberlain "Urban Crime and Spatial Proximity to Liquor: Evidence from a Quasi-Experiment in Seattle"

The board members of Uncork Kansas is predominately seated with "individuals" who represent grocers and convenience stores that do not even "headquarter" their business in Kansas; much less reside in Kansas. The Uncork Kansas push towards allowing alcohol in grocery and convenience stores does not take into account the number of families, communities and lives that will be negatively impacted by this bill.³ I have heard members of Uncork Kansas quoted as saying, "give the consumer the convenience of one stop shopping." Since when did family values, protection for victims of domestic violence and violent crime and the safety of our children become less important than "convenience for consumers"?

How do you tell a mother of 4 children who sent her husband; who happens to be a recovering alcoholic that the "temptation" in the grocery store isn't there when he leaves to take the children to the store and returns having succumbed to the temptations of the liquor or wine bottle next to the bread?


The concerns are not only realistic but proven by a number of studies throughout the country.

Please consider the family values, protection for victims of domestic violence and violent crime and the safety of our children as the reason you need to say NO to Uncork Kansas and HB 2200 and yes to Kansas families.

Thank you for your time and consideration.

Respectfully,

Joyce Jabara



³ See William Alex Pridemore and Tony Grubestic "Alcohol Outlets and Community Levels of Interpersonal Violence: Spatial Density, Outlet Type and Seriousness of Assault"

Reducing Alcohol-Related Harms in Los Angeles County

A Cities and Communities Health Report

Excessive alcohol consumption costs
LA County 2,500 lives and \$10.8 billion
each year.

Alcohol misuse and abuse is not only
treatable, but preventable!

How communities can take action:

- Stop alcohol sales to minors
- Reduce youth exposure to alcohol advertising
- Limit the density of alcohol outlets
- Increase youth awareness of the hazards of alcohol

Message from the Health Officer

As the second-leading cause of premature death and disability in Los Angeles County,¹ excessive alcohol consumption continues to be a serious public health concern. Each year 2,500 people in the county die from alcohol-related causes, with the loss of approximately 78,000 years of potential life. In addition to the devastating personal and societal effects of alcohol abuse on individuals, families, and communities, excessive alcohol consumption costs Los Angeles County an estimated \$10.8 billion annually, or roughly \$1,000 for every resident.²



More than half of adults in Los Angeles County report drinking alcohol in the past month. When used in moderation, alcohol use may have modest health benefits. However, excessive alcohol consumption, which includes binge drinking³ and heavy drinking,⁴ leads to serious medical illnesses, impaired mental health, increased motor vehicle crashes, increased rates of violent crime, and a multitude of other harmful social consequences on family interactions, work productivity, and school performance.

An estimated 16.2% (or 1,190,000) of county adults are binge drinkers (Figure 1) and an additional 3.3% (or 242,000) are heavy drinkers (Figure 2). Both binge drinking and heavy drinking are more common among males and young adults; heavy drinking is also more common among whites and those of higher socioeconomic status.⁵ The high rates of binge drinking among teens and young adults are a particular cause for concern, as close to 1 in 5 high school students in Los Angeles reported at least one episode of binge drinking in the past month.

A high density of alcohol outlets increases alcohol consumption,⁶ motor vehicle crashes,⁷ alcohol-related hospital admissions,⁸ injury deaths,⁹ assaults and violent crime,¹⁰ suicides,⁷ drinking and driving,^{11,12} child maltreatment,¹³ and neighborhood disturbances.¹⁴ In this report, we examined the relationship between the density of alcohol outlets and three alcohol-related harms in 117 cities and communities across Los Angeles County and found similar results; increased rates of violent crime, alcohol-involved motor vehicle crashes, and alcohol-related deaths were all associated with having a high density of alcohol outlets in that city or community.

Limiting the density of alcohol outlets is one effective approach to reducing excessive alcohol consumption and alcohol-related harms.¹⁵ To assist communities in designing strategies and in policy making efforts to prevent alcohol-related harms, this report provides a profile of alcohol outlet density and alcohol-related consequences by city and community. We hope the information provided will help support and strengthen efforts to prevent alcohol-related diseases and injuries throughout the county.

A handwritten signature in black ink that reads "Jonathan E. Fielding". The signature is written in a cursive, flowing style.

Jonathan E. Fielding, MD, MPH
Director of Public Health and Health Officer

Figure 1. Percent of Adults Who Reported Binge Drinking in the Past Month, by Age Group, 2007
 Binge drinking for females is drinking 4 or more drinks, and for males 5 or more drinks, on one occasion at least one time in the past month. *Source: 2007 Los Angeles County Health Survey*

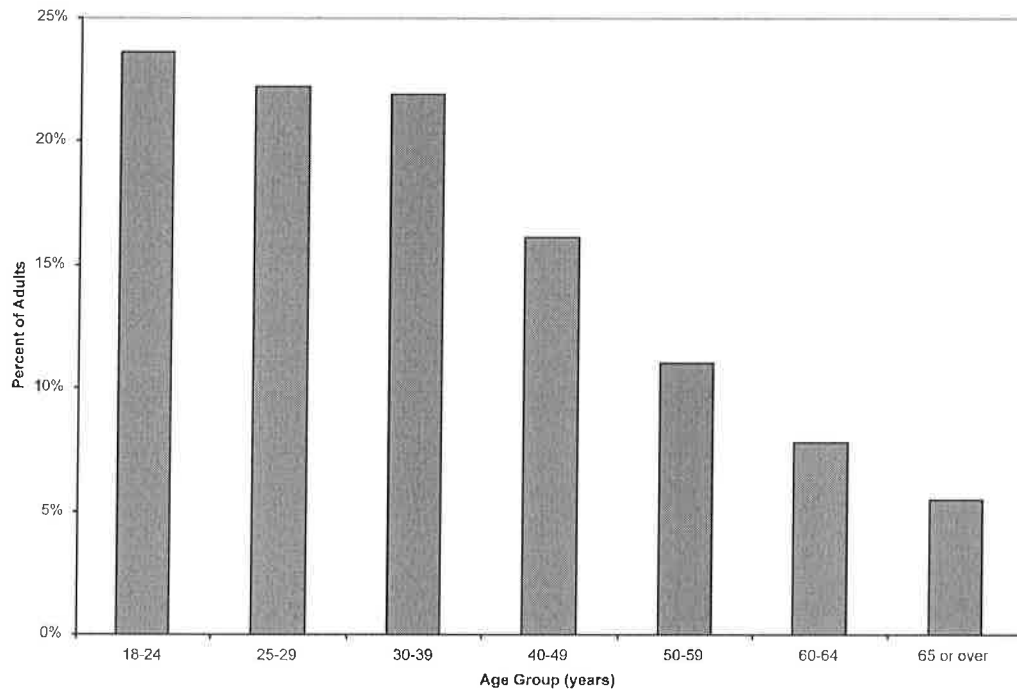
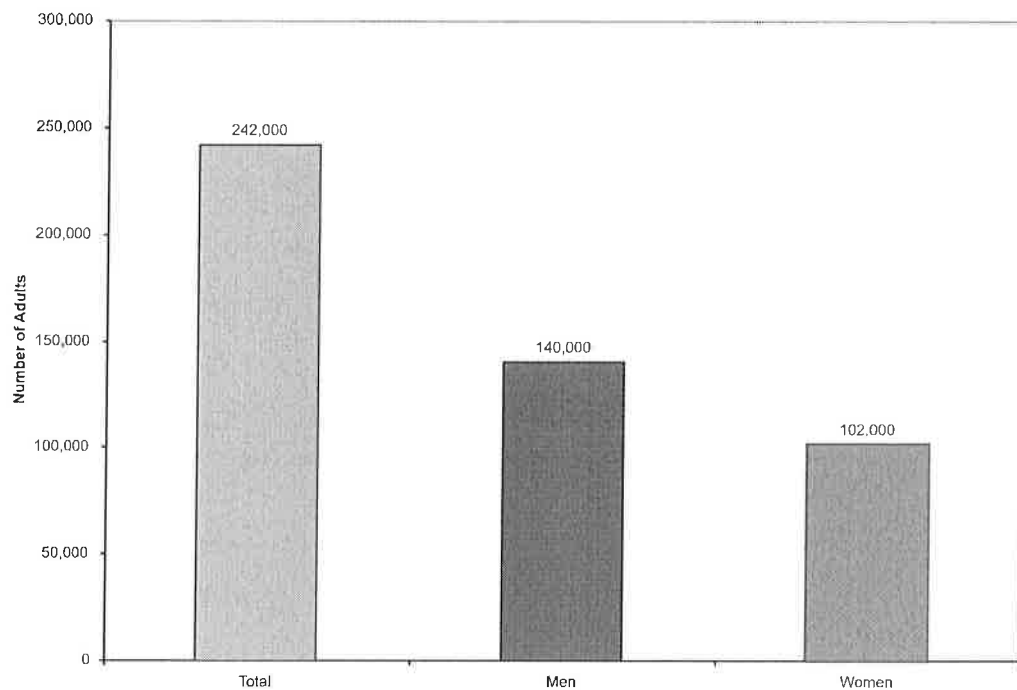


Figure 2. Number of Adults Who Reported Heavy Drinking in the Past Month, by Gender, 2007
 Heavy drinking for males is consuming more than 60 drinks, and for females more than 30 drinks, in the past month. *Source: 2007 Los Angeles County Health Survey*



Study Methods

Defining Cities and Communities within Los Angeles County

Cities and communities (unincorporated areas) in Los Angeles County were defined using the Census 2000 Incorporated Places and Census Designated Places. The city of Los Angeles was further divided into its 15 city council districts to provide more local information.¹⁶

The 2007 population estimates for Los Angeles County¹⁷ were used to determine density and those at risk for alcohol-related harms. Cities and communities with less than 10,000 residents are excluded from this report because estimates for these areas are unreliable. For each of the remaining 117 cities and communities, the density of alcohol outlets and the rates of several alcohol-related harms were examined.

Determining Alcohol Outlet Density

Information on alcohol outlets within Los Angeles County was obtained from the California Department of Alcoholic Beverage Control (ABC).¹⁸ ABC categorizes alcohol outlets as:

- *on-premises* – outlets where alcohol is served to be consumed on site, e.g. bars and restaurants.
- *off-premises* – outlets where alcohol is sold to be consumed off site, e.g. liquor stores and grocery stores.¹⁹

A total of 16,039 alcohol outlets in LA County were identified and included in the analysis. The densities (number of outlets per 10,000 residents) of on-premises and off-premises alcohol outlets were calculated separately, and categorized into tertiles of “low,” “medium,” or “high” density.

Measuring Alcohol-Related Harms

In this report, three alcohol-related harms were examined: alcohol-involved motor vehicle crashes,²⁰ violent crimes,²¹ and alcohol-related deaths.²² These three harms were analyzed because city/community-level data were available and because they have been found in other studies to be related to alcohol outlet density.

Data Analysis

As the intent of this report was to explore the potential impact of the density of alcohol outlets on cities and communities, all data were aggregated at the city and community level. The density of on-premises and off-premises alcohol outlets and the rates of alcohol-related harms (motor vehicle crashes, violent crime, and deaths) were calculated for each city/community. Each city/community was then ranked relative to others in Los Angeles County, where a low ranking indicates fewer alcohol outlets per resident and a high ranking indicates more alcohol outlets per resident. While the relative rankings are listed, alcohol outlet density was also categorized into three groups (low/medium/high) by tertile, and alcohol-related harms were categorized into four groups (lowest/low/high/highest) by quartile, to allow for more stable and easily interpretable comparisons.

Logistic regression modeling was performed to examine the associations between alcohol outlet density and alcohol-related harms, adjusting for economic hardship to account for neighborhood socioeconomic conditions. Details regarding the economic hardship index have been published elsewhere.²³ No adjustments were made for other neighborhood characteristics; e.g., population density, neighborhood diversity, or urban versus rural.

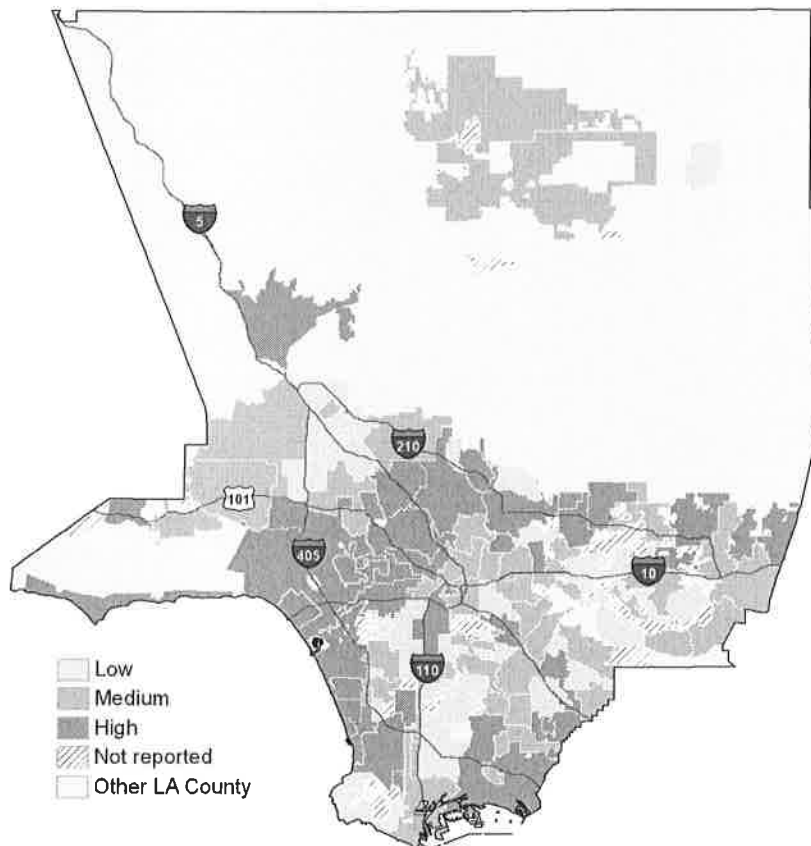
Findings

Alcohol Outlet Density

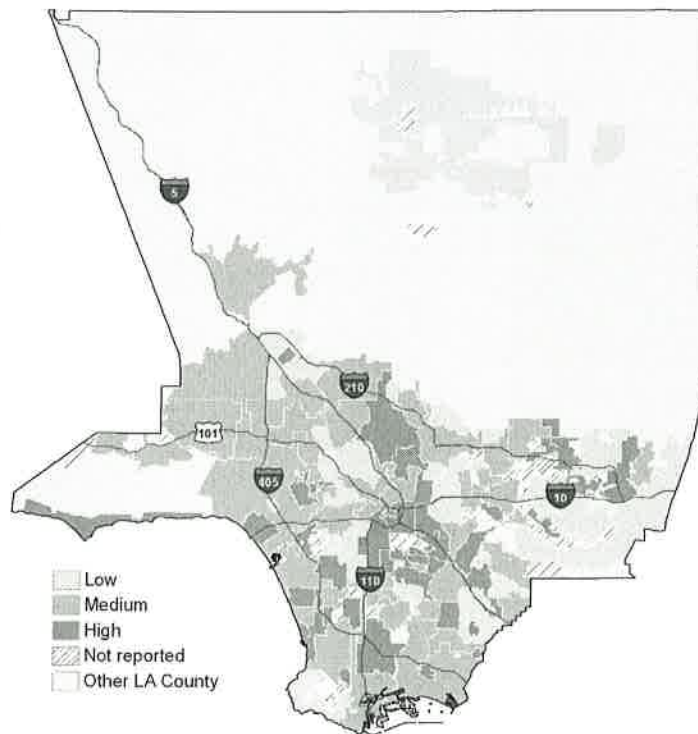
In Los Angeles County, there is an average of 16 alcohol outlets (on- and off-premises combined) per 10,000 people and about four alcohol outlets per square mile. This is slightly lower than the statewide average for California of 18 outlets per 10,000 people. However, outlet density varies widely among cities and communities across the county, ranging from 0 to 47.3 (West Hollywood) on-premises alcohol outlets, and 0 to 23.8 (Commerce) off-premises alcohol outlets per 10,000 residents. *Table 1* presents the density of on-premises and off-premises alcohol outlets for each city and community.

The geographic distribution of on- and off-premises outlets differs (Maps 1 and 2). There is a higher density of on-premises outlets in affluent communities, including the Beach Cities, West Hollywood, and some Foothill communities (Map 1, $p < 0.001$). On the other hand, a higher density of off-premises outlets was only weakly associated with less affluent communities (Map 2, $p = 0.076$), with higher density seen in some central and south Los Angeles communities, as well as the cities of Commerce, Malibu, and Sante Fe Springs.

Map 1. On-Premises Alcohol Outlet Density among Los Angeles County Cities and Communities, 2009



Map 2. Off-Premises Alcohol Outlet Density among Los Angeles County Cities and Communities, 2009



Association Between Alcohol Outlet Density and Alcohol-Related Harms

Using logistic regression to adjust for community-level economic hardship, we found that having a high density of either on-premises or off-premises outlets was associated with significantly higher rates of alcohol-related harms.

Violent Crime

Communities with a high density* of either On- or Off-Premises outlets were...

- 9 to 10 times more likely to have increased rates of violent crime ($p < 0.01$)
- While rates of Violent Crime were generally lower in areas of low economic hardship (i.e. more affluent areas), areas with higher on- or off-premises outlet density were much more likely to have increased rates of violent crime, when comparing communities with similar levels of economic hardship.

Alcohol-involved Motor Vehicle Crashes

Communities with a high density of On-Premises alcohol outlets were...

- 4 times more likely to have increased rates of alcohol-involved crashes ($p = 0.008$)

Alcohol-related Deaths

Communities with a high density of Off-Premises alcohol outlets were...

- 5 times more likely to have increased rates of alcohol-related deaths ($p = 0.004$)

* compared to low density

The rates of violent crimes, alcohol-involved motor vehicle crashes, and alcohol-related deaths for each city and community are presented in Table 2.

Table 1. On-Premises and Off-Premises Alcohol Outlet Density, by City and Community, Los Angeles County, 2009^{18,19}

City/Community Name	On-Premises AOD	Rank/Tertile	Off-Premises AOD	Rank/Tertile
Los Angeles County	8.9	—	6.7	—
Agoura Hills	15.5	101	6.9	62
Alhambra	8.1	71	4.6	22
Altadena	1.6	9	4.6	22
Arcadia	13.5	95	7.1	70
Artesia	23.1	111	8.4	91
Avocado Heights	4.0	28	6.2	53
Azusa	8.9	75	9.3	101
Baldwin Park	3.7	25	5.6	38
Bell	5.4	44	8.5	93
Bell Gardens	3.5	23	9.9	105
Bellflower	5.6	47	7.7	81
Beverly Hills	41.4	116	10.3	107
Burbank	13.6	96	7.3	72
Calabasas	8.4	73	6.7	59
Carson	4.3	33	8.3	88
Cerritos	12.4	94	5.3	33
Citrus	0.0	1	0.8	3
Claremont	11.9	91	3.5	13
Commerce	10.4	85	23.8	117
Compton	1.5	7	6.4	55
Covina	9.9	82	8.3	88
Cudahy	2.7	18	6.6	57
Culver City	20.6	109	11.3	109
Del Aire	8.9	75	8.9	99
Diamond Bar	6.8	56	4.5	21
Downey	8.8	74	5.9	46
Duarte	6.9	62	9.1	100
East Compton	0.8	5	4.1	18
East La Mirada	2.0	13	3.0	7
East Los Angeles	4.2	32	8.0	83
East San Gabriel	1.9	12	3.1	9
El Monte	4.5	36	6.8	60
El Segundo	38.7	115	12.3	112
Florence-Graham	3.2	21	8.3	88
Gardena	15.8	102	8.4	91
Glendale	9.2	79	8.2	86
Glendora	9.9	82	4.8	26
Hacienda Heights	4.6	38	3.9	17
Hawaiian Gardens	11.9	91	11.9	111
Hawthorne	5.1	41	6.2	53
Hermosa Beach	38.6	114	11.3	109
Huntington Park	6.8	56	9.7	104
Inglewood	5.5	45	8.7	96
La Canada Flintridge	10.4	85	5.7	40
La Crescenta-Montrose	2.2	14	3.3	10
La Mirada	7.7	66	6.6	57
La Puente	5.6	47	8.1	84
La Verne	10.8	89	5.7	40
Lake Los Angeles	2.5	16	4.2	19
Lakewood	6.6	54	7.0	67
Lancaster	7.8	67	5.4	35
Lawndale	4.5	36	8.7	96
Lennox	1.5	7	5.8	42
Lomita	17.1	106	7.6	79
Long Beach	10.7	88	7.0	67
Los Angeles, All Districts	8.7	—	6.5	—
LA City Council District 01	6.3	50	7.3	72
LA City Council District 02	6.8	56	7.3	72
LA City Council District 03	9.1	78	6.1	50
LA City Council District 04	14.3	99	5.4	35

City/Community Name	On-Premises AOD	Rank/Tertile	Off-Premises AOD	Rank/Tertile
LA City Council District 05	18.5	108	5.8	42
LA City Council District 06	4.1	31	6.5	56
LA City Council District 07	2.8	19	4.7	24
LA City Council District 08	1.7	10	4.9	30
LA City Council District 09	10.4	85	8.5	93
LA City Council District 10	10.3	84	5.9	46
LA City Council District 11	14.5	100	7.0	67
LA City Council District 12	7.1	63	6.1	50
LA City Council District 13	12.1	93	6.9	62
LA City Council District 14	5.9	49	8.2	86
LA City Council District 15	6.5	52	7.2	71
Lynwood	3.4	22	5.3	33
Malibu	27.0	113	12.4	113
Manhattan Beach	22.5	110	7.4	77
Maywood	4.7	39	10.1	106
Monrovia	14.0	98	6.9	62
Montebello	6.7	55	6.9	62
Monterey Park	7.9	68	5.0	31
Norwalk	4.3	33	5.4	35
Palmdale	6.8	56	3.6	15
Palos Verdes Estates	3.6	24	4.3	20
Paramount	5.5	45	7.3	72
Pasadena	16.6	104	5.9	46
Pico Rivera	6.3	50	8.1	84
Pomona	6.5	52	5.6	38
Rancho Palos Verdes	4.0	28	3.5	13
Redondo Beach	18.0	107	8.6	95
Rosemead	6.8	56	5.8	42
Rowland Heights	8.0	69	3.0	7
San Dimas	8.1	71	7.6	79
San Fernando	6.8	56	9.5	103
San Gabriel	16.9	105	7.3	72
San Marino	3.7	25	0.7	2
Santa Clarita	9.8	81	6.9	62
Santa Fe Springs	16.3	103	23.6	116
Santa Monica	25.5	112	8.7	96
Sierra Madre	10.9	90	3.6	15
Signal Hill	8.0	69	12.5	114
South El Monte	7.1	63	13.4	115
South Gate	4.7	40	7.9	82
South Pasadena	9.7	80	4.7	24
South San Jose Hills	0.4	4	1.7	4
South Whittier	2.5	16	4.8	26
Temple City	5.3	42	5.9	46
Torrance	13.6	96	7.5	78
Valinda	1.8	11	3.3	10
View Park-Windsor Hills	3.9	27	4.8	26
Vincent	2.2	14	2.2	5
Walnut	4.0	28	2.8	6
Walnut Park	4.3	33	4.8	26
West Carson	5.3	42	9.3	101
West Covina	7.2	65	5.1	32
West Hollywood	47.3	117	11.0	108
West Puente Valley	0.0	1	0.0	1
West Whittier-Los Nietos	2.8	19	3.4	12
Westmont	0.0	1	6.1	50
Whittier	9.0	77	6.8	60
Willowbrook	0.8	5	5.8	42

Low
 Medium
 High
 Excludes cities/communities with populations less than 10,000;
 AOD = Alcohol Outlet Density/10,000 population

Table 2. Alcohol-Related Harms, by City and Community, Los Angeles County²⁰⁻²²

City/Community Name	Violent Crime Rate (/1,000)	Rank/Quartile		Motor Vehicle Crash Rate (/10,000)	Rank/Quartile		Alcohol-Related Death Rate (/100,000)	Rank/Quartile	
		Rank	Quartile		Rank	Quartile		Rank	Quartile
Los Angeles County	6.1	—	—	12.8	—	—	8.9	—	—
Agoura Hills	1.9	15	Lowest (1st to 29th)	12.9	86	High (59th to 88th)	3.2	6	Lowest (1st to 29th)
Alhambra	3.2	37	Low (30th to 58th)	7.8	29	Lowest (1st to 29th)	6.3	27	Low (30th to 58th)
Altadena	4.1	57	Low (30th to 58th)	7.5	26	Lowest (1st to 29th)	5.8	22	Lowest (1st to 29th)
Arcadia	2.6	30	Low (30th to 58th)	10.2	56	High (59th to 88th)	6.2	25	Low (30th to 58th)
Artesia	4.7	68	High (59th to 88th)	8.4	35	Low (30th to 58th)	9.8	69	High (59th to 88th)
Avocado Heights	3.2	37	Low (30th to 58th)	18.5	113	High (59th to 88th)	10.6	85	High (59th to 88th)
Azusa	4.1	57	Low (30th to 58th)	14.9	100	High (59th to 88th)	11.6	99	High (59th to 88th)
Baldwin Park	3.6	45	Low (30th to 58th)	13.0	88	High (59th to 88th)	10.0	71	High (59th to 88th)
Bell	4.5	63	High (59th to 88th)	15.2	104	High (59th to 88th)	8.0	40	Low (30th to 58th)
Bell Gardens	5.4	76	High (59th to 88th)	5.6	10	Lowest (1st to 29th)	8.6	48	High (59th to 88th)
Bellflower	6.4	86	High (59th to 88th)	9.3	41	Low (30th to 58th)	11.4	95	High (59th to 88th)
Beverly Hills	3.9	53	Low (30th to 58th)	8.0	33	Low (30th to 58th)	2.1	5	Lowest (1st to 29th)
Burbank	2.4	27	Low (30th to 58th)	11.5	71	High (59th to 88th)	8.1	43	High (59th to 88th)
Calabasas	0.8	2	Lowest (1st to 29th)	9.0	38	Low (30th to 58th)	4.2	9	Lowest (1st to 29th)
Carson	6.8	90	High (59th to 88th)	10.8	64	High (59th to 88th)	7.9	39	High (59th to 88th)
Cerritos	2.7	32	Low (30th to 58th)	15.2	103	High (59th to 88th)	3.2	6	Lowest (1st to 29th)
Citrus	3.0	34	Low (30th to 58th)	7.8	32	Lowest (1st to 29th)	7.8	38	High (59th to 88th)
Claremont	2.2	21	Lowest (1st to 29th)	11.3	67	High (59th to 88th)	9.1	58	High (59th to 88th)
Commerce	10.1	110	High (59th to 88th)	50.2	117	High (59th to 88th)	15.8	116	High (59th to 88th)
Compton	16.8	115	High (59th to 88th)	9.7	47	Low (30th to 58th)	10.8	88	High (59th to 88th)
Covina	3.6	45	Low (30th to 58th)	6.9	22	Lowest (1st to 29th)	9.3	62	High (59th to 88th)
Cudahy	5.4	76	High (59th to 88th)	6.3	15	Lowest (1st to 29th)	5.3	15	Lowest (1st to 29th)
Culver City	4.3	61	High (59th to 88th)	13.7	94	High (59th to 88th)	8.6	48	High (59th to 88th)
Del Aire	3.5	42	Low (30th to 58th)	7.3	24	Lowest (1st to 29th)	11.1	94	High (59th to 88th)
Diamond Bar	1.8	13	Lowest (1st to 29th)	12.7	82	High (59th to 88th)	4.6	12	Lowest (1st to 29th)
Downey	4.2	59	Low (30th to 58th)	15.4	105	High (59th to 88th)	9.0	56	High (59th to 88th)
Duarte	4.0	55	Low (30th to 58th)	5.2	8	Lowest (1st to 29th)	9.2	60	High (59th to 88th)
East Compton	14.5	112	High (59th to 88th)	10.1	54	Low (30th to 58th)	7.2	35	Low (30th to 58th)
East La Mirada	2.2	21	Lowest (1st to 29th)	4.6	7	Lowest (1st to 29th)	14.8	112	High (59th to 88th)
East Los Angeles	7.3	98	High (59th to 88th)	14.2	98	High (59th to 88th)	15.2	115	High (59th to 88th)
East San Gabriel	1.5	9	Lowest (1st to 29th)	2.5	1	Lowest (1st to 29th)	6.2	25	Low (30th to 58th)
El Monte	5.6	79	High (59th to 88th)	11.7	75	High (59th to 88th)	9.2	60	High (59th to 88th)
El Segundo	2.1	19	Lowest (1st to 29th)	17.6	111	High (59th to 88th)	10.3	77	High (59th to 88th)
Florence-Graham	12.2	111	High (59th to 88th)	10.3	59	Low (30th to 58th)	10.9	90	High (59th to 88th)
Gardena	7.1	95	High (59th to 88th)	15.9	106	High (59th to 88th)	8.5	47	High (59th to 88th)
Glendale	1.8	13	Lowest (1st to 29th)	9.8	51	Low (30th to 58th)	7.0	33	Low (30th to 58th)
Glendora	1.4	7	Lowest (1st to 29th)	11.6	72	High (59th to 88th)	10.7	87	High (59th to 88th)
Hacienda Heights	2.3	23	Lowest (1st to 29th)	10.9	65	High (59th to 88th)	5.7	21	Lowest (1st to 29th)
Hawaiian Gardens	9.1	108	High (59th to 88th)	7.5	27	Lowest (1st to 29th)	13.4	110	High (59th to 88th)
Hawthorne	8.0	102	High (59th to 88th)	13.2	90	High (59th to 88th)	9.4	63	High (59th to 88th)
Hermosa Beach	3.5	42	Low (30th to 58th)	12.5	80	High (59th to 88th)	5.2	14	Lowest (1st to 29th)
Huntington Park	8.8	106	High (59th to 88th)	15.0	102	High (59th to 88th)	10.4	79	High (59th to 88th)
Inglewood	8.6	103	High (59th to 88th)	7.8	30	Low (30th to 58th)	10.8	88	High (59th to 88th)
La Canada Flintridge	1.0	4	Lowest (1st to 29th)	6.6	17	Lowest (1st to 29th)	5.3	15	Lowest (1st to 29th)
La Crescenta-Montrose	1.9	15	Lowest (1st to 29th)	8.2	34	Low (30th to 58th)	6.8	31	Low (30th to 58th)
La Mirada	2.4	27	Low (30th to 58th)	10.7	61	High (59th to 88th)	8.1	43	High (59th to 88th)
La Puente	5.8	81	High (59th to 88th)	9.6	43	Low (30th to 58th)	10.4	79	High (59th to 88th)
La Verne	2.0	18	Lowest (1st to 29th)	8.9	37	Low (30th to 58th)	7.1	34	Low (30th to 58th)
Lake Los Angeles	5.9	83	High (59th to 88th)	7.8	31	Low (30th to 58th)	11.5	98	High (59th to 88th)
Lakewood	4.9	70	High (59th to 88th)	6.4	16	Lowest (1st to 29th)	6.4	28	Low (30th to 58th)

Lowest (1st to 29th) Low (30th to 58th) High (59th to 88th) Highest (89th to 117th)

Excludes cities/communities with populations less than 10,000

Table 2. Alcohol-Related Harms, by City and Community, Los Angeles County²⁰⁻²²

City/Community Name	Violent Crime Rate (/1,000)	Rank/Quartile	Motor Vehicle Crash Rate (/10,000)	Rank/Quartile	Alcohol-Related Death Rate (/100,000)	Rank/Quartile
Lancaster	8.8	106	9.8	50	10.4	79
Lawndale	6.7	88	11.6	74	10.1	76
Lennox	6.5	87	11.6	73	10.9	90
Lomita	5.3	73	5.7	11	9.5	65
Long Beach	6.8	90	13.8	96	9.4	63
Los Angeles, All Districts	6.5	—	11.6	—	9.4	—
LA City Council District 01	6.8	90	14.6	99	12.1	103
LA City Council District 02	4.9	70	12.9	87	9.0	56
LA City Council District 03	1.7	12	10.5	60	7.5	37
LA City Council District 04	4.6	67	13.3	91	6.5	29
LA City Council District 05	2.9	33	10.0	52	4.3	11
LA City Council District 06	4.5	63	12.8	85	9.7	68
LA City Council District 07	3.1	35	9.4	42	10.9	90
LA City Council District 08	15.3	113	11.1	66	10.5	82
LA City Council District 09	17.0	116	15.0	101	12.7	107
LA City Council District 10	6.8	90	12.0	76	8.4	46
LA City Council District 11	3.9	53	9.7	49	8.1	43
LA City Council District 12	2.6	30	10.1	55	6.9	32
LA City Council District 13	7.1	95	11.5	70	9.9	70
LA City Council District 14	6.9	94	10.8	63	12.4	104
LA City Council District 15	8.6	103	10.2	58	11.4	95
Lynwood	9.5	109	9.7	48	10.3	77
Malibu	1.9	15	25.0	114	5.5	17
Manhattan Beach	1.4	7	11.4	68	5.5	17
Maywood	5.7	80	6.7	18	8.8	51
Monrovia	3.3	41	12.6	81	11.8	101
Montebello	3.7	50	11.4	69	13.9	111
Monterey Park	2.5	29	9.1	40	5.6	20
Norwalk	5.1	72	12.8	84	10.6	85
Palmdale	6.7	88	10.2	57	8.0	40
Palos Verdes Estates	0.3	1	5.5	9	1.8	2
Paramount	7.3	98	9.7	46	8.6	48
Pasadena	4.5	63	13.7	93	4.2	9
Pico Rivera	4.0	55	6.8	19	12.5	105
Pomona	7.5	101	17.1	109	8.8	51
Rancho Palos Verdes	0.9	3	3.7	4	5.8	22
Redondo Beach	3.1	35	16.7	108	8.9	53
Rosemead	4.2	59	7.3	23	9.6	67
Rowland Heights	3.2	37	6.2	14	1.6	1
San Dimas	2.3	23	10.1	53	9.5	65
San Fernando	4.8	69	13.8	95	16.9	117
San Gabriel	4.5	63	12.0	77	10.0	71
San Marino	1.0	4	8.7	36	1.9	3
Santa Clarita	2.3	23	6.8	21	5.8	22
Santa Fe Springs	7.2	97	45.8	116	13.3	109
Santa Monica	6.3	85	18.1	112	10.0	71
Sierra Madre	1.1	6	3.0	2	9.1	58
Signal Hill	5.8	81	17.6	110	10.0	71
South El Monte	6.0	84	7.6	28	15.1	114
South Gate	5.5	78	13.2	89	11.8	101
South Pasadena	1.5	9	10.7	62	3.9	8

Lowest (1st to 29th)
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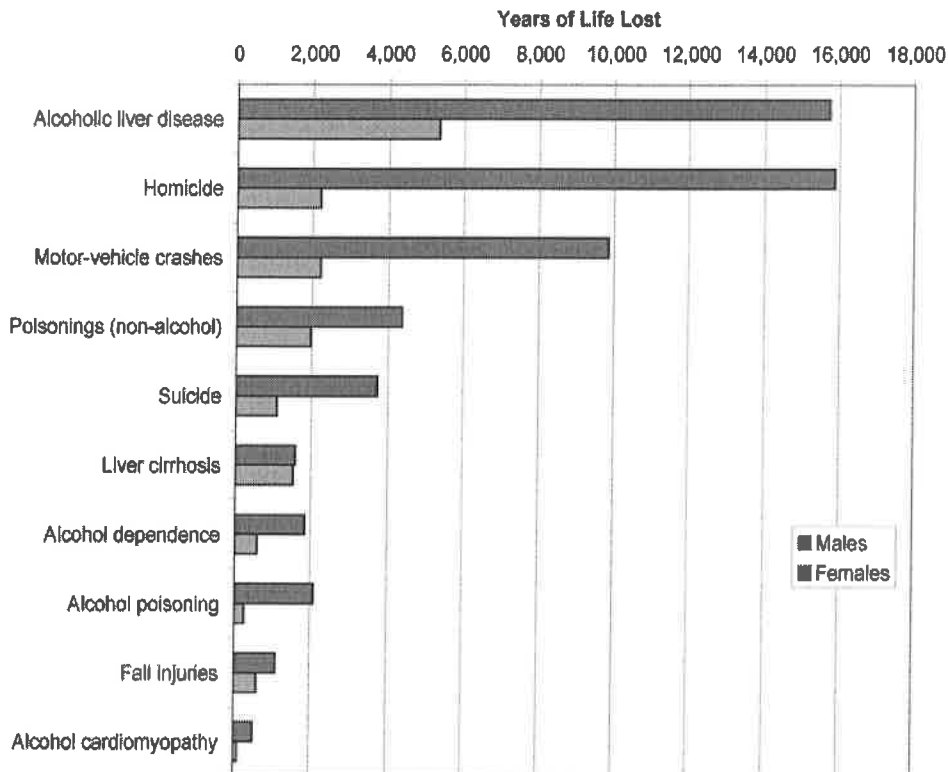
Table 2. Alcohol-Related Harms, by City and Community, Los Angeles County²⁰⁻²²

City/Community Name	Violent Crime Rate (/1,000)	Rank/Quartile	Motor Vehicle Crash Rate (/10,000)	Rank/Quartile	Alcohol-Related Death Rate (/100,000)	Rank/Quartile
South San Jose Hills	4.3	61	7.4	25	11.4	95
South Whittier	3.6	45	9.1	39	12.7	107
Temple City	2.1	19	3.2	3	6.7	30
Torrance	2.3	23	3.8	5	7.3	36
Vallinda	3.5	42	6.1	12	5.5	17
View Park-Windsor Hills	7.3	98	13.9	97	4.8	13
Vincent	3.2	37	6.8	20	8.9	53
Walnut	1.6	11	4.2	6	1.9	3
Walnut Park	5.3	73	9.6	44	8.0	40
West Carson	5.3	73	9.6	45	15.0	113
West Covina	3.6	45	16.1	107	8.9	53
West Hollywood	8.7	105	35.1	115	10.0	71
West Puente Valley	3.6	45	6.1	13	10.9	90
West Whittier-Los Nietos	3.8	52	12.2	78	11.6	99
Westmont	20.8	117	12.5	79	10.5	82
Whittier	3.7	50	12.7	83	12.6	106
Willowbrook	15.4	114	13.3	92	10.5	82

Lowest (1st to 29th)
 Low (30th to 58th)
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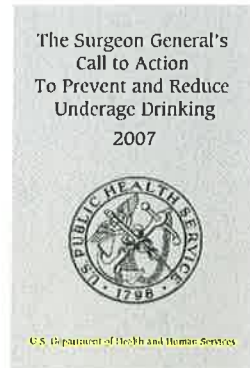
Excludes cities/communities with populations less than 10,000

Figure 3. Leading Causes of Years of Life Lost Due to Alcohol for Males and Females, Los Angeles County, 2007²⁴



Discussion

Alcohol is the third-leading cause of preventable death in the United States,¹⁵ and accounts for 2,500 deaths in Los Angeles County each year, 75% of which occur in men.²⁴ It also results in 78,000 years of potential life lost due to premature death from alcohol use (Figure 3), with premature deaths among young people (less than age 21) accounting for more than 12% of the years of life lost. Excessive consumption of alcohol is a major public health concern among teenagers and adults in Los Angeles County, with significant health and economic impacts. These include societal harms not only from illnesses, but also due to injuries, violent crimes and property crimes, traffic accidents, work loss, and community and family disruptions.



The findings in this analysis are consistent with previous studies which have shown significant associations between alcohol availability and alcohol-related harms. For example, environmental factors such as the density of alcohol outlets have been found to play an important role in teenage drinking. Among teenagers in California, binge drinking and driving after drinking have been associated with the availability of alcohol outlets within a half-mile from home.²⁵

Preventing alcohol misuse and abuse among teenagers and young adults is especially critical. Attitudes toward drinking and drinking behaviors are formed during youth, and alcohol is the most frequently used drug among teenagers. Underage drinking is a major cause of death from injuries among persons under the age of 21, and the early onset of drinking increases the risk of alcohol-related problems later in life.²⁶ The seriousness of this problem led the U.S. Surgeon General to issue a "Call to Action to Prevent and Reduce Underage Drinking" in 2007.

Excessive alcohol use also disproportionately affects some racial/ethnic groups. For example, although rates of heavy drinking are highest among whites, the death rate from alcohol-related liver disease and cirrhosis is much higher among Hispanics.²²

Fortunately, alcohol misuse and abuse is not only highly treatable, but largely preventable. Drinking among youth and adults is strongly influenced by alcohol control policies,²⁷ and the findings in this report emphasize the need to take preventive actions at the community level and to implement targeted interventions that reduce alcohol outlet density.

In California, laws and regulations that determine alcohol access and availability primarily rest with the state, and to a lesser degree, local government. The California Department of Alcoholic Beverage Control (ABC), has the authority to license and regulate the manufacture, importation, and sale of alcoholic beverages. This includes reviewing and approving new outlet licenses, ensuring compliance with laws and regulations, and conducting limited prevention and education programs. Local governments can influence the licensing and compliance process and help minimize harms associated with problem alcohol outlets through their land use policies (e.g., zoning, conditional use permits, ordinances). Communities can also participate in public hearings and work with ABC to identify outlets that fail to comply with requirements.

The State has the sole authority to impose alcohol taxes. State excise taxes are levied on the sale of specific goods or commodities (e.g., alcohol), and are controlled at the State level, with revenues benefiting the State General Fund. Recently, State and local policy-makers have considered mitigation fees as a way to address adverse affects on public health by funding programs to address or prevent those harms at the State or local level. The passage of Proposition 26 in 2010 will make adoption of mitigation fees more difficult to enact because the measure increased the vote requirement to enact from a simple majority to a 2/3 majority. It is important for communities to understand these processes and authorities so they can best effect needed changes.

Strategies to Reduce Alcohol-Related Harms in Our Cities and Communities

The following are eight recommendations that policymakers, communities, businesses, schools, and health care providers can use to reduce alcohol-related consequences in our cities and communities.

1. Take actions to limit alcohol outlet density.

ABC has the authority to license and regulate the sale of alcoholic beverages. As part of the licensing process, ABC is required to inform local government of applications. Local government and communities can play an important role in the ABC decision-making process, including commenting on or protesting an application. Additionally, as recommend by the Community Guide,²⁸ local government can use land use powers to influence the process by limiting the number of new alcohol outlets allowed by the city or county general plans, or by imposing operating restrictions on new or existing outlets.

New Alcohol Outlets: Local jurisdictions can implement zoning ordinances or require applicants to obtain a “conditional use permit” prior to ABC license approval that includes conditions such as restrictions on location/density, hours of sale, types of beverages sold, and licensee conduct. Community members can also participate in public hearings for new outlets, e.g., by highlighting areas where on-premises or off-premises outlets are oversaturated.

Existing Alcohol Outlets: Local jurisdictions can implement “deemed approved” ordinances that require off-premises outlets to comply with performance standards (e.g., properly maintained premises that do not adversely affect the surrounding community), and require that owners/employees do not permit or facilitate unlawful behavior (e.g., sales to minors, public consumption on the property or surrounding sidewalk, or other illegal activity). Community members can inform or collaborate with ABC in identifying problem outlets or encouraging revocation of a license for continued violations.^{28,29}

2. Change the economics of alcoholic beverages.

Despite the clear link between alcohol consumption and alcohol-related harms (e.g., motor vehicle crashes, alcohol-impaired driving, liver cirrhosis, illness/injury, crime), California’s alcohol taxes per gallon are below the national average for beer (20¢ vs. 28¢), liquor (\$3.30 vs. \$3.70), and wine (20¢ vs. 79¢); only Louisiana has a lower wine tax than California.^{30,31} California’s last increase in alcohol taxes occurred in 1991; the increase was 1¢ per glass of wine and 2¢ per serving of beer and liquor. Alcohol-related harms cost California \$38.0 billion annually, including \$10.8 billion in Los Angeles County.² The Community Guide has found that higher alcohol taxes can reduce over-consumption and youth access, as well as provide funds for prevention and health care.^{28,29} In California, efforts to raise taxes begin at the state level, but communities can inform legislators regarding the benefits of such legislation and mobilize support around related ballot initiatives.

3. Restrict alcohol availability and accessibility to minors.

Underage drinking and early initiation of alcohol use are associated with greater alcohol-related problems in adulthood. Restricting the ability of minors to obtain alcohol in the home and community can change social norms regarding the permissibility of underage drinking and delay early initiation of alcohol use. Parents and guardians should closely monitor alcoholic beverages in the home and ensure underage drinking does not occur at family events. Furthermore, communities can implement and enforce social host ordinances that increase consequences for adults who knowingly permit underage drinking in private settings, such as parties.



Communities can also support the implementation of policies to limit the consumption of alcohol in public places (e.g., parks, beaches) and to decrease the possibility of minors obtaining alcohol at events highly attended by youth (e.g., by requiring ID bracelets).³²

4. Reduce alcohol advertising in public places and in areas commonly seen by minors.

Exposure to alcohol advertising influences youths' beliefs about alcohol and their intention to drink. Restricting alcohol advertising in public places (e.g., billboards, sporting events) and enforcing signage restrictions at liquor and convenience stores (e.g., no more than 33% of square footage of window advertisements, specific area for alcohol product placement) reduces youth exposure to alcohol marketing.

5. Ensure compliance with responsible sales and serving practices.

Requiring regular retailer/vendor education to deter sales to underage youth (e.g., Responsible Beverage Sales and Service training, ID checks) in combination with compliance checks has been effective in limiting underage alcohol access and use. In California, completion of a Responsible Beverage Sales and Service training is voluntary, but it can be required locally through Conditional Use Permits. The Los Angeles Police Department's Standardized Training for Alcohol Retailers "STAR" training is one no-cost option for those employed in the alcoholic beverage service industry; additional trainers are listed on ABC's website.^{33,34} The Community Guide has also identified maintaining limits on hours of alcohol sales as effective in reducing excessive alcohol consumption and related harms.²⁹ In California, city and county governments have the authority to set different sale hours.

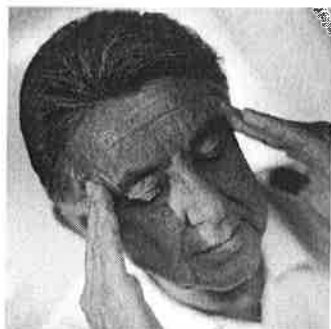
6. Provide educational services.

Providing alcohol education and training to youth in school and community settings can raise awareness, develop refusal skills, and reduce the likelihood they will ride with alcohol-impaired drivers. Information about the hazards of alcohol and the legal and social consequences of use can be disseminated through school and community programs. This will help change students' perceptions, decrease the public's acceptance of underage drinking, and support the message that underage drinking is not acceptable.^{29,35}



7. Increase screening by health care providers for alcohol use and misuse.

The U.S. Preventive Services Task Force recommends screening and behavioral counseling to reduce alcohol misuse by adults, including pregnant women. The 5A's framework may be helpful for behavioral counseling: ASSESS alcohol consumption with a brief screening tool followed by clinical assessment as needed; ADVISE patients to reduce alcohol consumption to moderate levels; AGREE on individual goals for reducing alcohol use or abstinence (if indicated); ASSIST patients with acquiring the motivations, self-help skills, or supports needed for behavior change; and ARRANGE follow-up support and repeated counseling, including referring dependent drinkers for specialty treatment. In addition, all pregnant women and women contemplating pregnancy should be informed of the harmful effects of alcohol on the fetus.³⁶



8. Provide access to mental health and substance abuse services.

Health care providers who are unable to directly provide substance abuse treatment should refer patients who screen positive for further assessment and treatment services, and then follow-up to ensure that the patient received needed services. In LA County, persons without insurance can call the Community Assessment Services Centers at (800) 564-6600 to find the nearest appropriate treatment center.

Helpful Online Resources

Substance Abuse Prevention and Control, LA County Department of Public Health

www.publichealth.lacounty.gov/sapc/

National Institute on Drug Abuse

www.nida.nih.gov/

Federal Resources to Stop Underage Drinking

www.stopalcoholabuse.gov/

**Substance Abuse and Mental Health Services Administration
Center for Substance Abuse Prevention**

www.samhsa.gov/prevention/

Centers for Disease Control and Prevention's Alcohol Program

www.cdc.gov/Alcohol/

The Guide to Community Preventive Services

www.thecommunityguide.org

Join Together: Advancing Effective Alcohol and Drug Policy, Prevention, and Treatment

www.jointogether.org

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16. Source: U.S. Department of Commerce, Census Bureau – 2000 Incorporated Places/Census Designated Places boundary file, <http://www.census.gov/geo/www/cob/pl2000.html>. More information about the L.A. City Council Districts is available at <http://www.lacity.org/YourGovernment/CityCouncil/>.
17. Population estimates are produced internally for the County of Los Angeles.
18. Listing of all licensed on-premises and off-premises alcohol outlets in Los Angeles County was downloaded January 2009 from the California ABC website [<http://www.abc.ca.gov/datport/DataExport.html>]. For this report, all outlets with active, pending, or revocation pending due to non-payment of recent renewal status were included (>97%).
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22. Source: 2000-2007 Death Statistical Master Files, California Department of Health Services, Center for Health Statistics. Definition for causes of alcohol-induced deaths is taken from the Centers for Disease Control and Prevention's (CDC) National Vital Statistics Report, volume 57, issue number 14, dated April 17, 2009 - page 120. [http://www.cdc.gov/nchs/data/nvsr/nvsr57/nvsr57_14.pdf]
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32. Preventing Adolescent Binge Drinking. www.youthbingedrinking.org.
33. Los Angeles Police Department, Standardized Training for Alcohol Retailers (STAR Training). [http://lapdonline.org/get_informed/content_basic_view/39961]
34. Department of Alcoholic Beverage Control – Approved RBS Training Providers. [http://www.abc.ca.gov/programs/RBS_Approved%20Training%20Providers.pdf]
35. Office of the Surgeon General. www.surgeongeneral.gov/topics/underageddrinking/.
36. U.S. Preventive Services Task Force. www.uspreventiveservicestaskforce.org/uspstf/uspdrin.htm.



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Urban Crime and Spatial Proximity to Liquor: Evidence from a Quasi-Experiment in Seattle

Andrew Chamberlain[†]

February 25, 2014

Abstract

There is a well-established correlation between retail liquor outlets and crime, but few studies identify causal effects. I exploit a unique source of identifying variation to establish causality: a 2012 privatization of liquor retailing in Washington State that rapidly expanded liquor availability into preexisting grocery and drug store chains. Based on 166,000 police reports from Seattle and a fixed-effects panel model, I find a significant positive effect of liquor availability on neighborhood crime both in OLS and IV estimates. Reducing the distance to the nearest liquor retailer by one mile leads to an average treatment effect of roughly 6 to 8 percent higher monthly crime rates. Violent crime and drug crimes are persistently affected, with more transitory effects on shoplifting and other non-violent crimes. Using an event study framework I investigate whether the results are due to new crime or spatial redistribution of existing crime, finding evidence of both effects. Overall, expanded liquor retailing appears to have had a significant causal effect on crime.

Keywords: Urban economics; Economics of crime; Liquor regulation; Privatization.

JEL Classification Numbers: D04, H70, Z18, L43, L33.

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1 Introduction

The issue of “spillover” crime from liquor retailing dominates local debates over alcohol policy. Neighborhood activists routinely oppose new liquor stores, warning of subsequent street crime and urban decay. Retailers counter that they are themselves victims of crime, the target of theft and burglary while attempting to serve local residents. This ongoing debate is reflected in the divided nature of U.S. state liquor laws, with 32 states exhibiting minimal restrictions on liquor retailing while 18 “control” states maintain heavy regulations or state-owned and operated liquor retailing systems.

At the heart of this debate is a simple empirical question: What is the causal effect of liquor retailing on neighborhood crime? Despite a large and diverse academic literature addressing that question, convincing answers remain elusive. Dozens of studies in the public health, epidemiology and sociology literatures have established, with varying degrees of sophistication, a clear correlation between liquor retailing and a variety of social problems including crime, traffic accidents, domestic abuse, youth violence and more. However, none of the existing research makes use of exogenous variation in liquor availability, delivering at best conditional correlations between liquor outlets and crime. Despite its limitations, this body of research has been embraced by reformers in recent years, leading in one case to a proposal to shutter hundreds of existing liquor stores in a major U.S. city.¹

This study contributes to the literature by exploiting a unique source of identifying variation to estimate the causal effect of liquor outlets on crime: a 2012 privatization of liquor retailing in Washington State. Following privatization, the number of liquor retailers in the City of Seattle grew more than six-fold from 20 to 134. A key provision of the policy change was a requirement that all new liquor retailers occupy commercial spaces of 10,000 square feet or above. This led nearly all expansion of liquor availability to occur at the

¹See Meredith Cohn, “Baltimore to Strip Some Liquor Stores of Licenses in Rezoning Effort,” June 18, 2012, *Baltimore Sun* (<http://bit.ly/1ipybK2>).

chain level as liquor permits were approved for essentially all large, preexisting grocery and drug store chains in the Seattle area. This rapid chain-level expansion into a broad swath of Seattle neighborhoods breaks the endogenous link between crime and retailer location decisions—both over time and across geographic space—that has plagued past research.

Combining information on liquor retail locations and data from Seattle police reports during the 33-month period surrounding privatization, I construct a series of longitudinal panels at various levels of geographic detail to assess the impact of liquor retailing on crime. I pursue two identification strategies. First, I estimate the effect of changes in distance to the nearest liquor retailer on neighborhood crime using a standard fixed-effects panel model, which is equivalent to a difference-in-differences estimator with continuous treatments and multiple periods. Second, I estimate the longer-term effect on crime trends surrounding newly opened liquor retailers using an event study framework. By incorporating various lags into the former strategy I am able to explore intertemporal “learning” effects of variation in liquor availability over time. Similarly, by examining crime in a series of concentric rings around new retailers in the latter strategy I am able to examine interspatial effects such as whether the impact on crime is due to additional criminal activity or simply a redistribution of existing crime inward from nearby areas.

In both approaches, I find a clear causal link between liquor retailing and crime. Using a fixed-effects panel approach, reducing the distance to the nearest liquor retailer by one mile increases total crime by 6.5 to 8.2 percent in the current month, and 5.4 to 6.2 percent in the subsequent month in nearby areas. When I decompose total crime into violent crime, nonviolent crime, shoplifting, and drug crime the model reveals an interesting intertemporal pattern. Shoplifting, drug crime, and nonviolent crime appear to respond immediately to contemporaneous changes in liquor availability, while violent and other “spontaneous” crimes plausibly related to alcohol consumption show effects only after a one-month lag. I find a similar pattern in all six geographic levels of detail, and my results are robust to estimation

both in first differences via OLS and in levels via a negative binomial model for count dependent variables. As a placebo test I show that unlike current and past changes in liquor availability, future leads of liquor distance have no effect on crime. As a robustness check I implement a 2SLS strategy using predicted liquor distance from the policy change as an instrument for observed distance, and find nearly identical results.

Using an event study approach, I find that opening a new liquor retailer leads to an average increase in total crime of 8.5 to 9.4 percent in the surrounding 0.1-mile radius area. Violent crime and drug crime are most clearly affected, increasing an average of 13.0-16.4 percent and 62.5-67.3 percent, respectively, while the effects on shoplifting and nonviolent crimes are more ambiguous. To assess whether the effects are due to redistribution of existing crime inward from nearby areas, I examine crime in two progressively more distant buffer rings around new retailers of 0.1-0.25 miles away, and 0.25-0.5 miles away. I find weak evidence that part of the effect of liquor retailing on nonviolent and shoplifting crimes is due to an inward spatial redistribution of preexisting crime. However, I find no evidence of spatial redistribution in the case of violent crime and drug crime, suggesting these effects are the result of additional criminal activity that would not have otherwise occurred in the absence of expanded liquor retailing.

I organize the remainder of the paper as follows. Section 2 reviews the related literature. Section 3 provides policy background on liquor privatization in Washington State. Section 4 presents a conceptual framework for my empirical strategy. Sections 5 and 6 present my data and identification strategy. Section 7 presents the empirical results, and Section 8 concludes.

2 Related Literature

There is a large and diverse literature examining the link between crime and liquor retailing.² Beginning in the early 1990s, the growth in geographic information systems (GIS) software and data led to a large number of empirical studies of the impact of liquor outlets on a variety of urban problems. The literature can be broadly divided into two groups: studies that use cross-sectional methods, and studies using longitudinal or panel methods.

2.1 Cross-Sectional Studies

The vast majority of research has been cross sectional.³ The typical study focuses on a single metropolitan area and uses variation in liquor density across Census blocks, Census tracts, ZIP-codes, or other neighborhood areas at a single point in time to identify the effect on crime. Most authors focus on assaults, homicides, robbery and other violent crimes, although traffic accidents, domestic violence and youth violence have also been examined. Studies in this vein have been conducted for over a dozen cities including Austin, Camden, Chicago, Cincinnati, Detroit, Kansas City, Minneapolis, New Orleans, Norfolk, Los Angeles, Washington D.C. and others. Without exception, the cross-sectional literature speaks with one voice in reporting a positive relationship between violent crime and liquor availability.

The basic weakness of this literature is the failure to identify causality. Liquor retailers are not randomly assigned throughout neighborhoods; like all firms, they endogenously choose retail locations. This process of firms optimally sorting into areas over time leads to a highly non-random assignment of retailers to neighborhoods, corrupting the basic identifying

²Extensive surveys of this literature are presented in White et al. (forthcoming), Roman et al. (2008), and Gruenewald et al. (1996).

³Cross-sectional studies include Grubestic and Pridemore (2011); Liang and Chikritzhs (2011); Franklin et al. (2010); Resko et al. (2010); Scribner et al. (2010); McKinney et al. (2009); Jones-Webb et al. (2008); Roman et al. (2008); Gruenewald et al. (2006); Britt et al. (2005); Zhu et al. (2004); Reid et al. (2003); Lipton and Gruenewald (2002); Gorman (2001); Gyimah-Brempong (2001); Scribner et al. (1999); Stevenson et al. (1999); Gorman et al. (1998); and Scribner et al. (1995).

variation in cross-sectional studies. Firms select locations based partly on unobservable neighborhood characteristics that are likely correlated both with the profitability of liquor retailing and the prevalence of crime.

One cross-sectional study that attempts to isolate exogenous variation in retailer locations is Gyimah-Brempong (2001). The author employs a two-stage least squares strategy using two instruments for liquor density: (1) median area rent, and (2) count of area gas stations. Comparing OLS and 2SLS estimates the author concludes that naive OLS estimates are downward biased, implying negative selection by firms away from high-crime areas. Unfortunately there are serious concerns about instrument validity, a limitation acknowledged in the paper. Density of gas stations is likely to be correlated with the same unobservable drivers of neighborhood crime contained in the error term that also affect the location of liquor outlets; after all, both establishments are firms endogenously choosing locations. Under such a failure of instrument validity, 2SLS estimates suffer from the same bias and inconsistency as naive OLS estimates, although possibly of different sign and magnitude, and do not identify causal effects.

2.2 Longitudinal Studies

A smaller number of studies have been longitudinal.⁴ The typical study uses a panel of N neighborhoods in a metropolitan area over T periods, using within-area variation over time to identify the effect of liquor outlets on crime. A number of cities have been examined in this way including Los Angeles, Melbourne, Norfolk, various counties in Texas and others. The earliest longitudinal study appears to be Gruenewald and Remer (2006) who examine the effect of liquor outlets on crime in 581 ZIP-code areas in California during a 6-year period. This was followed soon after by Teh (2007) who examines crime surrounding liquor outlets in Los Angeles between 1992 and 2004 using an event study framework. As with the cross-

⁴Longitudinal studies include White et al. (Forthcoming); Tang (2013); Livingston (2011); Parker et al. (2011); Cunradi et al. (2011); Yu et al. (2008); Teh (2007); and Gruenewald and Remer (2006).

sectional literature, longitudinal studies overwhelmingly find a positive relationship between liquor outlets and violence.

The main advantage of panel methods is well known: they allow researchers to control for unobserved area heterogeneity in a way that is impossible in cross-sectional studies. The usual fixed-effects (FE) panel estimator makes use of within-area variation in liquor outlets, a much cleaner source of identification than cross-sectional estimates. However, longitudinal data alone do not allow the identification of causal effects without strong identifying assumptions. Just as in the cross-section, changes in the presence of liquor outlets within areas over time is the result of endogenous firm location decisions, and may be correlated with unobserved drivers of crime.

This study contributes to the literature by making use of a unique source of identifying variation to estimate the causal effect of liquor retailing on crime: the 2012 privatization of liquor retailing in Washington State. The policy ushered in a rapid expansion of liquor availability into pre-existing grocery and drug store chains, providing plausibly exogenous identifying variation in liquor availability both across neighborhoods and over time. This quasi-experimental variation allows us to identify the causal effect of expanded liquor retailing on neighborhood crime.

3 Policy Background

In November 2011, Washington State voters approved ballot initiative I-1183, implementing wide-ranging reforms to the state’s liquor retailing and distribution system.⁵ Previously the industry had been state-owned and operated for more than seven decades under the supervision of the Washington State Liquor Control Board (WSLCB). Beginning June 1, 2012, the initiative ended the state’s monopoly on liquor retailing, closing state stores and liquidating the assets at auction. Before the policy, there were 329 liquor retailers statewide with 20 located in Seattle. One year after the policy, more than 1,400 liquor retailers were in operation with 133 in Seattle. Following the privatization, eighteen U.S. “control” states remain that maintain some form of state-controlled liquor retailing and distribution system.⁶

The key provision of I-1183 was a requirement that all new liquor retailers occupy commercial spaces of 10,000 square feet or larger.⁷ Ostensibly, the provision was designed to alleviate concerns about growth in smaller “nuisance” liquor stores following privatization. However, it had the effect of channeling nearly all expansion of liquor retailing into preexisting grocery and drug store chains satisfying the space requirement. The expansion occurred almost exclusively at the chain level, into every size-compliant retail location as permits were approved en masse by the WSLCB. For example, of the 20 Seattle locations of Bartell’s Drugs, 18 stores satisfy the space requirement.⁸ Of these, all 18 obtained liquor licenses as of September 2013, with 17 approved the day the policy went into effect. Similarly, of the 15 size-compliant Walgreens drug stores in Seattle, all 15 obtained liquor licenses within

⁵By “liquor” I refer specifically to alcoholic spirits such as vodka, whiskey and other distilled beverages. Beer and wine are privately retailed in Washington State and were largely unaffected by I-1183. The full text of I-1183 is available at <http://www.sos.wa.gov/elections/initiatives/text/i1183.pdf>.

⁶The remaining control states are Alabama, Iowa, Idaho, Maryland, Maine, Michigan, Mississippi, Montana, North Carolina, New Hampshire, Ohio, Oregon, Pennsylvania, Utah, Virginia, Vermont, West Virginia, and Wyoming. Source: National Alcohol Beverage Control Association (<http://www.nabca.org>).

⁷Two exceptions are allowed for the square-footage provision: (1) a “grandfathering” clause for former state-owned liquor stores, and (2) retailers in “trade areas” where no building exists that meets the 10,000 square-foot requirement. A “trade area” is defined as having no other liquor retailer within 20 miles, and no trade-area exemptions had been granted at the time of this writing.

⁸The noncompliant locations are at 4344 University Way (University District) and 1820 N. 45th Street (Wallingford).

the first two months of the policy. In these and similar cases, the policy expanded liquor availability in a way that was unaffected by endogenous selection either in timing or location. Of the 108 liquor retailers granted permits during the first three months of privatization, 97 were into similar large, established grocery and drug chains including Albertson's, Cost Plus World Market, Costco, Fred Meyer, Kress IGA Supermarket, QFC, Rite Aid, Safeway, Target, Trader Joe's, and Whole Foods.⁹ Each of these chains previously selected locations years and in some cases decades before the policy change for reasons presumably unrelated to liquor retailing. This expansion into a broad swath of Seattle neighborhoods provides time- and area-exogenous variation in liquor availability that can be used to identify the causal effect on crime.

In addition to increasing the number of retailers, the policy also expanded the number of hours per day when liquor is available for purchase. The combination of expanded retail outlets and broadened for-sale hours led to a statewide increase in liquor consumption following privatization. Despite higher retail prices due to the policy's increased liquor taxes, liquor consumption grew by roughly 7 percent in the nine months following privatization compared with a similar period in the prior year.¹⁰ Following privatization, numerous media accounts reported a surge in liquor shoplifting in newly privatized retailers.¹¹ One of the few reports on impacts on overall crime comes from an NBC story from October 23, 2013 reporting that alcohol-related arrests continued their downward trend following privatization.¹² Aside from these occasional media reports, there has been no systematic study to date of the effect of Washington State's liquor privatization on ancillary crime.

⁹The remaining eleven stores were independent, non-chain grocery stores and wine merchants satisfying the space requirement.

¹⁰Liquor consumption averaged 2,521,843 liters from June 2011 to February 2012, compared with 2,699,263 liters from June 2012 to February 2013. Source: Washington State Department of Revenue.

¹¹See for example Jeremy Pawloski, "Teen Shoplifting, Liquor a Bad Mix," *The Olympian*, December 9, 2012 (<http://bit.ly/MXXXdY>); Kendall Watson, "State May Begin Requiring Stores to Report Liquor Thefts," *Mercer Island Patch*, February 21, 2013 (<http://bit.ly/1cRza4E>); and Michelle Esteban, "Stores Seeing Huge Spike in Liquor Thefts," *KOMO News*, November 1, 2012 (<http://bit.ly/1brm25w>).

¹²See Rachel Hoops, "Alcohol-Related Arrests Continue to Decrease After Liquor Privatization in Washington State," *NBC News*, October 23, 2013 (<http://bit.ly/1c0uTYJ>).

4 Conceptual Framework

4.1 Basic Model

To help motivate my empirical strategy I present a simple model linking crime and retail liquor availability. The model is a straightforward extension of the classic Becker (1968) theory of criminal behavior, which models the individual decision to engage in illicit activity as a function of expected criminal penalties, gains from the activity and preferences. The presentation closely follows Ehrlich (1973) and similar models are presented in Gyimah-Brempong (2001) and Markowitz and Grossman (1998a, 1998b).

In Ehrlich (1973) an extension of the Becker (1968) model is developed in which individuals choose between legal and illegal behavior based on a standard utility maximization problem under uncertainty. Individuals maximize utility over a basket of goods—including earnings from both legal and illegal activities—and leisure, subject to a time constraint on hours spent in legal and illegal activities. Expected utility is maximized over two possible states of the world: (1) apprehension and punishment for illicit behavior, and (2) getting away with crime. The resulting optimal division between time spent in legal versus illegal activity is shown to depend on the probability of apprehension, the expected penalty if apprehended, and the relative economic returns from legal and illegal activities.

A useful feature of this class of models is that it is possible to derive a reduced-form “supply of offenses” function via the usual comparative statics, which specifies the causal determinants of crime at time t as,

$$c_{it} = \phi_{it}(p_{it}, f_{it}, w_{it}^L, w_{it}^I, \pi_{it}) \quad (1)$$

where c_{it} is the count of crimes committed in area i and period t , p_{it} is the probability of apprehension by local police, f_{it} is the criminal penalty if apprehended, w_{it}^L and w_{it}^I are the

economic returns to legal and illegal activity respectively, and π_{it} is a collection of other socioeconomic factors that exert a causal effect on crime. It is straightforward to show that $\partial c_{it}/\partial p_{it}, \partial c_{it}/\partial f_{it}, \partial c_{it}/\partial(w_{it}^L - w_{it}^I) < 0$ under mild regularity conditions, so that crime is negatively related to the probability of apprehension, the severity of penalties, and the relative economic returns to legal and illegal activities.

Following Gyimah-Brempong (2001) I connect alcohol consumption to this model by specifying it as one of the “other” socioeconomic factors contained in the vector π_{it} , so that,

$$\pi_{it} = (l_{it}, z_{it}) \tag{2}$$

where l_{it} is liquor consumption in area i and period t and z_{it} is all other socioeconomic determinants of crime. There is a well-established basis for doing so: the causal link between individual alcohol consumption and physical violence and aggression has been confirmed by a large number of experimental and observational studies throughout the epidemiology and psychology literatures.¹³ A variety of theories have been proposed regarding the exact physiological and psychological mechanisms by which alcohol induces violent behavior,¹⁴ but while interesting, the underlying mechanisms are unimportant from the standpoint of modeling the observed effect on crime. For the purposes of the descriptive model, I treat the increased likelihood of crime as a negative consumption externality from alcohol. For simplicity I assume a locally monotonic relationship between alcohol consumption and these associated crime externalities so that $\partial c_{it}/\partial l_{it} > 0$.

The link between retail liquor locations and alcohol consumption is provided via a standard consumer demand model. Individuals maximize utility from alcohol and other goods subject to prices, incomes, and travel distances to the nearest retail locations. For each area

¹³For example, see Parker and Auerhahn (1998), Chermak and Taylor (1995), Taylor and Chermak (1993) and the various studies cited therein.

¹⁴See for example Parker and Auerhahn (1998).

i in period t a typical consumer solves,

$$\underset{l_{it}, x_{it}}{\text{maximize}} U(l_{it}, x_{it}) \text{ subject to } (p_{it}^l + d_{it}^l t)l_{it} + (p_{it}^x + d_{it}^x t)x_{it} \leq Y_{it} \quad (3)$$

where l_{it} is liquor consumption, x_{it} is a composite of all other goods, p_{it}^l and p_{it}^x are prices of liquor and all other goods, d_{it}^l and d_{it}^x are the distances per unit to the nearest consumption point (i.e., the nearest retailer) for goods l and x , and t is the mean cost of travel per distance.¹⁵ Thus, in addition to the money price of liquor p_{it}^l , the term $d_{it}^l t$ represents the cost per unit consumers bear for travel to the nearest liquor retailer. Denote the optimal solutions $l^*(p^l, p^x, d^l, d^x, Y)$ and $x^*(p^l, p^x, d^l, d^x, Y)$.

The effect of changes in distance to the nearest liquor retailer on liquor demand, and thus indirectly on crime, can be seen via the usual comparative statics. Totally differentiating the first-order conditions from (3) we can show that,

$$\frac{\partial l_{it}}{\partial d_{it}^l} = \frac{(t/(p_{it}^x + d_{it}^x t)) \frac{\partial U}{\partial x_{it}}}{\frac{\partial^2 U}{\partial l_{it}^2}} = \frac{(+)}{(-)} < 0 \quad (4)$$

As expected, the model predicts a simple negative relationship between distance to the nearest liquor retailer and liquor consumption. The resulting effect on crime is easily obtained by substituting the Marshallian liquor demand $l^*(\cdot)$ into the crime equation from (1) and differentiating with respect to retailer distance d_{it}^l which yields,

$$\frac{\partial c_{it}}{\partial d_{it}^l} = \frac{\partial c_{it}}{\partial l_{it}} \frac{\partial l_{it}}{\partial d_{it}^l} = (+)(-) < 0 \quad (5)$$

This inverse relationship between crime and distance to the nearest liquor retailer provides the conceptual basis for the empirical strategy presented in Section 6.¹⁶

¹⁵I make the usual assumptions that utility is differentiable, strictly increasing, quasiconcave. To simplify the math below I also assume without loss of generality that utility is separable in l and x so that the cross partial $\partial^2 U / \partial l_{it} \partial x_{it} = 0$.

¹⁶Much of the previous literature has modeled a relationship between crime and the count of liquor outlets, rather than minimum distance to the nearest retailer. To the extent that outlet counts are a proxy

5 Data

The crime data consist of 166,393 police incident reports from the Seattle Police Department between January 2011 and September 2013. They include all reported crimes for which an incident report was filed by officers during the 33-month period. Crimes are coded with 193 unique offense codes, including assault, theft, public disturbance, property damage, fraud, harassment, homicide, narcotics offenses, burglary and more. Table 1 presents the count and frequency of the 10 most commonly reported offenses during the sample period.

The crime reports are coded with two separate geographic identifiers: the approximate street address of the offense (known as the “hundred block location”), and the latitude and longitude. Approximately 2,200 of the roughly 166,000 reports had either blank or clearly incorrect geocoding, and these offenses were recoded using the hundred block location and the MapQuest Geocoding API web service.¹⁷ Roughly 200 offenses had no geocoding nor hundred block location, and these were omitted from the file. All offenses falling outside city limits were also excluded, based on city boundary files provided by the Seattle Public Utilities’ GIS unit.¹⁸

For the analysis I classified crimes into five categories:¹⁹ (1) Total Crime, which consists of all reported offenses; (2) Violent Crime, which consists of assaults, property damage, harassment, robbery, and homicides as well as other “spontaneous” types of offenses plausibly related to alcohol consumption such as drunk driving, public urination, liquor law violations, disturbances and disorderly conduct; (3) Non-Violent Crime, which is composed of total crime minus the “violent crime” category; (4) Shoplifting, which consists of retail

for minimum distance, the approaches will yield similar results. However, because minimum distance is more clearly grounded in microeconomic theory I use distance as my measure of liquor availability.

¹⁷Information about the MapQuest Geocoding API service is available at <http://developer.mapquest.com/web/products/dev-services/geocoding-ws>.

¹⁸Official GIS boundary files for the City of Seattle are available at <http://www.seattle.gov/gis/>.

¹⁹A complete crosswalk of offense codes into crime categories is included in the Appendix.

theft offenses; and (5) Drug Crime, which consists of all narcotics-related offenses including possession, trafficking, manufacturing and smuggling.

Data on the location of liquor retailers are from public records provided by the Washington State Liquor Control Board (WSLCB). As in most municipalities, liquor retailers are classified into on- and off-premises establishments. WSLCB data provide the business name, street address and active date of the liquor license for all establishments. For each of the 33 months from January 2011 from September 2013 I constructed a historical listing of active on- and off-premise liquor establishments in Seattle. I then geocoded the locations using street addresses and the MapQuest Geocoding API web service.

Using the geocoded crime and liquor-location data, I compiled six area-month panels at varying levels of geographic detail: (1) Census blocks, (2) Census block groups, (3) Census tracts, and three uniform rectangular grids that partition the city into (4) 120 x 120 areas (442 feet wide by 731 feet long), (5) 50 x 50 areas (1,060 feet wide by 1,756 feet long), and (6) 25 x 25 areas (2,121 feet wide by 3,511 feet long). For each area and month, I coded a Python script in ArcGIS to perform a spatial join between crimes and areas, providing crime counts for area i in month t . Similarly, I calculated the minimum distance to the nearest on- and off-premise liquor establishment from the center point of each area in each month. The process resulted in six distinct longitudinal files, each with crime and liquor availability for N neighborhoods over T months. In Section 7, I present results for the largest and most detailed of the panels at the Census block level, and all other results are presented in the Appendix. Table 2 presents summary statistics for the Census-block-level panel.²⁰

To help visualize the rapid expansion of liquor availability following privatization, Figure 1 plots the locations of Seattle retailers before and after the policy. The left panel shows liquor outlets two months before privatization in April 2012. The right panel shows liquor outlets 16 months after privatization in September 2013. The map lines show the city's 134 Census

²⁰Summary statistics for all six panels are available upon request.

tracts. During the pre-policy period there were 20 state-owned liquor outlets. By September 2013 that number had expanded to 134 retailers. As is clear from the figure, the expansion was broad-based and affected virtually every neighborhood in the city. This broad pattern of expansion is largely the result of the 10,000-square-foot requirement for new retailers, and reflects the location of the city's preexisting large grocery and drug store chains. Figure 2 shows the resulting PDFs for the distribution of distance to the nearest liquor retailers among Census tracts during the pre- and post-policy periods. The pre-policy distribution is shown with wide grey bars, and the post-policy distribution is shown with narrow black bars. The pronounced leftward shift in the distribution of distances to the nearest retailer is clear from the figure, illustrating the broad-based nature of the retail expansion following privatization.

Figure 3 illustrates the basic identifying variation in distance to the nearest liquor retailer. For each of the 134 Census tracts in the city, it shows the distance to the nearest liquor retailer in feet from six months before privatization in December 2011 to 16 months after privatization in September 2013. The left panel shows the distance to the nearest retailer in levels, while the right panel shows changes or first-differences from the previous month. For reference, the policy change occurs in $t = 18$ along the horizontal axis. Liquor distance temporarily rose in a small number of neighborhoods as the WSLCB closed 14 retailers statewide in the months leading up to the privatization, three of which were in Seattle.²¹ On June 1, 2012, roughly 80 new retailers began selling liquor, almost exclusively large grocery and drug stores. Distances to the nearest retailer fell dramatically in most neighborhoods as permits were approved by the WSLCB in the subsequent months.

Figure 4 shows the evolution of total crime counts in "treatment" and "control" neighborhoods before and after the I-1183 policy change. The top line corresponds to the most heavily treated Census blocks, which fall into the top decile in terms of percentage drop in

²¹See Megan Managan, "Mercer Island Liquor Store Closes Thursday, Store Sold at Auction for \$200,000," *Mercer Island Reporter*, April 23, 2012. Available at <http://www.mi-reporter.com/news/148562485.html>.

distance to the nearest liquor retailer following privatization. The bottom line corresponds to the most lightly treated areas, which fall into the bottom decile which experienced little or no change in liquor distance. As above, the policy change occurs at $t = 18$ in the figure. Overall, crime trends in the two areas are similar both before and after privatization. However, two patterns are clear in the figure. First, treatment areas experience an upward bump in crime at the time of the policy change that, while small, is noticeably larger than in control neighborhoods. Second, total crime appears to be somewhat more volatile in treatment areas during the post-policy period than in control neighborhoods. Both patterns are broadly suggestive of a possible causal relationship between proximity to liquor retailing and neighborhood crime trends.

6 Identification Strategy

I pursue two identification strategies. First, I estimate a standard fixed-effects (FE) panel model to identify the effect of variation in the distance to the nearest liquor retailer on crime rates, via OLS and 2SLS. Second, I estimate an event study framework to identify the effect on crime rates in narrow areas surrounding liquor retailers before and after new store openings. The former strategy allows us to explore intertemporal “learning” effects of liquor availability on crime, while the latter strategy allows us to identify interspatial effects such as redistribution of preexisting crime between areas.

6.1 Fixed-Effects Panel Model

As a starting point, consider a standard fixed-effects panel model of the form,

$$y_{it} = \alpha_i + \gamma_t + \eta_{it} + X'_{it}\beta + d_{it}\delta + \epsilon_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \quad (6)$$

where y_{it} is the number of crimes in area i at time t ; α_i and γ_t are area- and time-specific fixed-effects; η_{it} is an area-specific fixed time trend; X_{it} is a vector of observable time-varying area determinants of crime; d_{it} is distance to the nearest liquor retailer; and ϵ_{it} is a mean-zero error term. The coefficient of interest is δ , which gives the effect of distance to the nearest liquor retailer on crime. Based on the model from Section 4 I expect to find $\delta < 0$. Due to the exogenous nature of the identifying variation in d_{it} we can interpret the resulting estimate of $\hat{\delta}$ as the causal effect of distance to the nearest liquor retailer on crime. It is straightforward to show this approach is equivalent to a difference-in-differences estimator with arbitrary continuous treatments over T periods.²²

One advantage of the above specification is that it allows us to investigate possible learning behavior over time due to changes in liquor availability in neighborhoods. Alcohol-related

²²See Imbens and Wooldridge (2007), in particular Equation (4.5).

crime may not adjust immediately to openings of new liquor retailers, and may instead adapt slowly over time to the changing retail landscape. To allow for this possibility I estimate a version of (6) that includes a series of lagged distances to the nearest retailer,

$$y_{it} = \alpha_i + \gamma_t + \eta_{it} + X'_{it}\beta + \sum_{j=0}^3 d_{it-j}\delta_j + \epsilon_{it} \quad (7)$$

where the terms $d_{it}, d_{it-1}, \dots, d_{it-3}$ are the contemporaneous and three lagged values of distance to the nearest liquor retailer. Equation (7) is the basic estimating equation for the fixed-effects model. The coefficients of interest are $\delta_0, \delta_1, \delta_2,$ and δ_3 , which allow us to assess the intertemporal effects of liquor availability on crime for up to three subsequent months. The vector X_{it} consists of contemporaneous and three lagged values of the distance to the nearest on-premises bar or restaurant for each area and month.²³ As a placebo test, I also estimate a version of (7) that includes three leads of future distance to liquor retailers, illustrating that future liquor availability has no effect on contemporaneous crime as expected; I present these results in the Appendix.

To exploit my cleanest form of identifying variation I estimate equation (7) via OLS in first differences. Thus, the estimates are identified off month-to-month changes in crime counts and liquor distances rather than absolute levels. As a robustness check, I also estimate (7) in levels using a negative binomial model, a conventional approach for count dependent variables; I also present these results in the Appendix. For the purposes of presentation, I focus on the linear panel model for the simplicity of the estimation procedure and the straightforward interpretation of coefficients as the marginal causal effect of liquor availability on crime. To show the importance of including area and time fixed effects in the specification, the first two columns of all tables show results that exclude them.

As an additional robustness check we also estimate equation 7 via 2SLS. While the above

²³Because on-premise locations were unaffected by the 2012 privatization, the estimates of $\hat{\beta}$ do not have a causal interpretation and are presented as an exhibit only.

OLS estimates rely partly on exogenous variation in liquor availability, it is possible that they do not completely isolate the exogenous component. Following privatization, some retail chains might have endogenously selected which locations obtained liquor permits; some state stores may have endogenously closed; or some independent retailers opening months after the policy change may reflect endogenous firm location decisions. To address these concerns I implement an IV procedure designed to isolate only the exogenous variation. First, I construct a counterfactual distribution of liquor retailers in which (1) all retail chains that obtained liquor licenses do so at once for all locations; (2) all former state stores remain open; and (3) no independent retailers open later than June 2012. These counterfactual retail locations are then used to calculate a “projected liquor distance” variable. The fitted values from the first-stage regression of actual liquor distance on projected distance (along with distances to on-premise locations and area and time fixed effects) isolate the exogenous variation in liquor availability that is predictable from the policy change.

The sample period for my fixed-effects estimation is the 22 months from December 2011 to September 2013, which makes use of 110,346 crime reports. I estimate equation (7) using six panels for Census blocks, Census block groups, Census tracts, and three uniform grids dividing the city into 25 x 25, 50 x 50, and 120 x 120 areas. For each panel I use five dependent crime variables for y_{it} : (1) total crime, (2) violent crime, (3) nonviolent crime, (4) shoplifting, and (5) drug crime. As with most spatial data, observations from nearby neighborhoods are unlikely to be statistically independent, with the degree of dependence growing more severe the closer the neighborhoods. The narrow-area panels exhibit a high degree of cross-sectional spatial autocorrelation between areas. To account for this feature, I report Driscoll and Kraay (1998) cluster- and auto-correlation-robust standard errors, which use a nonparametric covariance matrix estimator that is robust to very general forms of spatial and temporal heteroskedasticity and autocorrelation. I implement Driscoll-Kraay

standard errors using a 3-period lag structure and the *xtscc* Stata command, and report the resulting *t*-statistics in the tables below.²⁴

6.2 Event Study Framework

To assess the interspatial effects of liquor retailer openings on nearby crime, I estimate an event study framework similar to Teh (2007). Detailed discussions of the event study methodology are available in Binder (1998) and Fama et al. (1969). The conceptual approach is illustrated in Figure 5. The policy “event” is the exogenous opening of new liquor retailers in Seattle following the 2012 privatization, which occurs at $t = 0$ in the figure. For each store opening, I examine crime trends in the surrounding neighborhood based on 14 months of observations before and after the event. I allow the intercepts and slopes to differ on either side of the policy change, labeled γ and δ in the figure. The estimate of γ identifies the local-area causal effect on crime trends from the exogenous opening new liquor retailers.

In the three months following the June 2012 privatization, 108 new retail locations opened in Seattle. Using ArcGIS software I drew circular 0.1 mile buffers around each location. These areas surrounding new retailers serve as the basic panel unit for the event study. For each area and month, I compiled counts of offenses for each of the five crime categories from January 2012 through September 2013. Additionally, I calculated the distance to the nearest on-premises bar or restaurant from each area. I used 14 months of observations on either side of these 108 store openings for the estimation, resulting in a panel of size $NT = 3,024$. To explore the interspatial effects of store openings on nearby crime, I examined two concentric rings surrounding new retailers extending outward from 0.1-0.25 miles and from 0.25-0.5 miles. Examining crime trends in these concentric buffer rings allows us to assess whether store openings induced new criminal activity or simply redistributed preexisting crime inward toward retailers from nearby areas.

²⁴See Driscoll and Kraay (1998) and Hoechle (2007).

The basic estimating equation for the event study is,

$$y_{it} = \alpha_i + \lambda_t + \eta_i t + \delta_i t \mathbb{1}\{t > 0\} + \gamma \mathbb{1}\{t > 0\} + X'_{it} \beta + \epsilon_{it} \quad (8)$$

where y_{it} is crime surrounding liquor retailer i in month t . The time variable is scaled so that $t = 0$ at the time of opening for each retailer and ranges from $t = -14$ to $t = 14$. Retailer-specific and month-specific fixed effects are given by α_i and λ_t , and $\eta_i t$ is a retailer-specific fixed time trend estimated for the full 28-month period. The term $\delta_i t$ is an additional retailer-specific time trend estimated only for the post-policy period when $t > 0$, allowing trend slopes to flexibly vary on either side of the event. The coefficient of interest is γ , which corresponds to the post-policy intercept-shifter depicted in Figure 5, and gives the causal effect of exogenous store openings on area crime trends. X_{it} contains the minimum distance to the nearest on-premise bar or restaurant from area i at time t , and ϵ_{it} is a mean-zero error term. Note that on-premise bar and restaurant locations in X_{it} may change endogenously as a result of liquor store openings, and thus the estimate of $\hat{\beta}$ does not have a causal interpretation. I estimate equation (8) using three panels: (1) 0.1 mile areas around new liquor retailers, (2) 0.1-0.25 mile buffer areas, and (3) 0.25-0.5 mile buffer areas. As with the fixed-effects panel model above, all specifications report t -statistics based on Driscoll and Kraay (1998) cluster- and auto-correlation-robust standard errors to account for cross-sectional spatial autocorrelation in the data.

7 Results

7.1 Fixed-Effects Panel Results

7.1.1 Results for Census Block Panel

Census blocks are the smallest geographic unit defined by the U.S. Census Bureau, and divide Seattle into 11,485 neighborhood areas, many of which correspond to a single city block. Figure 6 illustrates the Census block areas based on GIS boundaries files provided by Seattle Public Utilities. When combined with 22 monthly observations of crime and liquor locations, the resulting panel contains $NT = 252,670$ month-area observations.

Tables 3 through 7 present my basic results. Each table shows the regression of a different category of crime on distance to the nearest liquor retailer, three lags of liquor distance, and distances to the nearest on-premise bar or restaurant. Table 3 shows the effect on total crime, while tables 4, 5, 6 and 7 show the effects on violent crime, non-violent crime, shoplifting and drug crime, respectively. Columns (1) and (2) are estimated in levels, and are presented as an illustration of the effect of excluding time and area fixed effects from the model. Columns (3) through (6) are estimated in first-differences, and Column (6) corresponds directly to my estimating equation. All coefficients have been scaled to represent the marginal effect of a one-mile change in the distance to the nearest liquor retailer. I also report the marginal effect relative to the mean for the coefficients of interest. I report t -statistics in parentheses based on Driscoll-Kraay cluster- and auto-correlation robust standard errors.

The impact of liquor availability on total crime is evident from Table 3. All estimated coefficients on distance to the nearest liquor retailer are negative as predicted by economic theory. Column (1) is the pooled OLS estimate that excludes all fixed effects and time trends, and results in a biased estimate of a 68.5 percent increase in crime. The effect falls significantly to a 16.4 percent increase when area fixed effects are included in Column

(2). The effect shrinks further when both area and time fixed effects are included, along with area-specific time trends. In Column (6) we add three lags of distance to the nearest liquor retailer, and find that both contemporaneous liquor distance and the first lag have significant effects on total crime. The effect is large: reducing the distance to off-premises liquor retailers by one mile in a typical area increases crime by 8.2 percent in the current period, and 6.2 percent in the following period. Neither the second nor third lag of liquor distance is significant, suggesting whatever intertemporal “learning” that occurs with respect to liquor availability and crime takes place within the first two months of retailer openings.

Table 4 shows the effect on violent crimes, including assaults, property damage, harassment, robbery, homicide and other plausibly alcohol-related offenses such as drunk driving, liquor law violations, and disorderly conduct. As with total crime, the pooled OLS estimate in Column (1) is large but shrinks considerably as fixed effects and lags are included. In Column (6), I find a lagged structure to the effect on violent crime. Contemporaneous changes in liquor availability appear to have little effect on violent crime. Instead, the first lag of liquor availability exerts a large and significant effect of a 19 percent increase in violent crime. The second and third lags of liquor distance have no additional effect, suggesting the impact of liquor availability on violent crime occurs lags slightly behind store openings.

Table 5 shows the effect on nonviolent crime, which is the logical complement of violent crime above. I find a significant effect on nonviolent crime both from current and lagged distances to off-premises liquor outlets. Contemporaneous changes in liquor distance appear to increase reports of nonviolent crime by 11.5 percent in typical neighborhoods, while the second lag of liquor distance increases nonviolent crime 3.3 percent. All other lags have small and insignificant effects. Results from the event study framework below suggest that unlike violent crime, this effect on nonviolent crime partly reflects a redistribution of existing crime inward toward liquor retailers rather than new crime. Overall, when total crime is decomposed into violent and nonviolent components we find the effect on contemporaneous

total crime is largely due to nonviolent offenses, while the one-month lagged effect is due primarily to violent crimes.

Table 6 shows the results for shoplifting offenses. Following liquor privatization in Washington State a large number of media outlets reported a surge in shoplifting at newly privatized liquor retailers. The results appear to confirm those reports. Changes in liquor availability had a large and significant contemporaneous effect on shoplifting; reducing liquor distance by one mile increased shoplifting by 47.6 percent in a typical area in the same month. However, none of the lagged changes in liquor availability had a significant effect. When combined with the finding below from the event study that longer-term trends in shoplifting were unaffected by liquor availability, the evidence suggests whatever surge in shoplifting that occurred following privatization may have been a temporary effect.

Table 7 presents the results for drug offenses. Psychological and epidemiological research has suggested a link between alcohol and drug use that exhibits characteristics of both substitute and complement goods.²⁵ I find a significant effect of expanded liquor availability on drug offenses. Contemporaneous liquor distance and its second lag both have a significant effect on drug crime, with one-mile effects of 36.8 percent and 23.1 percent, respectively. Neither the first nor third lags of liquor distance have a significant effect. The findings from the event study below suggest this effect is not due to a simple redistribution of narcotics offenses inward toward retailers from surrounding areas, and instead represents new crime. This pattern of effects is suggestive of a complementarity between alcohol availability and drug crime.

7.1.2 IV Results for Census Block Panel

Table 8 shows the first stage results from the 2SLS estimation. I use a “projected liquor distance” variable as an instrument for observed distance, based on a counterfactual distri-

²⁵See for example Parker and Auerhahn (1998) and the literature discussed therein.

bution of retailers in which (1) retail grocery and drug chains stock liquor in all locations simultaneously, (2) all former state stores remain open, and (3) no independent retailers enter the market after June 2012. The part of observed liquor distance that is predictable from this policy exercise represents strongly exogenous identifying variation. In the table, the large first-stage F statistic illustrates the strength of the instrument, and an R-squared of over 96 percent suggests only a small fraction of the observed variation in liquor availability cannot be predicted by the policy change.

Table 9 shows the second-stage of the 2SLS procedure. The columns correspond to each of the five categories of crime. In each case, I find results that are nearly identical to those obtained via OLS above. None of the estimated coefficients are significantly different from those presented in the previous section, suggesting the observed variation in liquor availability following privatization is sufficiently exogenous to allow us to identify the causal effect on crime via OLS.

7.2 Event Study Results

I present results from the event study in three tables. Table 10 shows the effect on crime in the narrow 0.1-mile (528 feet) radius surrounding new liquor retailers. Tables 11 and 12 show the effect on crime in two progressively more distant buffer rings of 0.1-0.25 miles and 0.25-0.5 miles away from retailers, allowing us investigate whether store openings contribute to additional crime or simply redistribute existing crime inward from surrounding neighborhoods. In each table, the coefficient of interest is “Store Opening,” corresponding to the intercept-shifter γ from my estimating equation 8. The columns display the effect on each of the five categories of crime. For each crime category, the first column corresponds directly to my estimating equation, while the second column includes an additional interaction term between store openings and distance to the nearest on-premises bar or restaurant to inves-

tigate whether the impact of liquor retailers is amplified or diminished by the proximity of on-premises establishments.

The impact of new liquor retailers on crime trends in surrounding areas is evident in Table 10. I find a positive and significant effect of liquor store openings on total crime, violent crime, and drug crime. In Column (1), we see the opening of a new liquor retailer leads to a 9.4 percent average increase in total crime nearby. This effect is slightly diminished to 8.5 percent when an interaction term with distance to the nearest on-premises bar or restaurant is included in Column (2), but the effect still approaches statistical significance with a *t*-statistic of over 1.65. These estimates are nearly identical to the the average treatment effects of 6.5 percent to 8.2 percent found in the fixed-effect panel model from the previous section.

In Columns (3) and (4) we see that violent crimes were also affected by liquor store openings, resulting in an average increase of 13 percent with the effect rising to 16.4 percent when the interaction term with on-premises locations is included. This provides some evidence that the presence of nearby bars and restaurants may amplify the causal effect of liquor retailing on violent crime. In Columns (5) and (6) I find no significant effect of liquor retailing on nonviolent crime. Similarly, I find no significant effect on shoplifting in Columns (7) and (8). Both of these results are inconsistent with the findings from the fixed-effects panel model above, suggesting that the impact of liquor availability on nonviolent and shoplifting crimes may simply reflect a temporary increase, leaving longer-term crime trends unaffected.

Columns (9) and (10) show the impact on drug crimes, for which I find a positive and significant effect of liquor retailing. New liquor outlets lead to a large 67.3 percent increase in average drug crimes in the surrounding neighborhood, an effect that declines to 62.5 percent when an interaction term is included in Column (10). Taken together with the results from the fixed-effects panel model above, these findings suggest a strong link between neighborhood expansion of liquor retailing and drug offenses.

Table 11 presents results for the closest buffer ring surrounding liquor retailers, ranging from 0.1-mile to 0.25-miles away. If the above effects are due primarily to redistribution of existing crime inward from nearby areas, I should find negative effects on crime in nearby buffer rings, possibly decreasing in magnitude with growing distance from retailers. By contrast, if the above effects are mainly due to new criminal activity I should observe zero or positive effects in outer ring areas.

For violent crime in Columns (3) and (4) and drug crime in Columns (9) and (10), I find clear evidence that the impact of liquor retailing is not primarily due to spatial redistribution. I find positive and significant effects of store openings for both types of crime in the 0.1-0.25 mile buffer areas. As expected, the effects are smaller in magnitude than in the directly surrounding 0.1-mile area: 6.9 percent and 24.3 percent for violent and drug crime, compared to 13 percent and 67.3 percent, respectively. For these two crime categories, new liquor retailers appear to induce additional criminal activity that would not have otherwise occurred. For total crime and nonviolent crime, the evidence is less clear. In each case, I find negative point estimates in Table 11, suggesting some degree of spatial redistribution of crime may have occurred. However, none of the four estimates are statistically significant. The clearest evidence for spatial redistribution is for nonviolent crime, whose negative estimates have sufficiently large *t*-statistics to reasonably conclude that some part of the effect identified above is due to inward redistribution of crime. This result is likely the driving force behind the weakly negative estimates for total crime, which is composed of both violent and nonviolent offenses.

Table 12 shows results for the most distant buffer ring of 0.25-0.5 miles from liquor retailers. As above, I find positive effects of liquor retailing on violent crime and drug crime although the former are imprecisely estimated, suggesting the above effects on these crimes are not simply due to spatial redistribution of crime. Similarly, I find negative coefficients on nonviolent crime and total crime, providing weak evidence that some of the above effects

are due to an inward redistribution of existing crime from nearby areas. For shoplifting, I find a statistically zero effect in the 0.25-0.5 mile buffer ring.

Taken together, these results suggest an interesting temporal and spatial relationship between crime and liquor retailing. In the months following new retailer openings, all five categories of crime are affected either immediately or within two periods. However, the effects on shoplifting and nonviolent crime appear to be transitory, while violent and drug crimes are affected in a more persistent way that is evident in longer-term crime trends. The temporary surge in nonviolent crimes appears to be partially the result of an inward redistribution of crime from surrounding neighborhoods, while the increase in violent and drug crimes appears to be due to new criminal activity.

8 Conclusion

The question of whether liquor stores attract crime to nearby areas dominates debates over local liquor policy. The issue has grown more pressing in recent years as Washington State's recent privatization has led to renewed interest in similar reforms in other remaining "control" states—most notably Pennsylvania, where there is currently an active political movement to privatize the state's retail monopoly.²⁶ I contribute to the large literature on liquor retailing and crime by exploiting a unique source of identifying variation in liquor availability to identify the causal effect of liquor outlets on crime.

Expanded liquor retailing in Seattle following privatization appears to have had a large and significant causal effect on crime, resulting in a 6.5 to 8.2 percent average increase in total crime from reducing the distance to the nearest liquor retailer by one mile. In the event study I find that opening a new liquor retailer induces an average increase in crime of 8.5 to 9.4 percent in the surrounding 0.1-mile neighborhood, with smaller effects in surrounding buffer areas of 0.1-0.25 miles and 0.25-0.5 miles away. The effects on violent and drug-related crimes appear to be persistent and the result of new criminal activity, while the impact on shoplifting and nonviolent crimes appears to be largely transitory and partially due to redistribution of preexisting crime from other areas.

These results are suggestive of the size and scope of the negative external costs imposed by expanded liquor retailing, which may be weighed by policymakers against offsetting social benefits of increased retail convenience. Lawmakers considering future expansions of liquor retailing should do so based on a full accounting of the likely effects on ancillary crime.

²⁶See Jeff Frantz, "Could 2014 be the Year Pennsylvania's Liquor Privatization Movement Reaches Full Proof?," *The Patriot News*, January 7, 2014 (<http://bit.ly/1kMZvmh>).

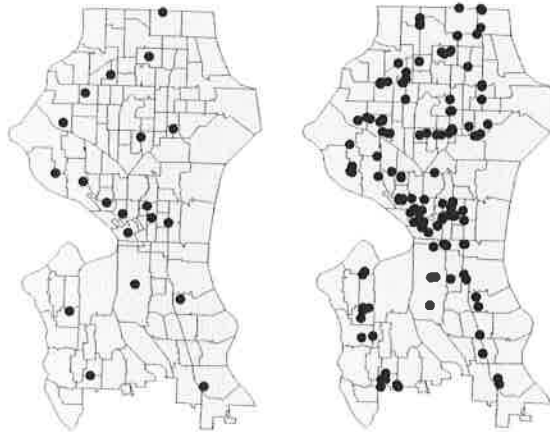
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Figure 1: Growth in the Number of Liquor Retailers Pre- and Post-Privatization



Note: Left panel displays off-premises liquor retailers as of April 2012. Right panel displays off-premises liquor retailers as of September 2013. Borders are for 134 Census tracts.

Source: Author's calculations based on historical WSLCB permit data.

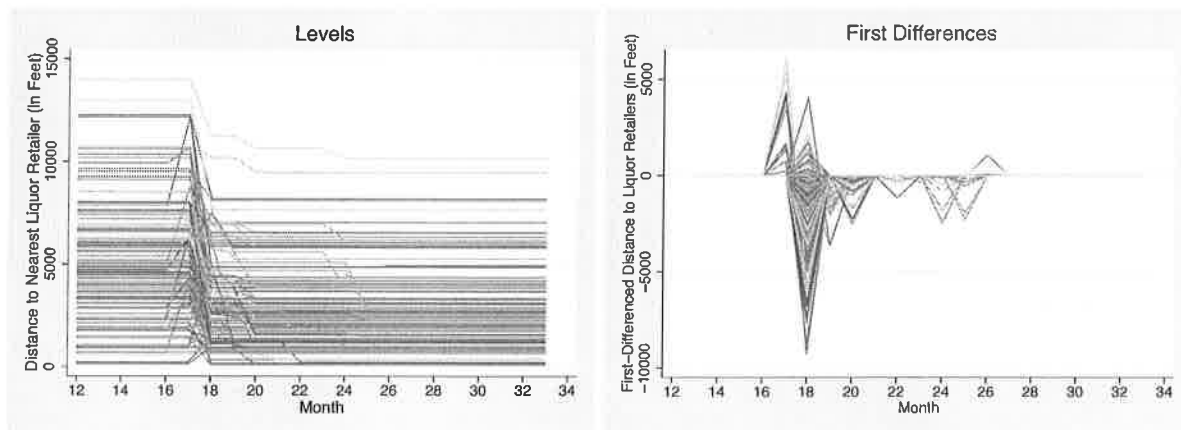
Figure 2: Pre- and Post-Policy PDFs of Area Distance to the Nearest Liquor Retailer



Note: The pre-policy PDF (wide grey bars) corresponds to March 2012 ($t = 15$). The post-policy PDF (narrow black bars) corresponds to January 2013 ($t = 25$).

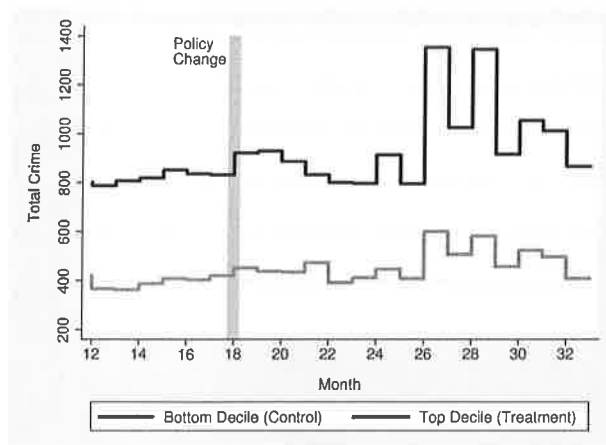
Source: Author's calculations.

Figure 3: Basic Identifying Variation in Distance to the Nearest Liquor Retailer



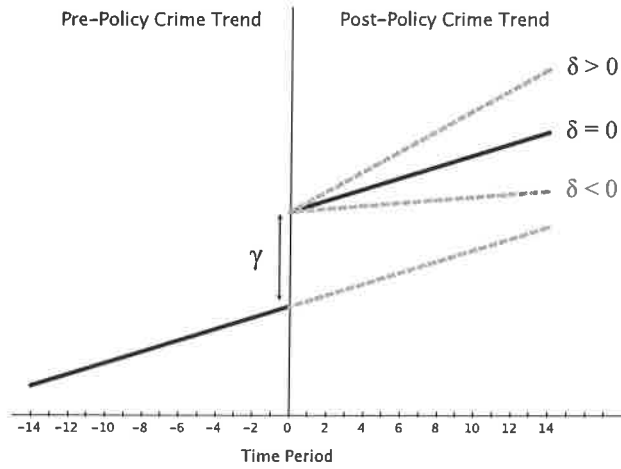
Note: Lines correspond to 134 Seattle Census tracts. Distances are measured in feet.
 The policy change (Initiative 1183) occurs at $t = 18$.
Source: Author's calculations.

Figure 4: Evolution of Total Crime in “Treatment” and “Control” Areas Before and After the Policy Change (Census Block Level)



Note: Top line (black) corresponds to “treatment” areas with the largest percentage decrease in distance to the nearest liquor retailer (top decile). Bottom line (grey) corresponds to “control” areas with the smallest decrease in liquor distance (bottom decile). Policy change occurs in $t = 18$
Source: Author's calculations.

Figure 5: Conceptual Framework for the Event Study



Source: Author, based on Teh (2007).

Figure 6: 2010 Census Block Areas for Seattle ($N = 11,485$)



Source: Seattle Public Utilities GIS Unit.

Table 1: Count and Frequency of Various Crimes in the Data File

Offense Type	Offense Count	Frequency (%)
Theft - Car Prowl	25,978	15.6
Theft - Other	10,876	6.5
Vehicle Auto Theft	9,955	6.0
Burglary - Forced Residential	8,212	4.9
Property Damage - Non-Residential	8,098	4.9
Assault - Non-Aggravated	6,417	3.9
Disturbance - Other	5,688	3.4
Illegal Property Possession	5,494	3.3
Theft - Shoplifting	5,393	3.2
Burglary - Non-Forced Residential	4,903	2.9
All Others	75,379	45.3
Total	166,393	100.0

Source: Crime data are from the Seattle Police Department's "Police Report Incident" file available at <http://data.seattle.gov>, from January 1, 2011 through September 30, 2013.

Table 2: Summary Statistics for the Census-Block-Level Panel ($N = 11485$; $T = 33$)

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Year	379,005	n.a.	n.a.	2011	2013
Total Crime	379,005	0.43	1.40	0	64
Violent Crime	379,005	0.14	0.67	0	43
Non-Violent Crime	379,005	0.29	0.96	0	55
Shoplifting Crime	379,005	0.01	0.22	0	32
Drug-Related Crime	379,005	0.01	0.19	0	30
Distance to Off-Premises Liquor	379,005	4,055	2,820	21	22,795
Distance to On-Premises Liquor	379,005	1,251	983	1.1	10,219

Note: Crime and liquor availability figures are for 11,485 year-2010 Census blocks areas in Seattle over the 33-month period from January 2011 to September 2013 ($NT = 379,005$). Distances are measured in feet. Similar panels were constructed for five other geographies: (1) Census block groups; (2) Census tracts; and three uniform rectangular grids measuring (3) 25 x 25; (4) 50 x 50; and (5) 120 x 120.

Sources: Crime data are from the Seattle Police Department's "Police Report Incident" file at <http://data.seattle.gov>. On- and off-premises liquor retailers locations are from historical Washington State Liquor Control Board (WSLCB) records at <http://liq.wa.gov/records/frequently-requested-lists>. Retailer locations were geocoded using the MapQuest Geocoding API website and ArcGIS software.

Table 3: Regression Results for Census Block Panel Model (1 of 5)

Variable	(1) Total Crime	(2) Total Crime	(3) Total Crime	(4) Total Crime	(5) Total Crime	(6) Total Crime
Liquor Distance (t)	-0.29553***	-0.07088**	-0.02906***	-0.03507***	-0.03484***	-0.03550***
t-statistic	(-6.029)	(-2.376)	(-3.761)	(-4.673)	(-4.794)	(-4.995)
Effect / Mean	-68.5%	-16.4%	-6.7%	-8.1%	-8.1%	-8.2%
Liquor Distance (t-1)				-0.02547***	-0.02565***	-0.02680***
t-statistic				(-2.978)	(-3.135)	(-3.104)
Effect / Mean				-5.9%	-5.9%	-6.2%
Liquor Distance (t-2)					-0.00240	-0.00498
t-statistic					(-0.294)	(-0.526)
Effect / Mean					-0.6%	-1.2%
Liquor Distance (t-3)						-0.00879
t-statistic						(-1.351)
Effect / Mean						-2.0%
On-Premise Dist. (t)	-0.80944***	0.05772	-0.07371	-0.06046	-0.06521	0.00749
t-statistic	(-23.322)	(0.820)	(-0.462)	(-0.392)	(-0.440)	(0.054)
On-Premise Dist. (t-1)				0.04588	0.02594	0.05094
t-statistic				(0.449)	(0.256)	(0.502)
On-Premise Dist. (t-2)					-0.08604	-0.05830
t-statistic					(-0.898)	(-0.570)
On-Premise Dist. (t-3)						0.09628
t-statistic						(1.208)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	252,670	252,670	241,185	229,700	218,215	206,730
Within R-Squared	0.0268	0.0005	0.0045	0.0047	0.0048	0.0050

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 4: Regression Results for Census Block Panel Model (2 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Violent Crime	Violent Crime	Violent Crime	Violent Crime	Violent Crime	Violent Crime
Liquor Distance (t)	-0.11007***	-0.03082***	0.00497***	-0.00186	-0.00070	-0.00213
t-statistic	(-6.163)	(-2.646)	(3.686)	(-0.837)	(-0.303)	(-0.820)
Effect / Mean	-77.8%	-21.8%	3.5%	-1.3%	-0.5%	-1.5%
Liquor Distance (t-1)				-0.02743***	-0.02515***	-0.02686***
t-statistic				(-6.135)	(-5.647)	(-5.427)
Effect / Mean				-19.4%	-17.8%	-19.0%
Liquor Distance (t-2)					0.00652	0.00449
t-statistic					(1.010)	(0.629)
Effect / Mean					4.6%	3.2%
Liquor Distance (t-3)						-0.00323
t-statistic						(-0.745)
Effect / Mean						-2.3%
On-Premise Dist. (t)	-0.32131***	0.01728	-0.03373	-0.04749	-0.05773	-0.03571
t-statistic	(-23.188)	(1.106)	(-0.747)	(-1.071)	(-1.265)	(-0.702)
On-Premise Dist. (t-1)				-0.05699	-0.06824	-0.04590
t-statistic				(-1.008)	(-1.306)	(-0.959)
On-Premise Dist. (t-2)					-0.01748	0.01722
t-statistic					(-0.364)	(0.322)
On-Premise Dist. (t-3)						0.10351**
t-statistic						(2.438)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	252,670	252,670	241,185	229,700	218,215	206,730
Within R-Squared	0.0177	0.0003	0.0019	0.0020	0.0021	0.0021

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 5: Regression Results for Census Block Panel Model (3 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime
Liquor Distance (t)	-0.18546***	-0.04005**	-0.03402***	-0.03321***	-0.03414***	-0.03336***
t-statistic	(-5.913)	(-2.144)	(-4.242)	(-4.108)	(-4.296)	(-4.481)
Effect / Mean	-64.0%	-13.8%	-11.7%	-11.5%	-11.8%	-11.5%
Liquor Distance (t-1)				0.00196	-0.00050	0.00005
t-statistic				(0.347)	(-0.084)	(0.010)
Effect / Mean				0.7%	-0.2%	0.0%
Liquor Distance (t-2)					-0.00892***	-0.00947**
t-statistic					(-2.682)	(-2.312)
Effect / Mean					-3.1%	-3.3%
Liquor Distance (t-3)						-0.00556
t-statistic						(-1.404)
Effect / Mean						-1.9%
On-Premise Dist. (t)	-0.48813***	0.04044	-0.03998	-0.01297	-0.00748	0.04320
t-statistic	(-19.517)	(0.549)	(-0.271)	(-0.093)	(-0.058)	(0.351)
On-Premise Dist. (t-1)				0.10286	0.09418	0.09684
t-statistic				(1.114)	(0.974)	(1.025)
On-Premise Dist. (t-2)					-0.06856	-0.07552
t-statistic					(-0.826)	(-1.052)
On-Premise Dist. (t-3)						-0.00723
t-statistic						(-0.121)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	252,670	252,670	241,185	229,700	218,215	206,730
Within R-Squared	0.0212	0.0002	0.0030	0.0031	0.0032	0.0033

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 6: Regression Results for Census Block Panel Model (4 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime
Liquor Distance (t)	-0.02496***	-0.00557***	-0.00767***	-0.00731***	-0.00743***	-0.00739***
t-statistic	(-4.405)	(-3.393)	(-3.825)	(-3.206)	(-3.230)	(-3.171)
Effect / Mean	-160.7%	-35.9%	-49.4%	-47.1%	-47.8%	-47.6%
Liquor Distance (t-1)				0.00138	0.00134	0.00142
t-statistic				(1.338)	(1.012)	(0.946)
Effect / Mean				8.9%	8.6%	9.1%
Liquor Distance (t-2)					0.00043	0.00048
t-statistic					(0.318)	(0.283)
Effect / Mean					2.8%	3.1%
Liquor Distance (t-3)						-0.00011
t-statistic						(-0.085)
Effect / Mean						-0.7%
On-Premise Dist. (t)	-0.05049***	0.00331	-0.00447	-0.00483	-0.00474	-0.00432
t-statistic	(-13.894)	(0.954)	(-0.466)	(-0.534)	(-0.497)	(-0.480)
On-Premise Dist. (t-1)				-0.00210	-0.00439	-0.00054
t-statistic				(-0.263)	(-0.851)	(-0.097)
On-Premise Dist. (t-2)					-0.01279	-0.00509
t-statistic					(-0.849)	(-0.397)
On-Premise Dist. (t-3)						0.02781**
t-statistic						(2.314)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	252,670	252,670	241,185	229,700	218,215	206,730
Within R-Squared	0.0048	0.0001	0.0005	0.0005	0.0006	0.0006

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 7: Regression Results for Census Block Panel Model (5 of 5)

Variable	(1) Drug Crime	(2) Drug Crime	(3) Drug Crime	(4) Drug Crime	(5) Drug Crime	(6) Drug Crime
Liquor Distance (t)	-0.01274***	-0.00033	-0.00521**	-0.00450*	-0.00471**	-0.00436**
t-statistic	(-6.540)	(-0.335)	(-2.392)	(-1.918)	(-2.145)	(-1.985)
Effect / Mean	-107.6%	-2.8%	-44.0%	-38.0%	-39.8%	-36.8%
Liquor Distance (t-1)				0.00301	0.00223	0.00265
t-statistic				(1.639)	(1.060)	(1.270)
Effect / Mean				25.4%	18.8%	22.4%
Liquor Distance (t-2)					-0.00337**	-0.00273**
t-statistic					(-2.333)	(-2.328)
Effect / Mean					-28.5%	-23.1%
Liquor Distance (t-3)						0.00154
t-statistic						(1.052)
Effect / Mean						13.0%
On-Premise Dist. (t)	-0.04281***	-0.00306	-0.01036	-0.01690	-0.01296	-0.01146
t-statistic	(-19.231)	(-0.350)	(-0.746)	(-0.997)	(-1.033)	(-0.739)
On-Premise Dist. (t-1)				-0.03094	-0.01949	-0.02079
t-statistic				(-1.166)	(-1.077)	(-1.109)
On-Premise Dist. (t-2)					0.05105	0.04604
t-statistic					(1.056)	(1.160)
On-Premise Dist. (t-3)						-0.02700
t-statistic						(-0.856)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	252,670	252,670	241,185	229,700	218,215	206,730
Within R-Squared	0.0029	0.0000	0.0003	0.0003	0.0003	0.0003

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 8: First-Stage IV Results for Census Block Panel Model

Variable	Observed Liquor Distance (t)
Policy-Predicted Liquor Distance (t)	0.98486***
t-statistic	(1784.310)
On-Premise Distance (t)	-0.01461***
t-statistic	(-3.762)
Area Fixed Effect	Yes
Time Fixed Effect	Yes
Area Time Trend	Yes
n	252,670
Within R-Squared	0.9668
F-statistic	305,473.8

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: *t*-statistics are presented in parentheses.

Table 9: Second-Stage IV Results for Census Block Panel Model

Variable	Total Crime	Violent Crime	Nonviolent Crime	Shoplifting Crime	Drug Crime
Liquor Distance (t)	-0.03306***	-0.00044	-0.03263***	-0.00839***	-0.00461*
t-statistic	(-3.799)	(-0.171)	(-3.988)	(-3.474)	(-1.751)
Effect / Mean	-7.7%	-0.3%	-11.3%	-54.0%	-38.9%
Liquor Distance (t-1)	-0.02564**	-0.02887***	0.00323	0.00231	0.00373
t-statistic	(-2.513)	(-5.692)	(0.518)	(1.34)	(1.577)
Effect / Mean	-5.9%	-20.4%	1.1%	14.9%	31.5%
Liquor Distance (t-2)	0.00216	0.01041	-0.00825	0.00006	-0.00325***
t-statistic	(0.194)	(1.566)	(-1.469)	(0.028)	(-2.690)
Effect / Mean	0.5%	7.4%	-2.8%	0.4%	-27.5%
Liquor Distance (t-3)	-0.01178	-0.00672	-0.00506	0.00085	0.00245
t-statistic	(-1.433)	(-1.297)	(-1.172)	(0.611)	(1.576)
Effect / Mean	-2.7%	-4.7%	-1.7%	5.5%	20.7%
On-Premise Dist. (t)	0.00728	-0.03564	0.04291	-0.00458	-0.01149
t-statistic	-0.052	(-0.701)	(0.348)	(-0.506)	(-0.741)
On-Premise Dist. (t-1)	0.05136	-0.04631	0.09767	-0.00042	-0.0206
t-statistic	(0.507)	(-0.967)	(1.036)	(-0.075)	(-1.099)
On-Premise Dist. (t-2)	-0.05692	0.01823	-0.07515	-0.0051	0.046
t-statistic	(-0.558)	(0.339)	(-1.049)	(-0.397)	(1.158)
On-Premise Dist. (t-3)	0.09607	0.10307**	-0.007	0.02800**	-0.02677
t-statistic	(1.212)	(2.436)	(-0.118)	(2.325)	(-0.848)
Area Fixed Effect	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Area Time Trend	Yes	Yes	Yes	Yes	Yes
n	206,730	206,730	206,730	206,730	206,730
Within R-Squared	0.0050	0.0021	0.0033	0.0006	0.0003

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: IV estimates instrument for observed liquor distance using a counterfactual variable for “predicted liquor distance” from the policy change. All columns are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 10: Event Study Results for 0.1-Mile Areas Surrounding Liquor Retailers (1 of 3)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Store Opening (γ)	1.10300** (2.563) 9.4%	1.00467 (1.657) 8.5%	0.57780*** (3.084) 13.0%	0.72755*** (3.252) 16.4%	0.5252 (1.406) 7.2%	0.27712 (0.537) 3.8%
On-Premise Distance (β)	-0.00258** (-2.342) 0.0%	-0.00272** (-2.270) 0.0%	-0.00072 (-0.873) 0.0%	-0.0005 (-0.665) 0.0%	-0.00185*** (-4.399) 0.0%	-0.00222*** (-3.346) 0.0%
Opening x On-Premise		0.0003 (0.476) 0.0%		-0.00046* (-1.803) 0.0%		0.00077 (1.364) 0.0%
n	3,024	3,024	3,024	3,024	3,024	3,024
Within R-Squared	0.265	0.265	0.223	0.223	0.189	0.189

Variable	(7)	(8)	(9)	(10)
Store Opening (γ)	-0.04234 (-0.280) -2.8%	-0.11147 (-0.754) -7.5%	0.42999*** (3.295) 67.3%	0.39935*** (2.206) 62.5%
On-Premise Distance (β)	-0.00095** (-2.336) -0.1%	-0.00105** (-2.341) -0.1%	0.00001 (0.138) 0.0%	-0.00003 (-0.203) 0.0%
Opening x On-Premise		0.00021*** (2.882) 0.0%		0.00009 (0.531) 0.0%
n	3,024	3,024	3,024	3,024
Within R-Squared	0.219	0.220	0.316	0.316

* **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively. Note: All specifications include area and month fixed effects and pre- and post-policy linear time trends. Robust t-statistics are reported in parentheses, based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 11: Event Study Results for 0.1-0.25 Mile Buffer Rings Surrounding Liquor Retailers (2 of 3)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Total Crime	Total Crime	Violent Crime	Violent Crime	Nonviolent Crime	Nonviolent Crime
Store Opening (γ)	-0.10472	-0.98650	0.83542*	0.63657	-0.94014	-1.62307
t-statistic	(-0.070)	(-0.584)	(1.828)	(1.546)	(-0.866)	(-1.217)
Effect / Mean	-0.3%	-3.0%	6.9%	5.3%	-4.6%	-8.0%
On-Premise Distance (β)	-0.00256	-0.00386**	-0.00112	-0.00142*	-0.00144	-0.00245**
t-statistic	(-1.600)	(-2.615)	(-1.331)	(-1.844)	(-1.399)	(-2.108)
Effect / Mean	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Opening x On-Premise		0.00272		0.00061		0.00211
t-statistic		(1.455)		(0.966)		(1.449)
Effect / Mean		0.0%		0.0%		0.0%
n	3,024	3,024	3,024	3,024	3,024	3,024
Within R-Squared	0.363	0.364	0.422	0.422	0.240	0.240

Variable	(7)	(8)	(9)	(10)
	Shoplifting	Shoplifting	Drug Crime	Drug Crime
Store Opening (γ)	-0.01788	-0.22393**	0.46965**	0.59890*
t-statistic	(-0.228)	(-2.577)	(2.017)	(1.972)
Effect / Mean	-1.2%	-14.9%	24.3%	31.0%
On-Premise Distance (β)	0.00007	-0.00023	0.00000	0.00019
t-statistic	(0.502)	(-1.424)	(0.006)	(0.452)
Effect / Mean	0.0%	0.0%	0.0%	0.0%
Opening x On-Premise		0.00064***		-0.00040
t-statistic		(4.215)		(-1.210)
Effect / Mean		0.0%		0.0%
n	3,024	3,024	3,024	3,024
Within R-Squared	0.174	0.175	0.346	0.346

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively. Note: All specifications include area and month fixed effects and pre- and post-policy linear time trends. Robust t-statistics are reported in parentheses, based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 12: Event Study Results for 0.25-0.5 Mile Buffer Rings Surrounding Liquor Retailers (3 of 3)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Total Crime	Total Crime	Violent Crime	Violent Crime	Nonviolent Crime	Nonviolent Crime
Store Opening (γ)	-0.65649	-2.37830	0.84946	0.85842	-1.50595	-3.23672
t-statistic	(-0.271)	(-0.743)	(0.891)	(0.817)	(-0.920)	(-1.360)
Effect / Mean	-0.9%	-3.1%	3.2%	3.2%	-3.0%	-6.5%
On-Premise Distance (β)	-0.00591***	-0.00846***	-0.00262	-0.00261	-0.00329**	-0.00585***
t-statistic	(-2.761)	(-3.020)	(-1.335)	(-1.303)	(-2.023)	(-2.662)
Effect / Mean	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Opening x On-Premise		0.00531		-0.00003		0.00534*
t-statistic		(1.377)		(-0.025)		(1.723)
Effect / Mean		0.0%		0.0%		0.0%
n	3,024	3,024	3,024	3,024	3,024	3,024
Within R-Squared	0.425	0.426	0.451	0.451	0.295	0.297

Variable	(7)	(8)	(9)	(10)
	Shoplifting	Shoplifting	Drug Crime	Drug Crime
Store Opening (γ)	0.13084	-0.09470	0.78937***	0.87545***
t-statistic	(0.991)	(-0.581)	(3.109)	(2.630)
Effect / Mean	4.7%	-3.4%	26.9%	29.9%
On-Premise Distance (β)	-0.00140**	-0.00174***	0.00007	0.00020
t-statistic	(-2.529)	(-3.559)	(0.236)	(0.554)
Effect / Mean	0.0%	-0.1%	0.0%	0.0%
Opening x On-Premise		0.00070**		-0.00027
t-statistic		(2.514)		(-0.791)
Effect / Mean		0.0%		0.0%
n	3,024	3,024	3,024	3,024
Within R-Squared	0.299	0.300	0.240	0.240

* **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively. Note: All specifications include area and month fixed effects and pre- and post-policy linear time trends. Robust t-statistics are reported in parentheses, based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

A Appendix

A.1 Placebo Test Results

Table 13 shows the results of a placebo test in which we include three leads of future distance to the nearest liquor retailer in the fixed-effects model from Section 7. Unlike lagged changes in liquor availability, future changes should have no causal effect on contemporaneous crime. Because $\Delta d_{it+1}^l = d_{it+1}^l - d_{it}^l$, changes in liquor distance at time $t+1$ contain information about current liquor availability at time t . Thus, we omit the first lead of liquor distance and instead include the second through fourth leads. All models are estimated in first differences. In Table 13, we see that all leads of future liquor distance are statistical zeros, suggesting the effect of liquor availability on crime from Section 7 is not the result of spurious time-series correlations.

Table 13: Placebo Test Results; FE Panel Model with Three Leads of Liquor Distance; Census Block Level

Variable	(1)	(2)	(3)	(4)	(5)
Total Crime					
Liquor Distance (t)	-0.02538***	0.00401	-0.02939***	-0.00846**	-0.00354*
t-statistic	(-3.658)	(0.626)	(-3.648)	(-2.559)	(-1.659)
Effect / Mean	-5.9%	2.8%	-10.1%	-54.5%	-29.9%
Violent Crime					
Liquor Distance (t-1)	-0.02296***	-0.02306***	0.00010	0.00068	0.00246
t-statistic	(-3.939)	(-3.087)	(0.014)	(0.254)	(1.017)
Effect / Mean	-5.3%	-16.3%	0.0%	4.4%	20.8%
Nonviolent Crime					
Liquor Distance (t-2)	-0.00079	0.00798	-0.00877	0.00007	-0.00307**
t-statistic	(-0.066)	(0.843)	(-1.287)	(0.028)	(-2.260)
Effect / Mean	-0.2%	5.6%	-3.0%	0.5%	-25.9%
Shoplifting					
Liquor Distance (t-3)	-0.00445	-0.00076	-0.00370	-0.00058	0.00121
t-statistic	(-0.550)	(-0.125)	(-0.650)	(-0.269)	(0.790)
Effect / Mean	-1.0%	-0.5%	-1.3%	-3.7%	10.2%
Drug Crime					
Liquor Distance (t+2)	0.01137	-0.00843	0.01980	-0.02668	-0.00264
t-statistic	(0.530)	(-0.374)	(1.132)	(-1.388)	(-0.659)
Liquor Distance (t+3)	0.00731	0.02486	-0.01755	0.02470	-0.00342
t-statistic	(0.076)	(1.225)	(-0.199)	(0.985)	(-1.025)
Liquor Distance (t+4)	-0.00437	0.00775	-0.01212	0.00719	-0.00059
t-statistic	(-0.071)	(0.203)	(-0.300)	(1.628)	(-0.192)
On-Premise Distance (+ 3 Lags)	Yes	Yes	Yes	Yes	Yes
Area Fixed Effect	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Area Time Trend	Yes	Yes	Yes	Yes	Yes
n	149,305	149,305	149,305	149,305	149,305
Within R-Squared	0.0041	0.0022	0.0024	0.0007	0.0004

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.
 Note: All specifications are estimated in first differences. Liquor distance at $t + 1$ is excluded as it contains information about distances at time t since $\Delta d_{it+1} = d_{it+1} - d_{it}$. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

A.2 Negative Binomial Model Results

Table 14 shows results for the the fixed-effects model from Section 7 estimated in levels via a negative binomial model. The model is specifically designed to account for the discrete and non-negative character of crime counts, as well as the over-dispersion that is common in applications. A Hausman specification test fails to reject the null hypothesis of equivalence between random and fixed effects models, and I present random effects results which are more precisely estimated. The columns corresponds to the five categories of crime. For comparison to the previous results, all estimates can be compared to Column (6) of the tables from Section 7.²⁷

In Table 14 we see the same basic pattern of results as in the linear fixed-effects model. All significant coefficients are negative. The effect on total crime is significant in Column (1), as is the effect on nonviolent crime and shoplifting in Columns (3) and (4). As above, violent crime is affected by the first lag of liquor distance, although it is imprecisely estimated and fails to reach conventional levels of significance. The effect on drug crime is more ambiguous, as only the second lag appears to have a significant effect. Overall, the results are broadly similar to those presented in Section 7.

²⁷I do not report marginal effects for the estimated negative binomial coefficients; they are available from the author upon request.

Table 14: Regression of Distance to the Nearest Liquor Retailer on Various Crimes, Estimated in Levels via a Negative Binomial Model (Random Effects) at the Census-Tract Level

Variable	(1)	(2)	(3)	(4)	(5)
Liquor Distance (t)	-0.0000156740*	-4.2506E-06	-0.0000214121*	-0.0000859802*	1.72877E-05
t-statistic	(-1.658)	(-0.289)	(-1.872)	(-1.806)	-0.294
Liquor Distance (t-1)	1.9063E-06	-2.20183E-05	1.00555E-05	-4.37374E-05	5.54507E-05
t-statistic	-0.186	(-1.395)	-0.804	(-0.868)	-0.858
Liquor Distance (t-2)	2.7424E-06	4.9473E-06	-7.624E-07	-3.07962E-05	-0.0001221544*
t-statistic	-0.272	-0.328	(-0.061)	(-0.688)	(-1.775)
Liquor Distance (t-3)	-6.6012E-06	1.10776E-05	-0.0000185290*	-7.179E-07	-2.55233E-05
t-statistic	(-0.724)	-0.825	(-1.664)	(-0.020)	(-0.449)
On-Premise Distance (t)	-0.00010174	-0.000174762	-0.000051142	3.12818E-05	0.000521203
t-statistic	(-1.210)	(-1.407)	(-0.492)	-0.064	-0.836
On-Premise Distance (t-1)	6.03599E-05	-8.32248E-05	0.000139851	0.000240944	3.00573E-05
t-statistic	-0.568	(-0.560)	-1.049	-0.372	-0.037
On-Premise Distance (t-2)	-0.000111017	-1.31039E-05	-0.000187082	-0.000466295	0.00030105
t-statistic	(-0.999)	(-0.089)	(-1.308)	(-0.676)	-0.324
On-Premise Distance (t-3)	-0.000136169	-0.000101789	-0.000153858	0.000227702	-0.001314974
t-statistic	(-1.336)	(-0.730)	(-1.206)	-0.404	(-1.494)
n	2,546	2,546	2,546	2,546	2,546

* **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

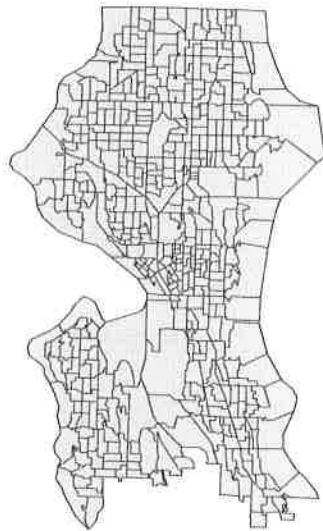
Note: All specifications include area and month fixed effects as well as area-specific linear time trends. I estimate via random effects. Reported coefficients are based on ten iterations of the MLE procedure employed by the *xtnbreg* Stata command. *t*-statistics are reported in parentheses.

A.3 Results for Additional Geographic Areas

Tables 15 to 39 show results of the fixed-effects model from Section 7 estimated using five additional geographic panels: Census block groups, Census tracts, 120 x 120 grid areas, 50 x 50 grid areas, and 25 x 25 grid areas. All tables are presented in the same format and order as in Section 7.

A.3.1 Results for Census Block Group Panel

Figure 7: 2010 Census Block Group Areas for Seattle ($N = 481$)



Source: Seattle Public Utilities GIS Unit.

Table 15: Regression Results for Census Block Group Panel Model (1 of 5)

Variable	(1) Total Crime	(2) Total Crime	(3) Total Crime	(4) Total Crime	(5) Total Crime	(6) Total Crime
Liquor Distance (t)	-3.96409***	-1.64464**	-0.90275***	-1.04243***	-1.02904***	-1.04086***
t-statistic	(-8.327)	(-2.422)	(-5.612)	(-6.269)	(-6.265)	(-5.908)
Effect / Mean	-38.4%	-15.9%	-8.8%	-10.1%	-10.0%	-10.1%
Liquor Distance (t-1)				-0.55962*	-0.55641*	-0.58115*
t-statistic				(-1.848)	(-1.865)	(-1.847)
Effect / Mean				-5.4%	-5.4%	-5.6%
Liquor Distance (t-2)					-0.05524	-0.11141
t-statistic					(-0.204)	(-0.401)
Effect / Mean					-0.5%	-1.1%
Liquor Distance (t-3)						-0.18569
t-statistic						(-0.694)
Effect / Mean						-1.8%
On-Premise Dist. (t)	-15.87732***	0.39643	0.07696	0.78144	0.78626	1.82999
t-statistic	(-20.321)	(0.301)	(0.021)	(0.233)	(0.231)	(0.562)
On-Premise Dist. (t-1)				3.14057	2.96050	3.15895
t-statistic				(1.179)	(1.139)	(1.187)
On-Premise Dist. (t-2)					-0.98465	-1.01016
t-statistic					(-0.438)	(-0.541)
On-Premise Dist. (t-3)						0.02419
t-statistic						(0.008)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,582	10,582	10,101	9,620	9,139	8,658
Within R-Squared	0.0676	0.0068	0.0801	0.0818	0.0842	0.0862

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 16: Regression Results for Census Block Group Panel Model (2 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Violent Crime	Violent Crime	Violent Crime	Violent Crime	Violent Crime	Violent Crime
Liquor Distance (t)	-1.63032***	-0.68827***	0.13790	-0.01969	0.02842	0.00612
t-statistic	(-7.687)	(-2.592)	(1.550)	(-0.185)	(0.252)	(0.057)
Effect / Mean	-48.2%	-20.3%	4.1%	-0.6%	0.8%	0.2%
Liquor Distance (t-1)				-0.58278***	-0.49369***	-0.52125***
t-statistic				(-3.817)	(-3.438)	(-3.262)
Effect / Mean				-17.2%	-14.6%	-15.4%
Liquor Distance (t-2)					0.22703	0.19324
t-statistic					(1.061)	(0.935)
Effect / Mean					6.7%	5.7%
Liquor Distance (t-3)						-0.05550
t-statistic						(-0.445)
Effect / Mean						-1.6%
On-Premise Dist. (t)	-6.30390***	-0.43938	-0.66761	-0.69065	-0.44085	-0.23560
t-statistic	(-17.569)	(-0.858)	(-0.545)	(-0.538)	(-0.332)	(-0.167)
On-Premise Dist. (t-1)				-0.17145	0.52415	0.76582
t-statistic				(-0.192)	(0.604)	(0.910)
On-Premise Dist. (t-2)					3.32152***	3.62735***
t-statistic					(3.415)	(4.856)
On-Premise Dist. (t-3)						0.99495
t-statistic						(0.502)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,582	10,582	10,101	9,620	9,139	8,658
Within R-Squared	0.0569	0.0046	0.0390	0.0401	0.0415	0.0426

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 17: Regression Results for Census Block Group Panel Model (3 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime
Liquor Distance (t)	-2.33377***	-0.95637**	-1.04065***	-1.02274***	-1.05746***	-1.04698***
t-statistic	(-8.581)	(-2.242)	(-4.660)	(-4.285)	(-4.392)	(-4.488)
Effect / Mean	-33.7%	-13.8%	-15.0%	-14.8%	-15.3%	-15.1%
Liquor Distance (t-1)				0.02316	-0.06273	-0.05990
t-statistic				(0.133)	(-0.333)	(-0.323)
Effect / Mean				0.3%	-0.9%	-0.9%
Liquor Distance (t-2)					-0.28227**	-0.30465**
t-statistic					(-2.226)	(-2.054)
Effect / Mean					-4.1%	-4.4%
Liquor Distance (t-3)						-0.13019
t-statistic						(-0.756)
Effect / Mean						-1.9%
On-Premise Dist. (t)	-9.57342***	0.83580	0.74457	1.47208	1.22711	2.06559
t-statistic	(-19.620)	(0.759)	(0.200)	(0.412)	(0.342)	(0.587)
On-Premise Dist. (t-1)				3.31202	2.43635	2.39313
t-statistic				(1.424)	(1.049)	(1.039)
On-Premise Dist. (t-2)					-4.30617**	-4.63752***
t-statistic					(-2.354)	(-2.630)
On-Premise Dist. (t-3)						-0.97076
t-statistic						(-0.697)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,582	10,582	10,101	9,620	9,139	8,658
Within R-Squared	0.0654	0.0040	0.0563	0.0582	0.0603	0.0622

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 18: Regression Results for Census Block Group Panel Model (4 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime
Liquor Distance (t)	-0.44175***	-0.09577***	-0.07644	-0.05892	-0.06544	-0.06388
t-statistic	(-5.178)	(-2.712)	(-1.463)	(-0.996)	(-1.119)	(-1.059)
Effect / Mean	-119.1%	-25.8%	-20.6%	-15.9%	-17.6%	-17.2%
Liquor Distance (t-1)				0.06632**	0.05173	0.05581
t-statistic				(2.135)	(1.601)	(1.508)
Effect / Mean				17.9%	13.9%	15.0%
Liquor Distance (t-2)					-0.04465*	-0.03388
t-statistic					(-1.798)	(-1.001)
Effect / Mean					-12.0%	-9.1%
Liquor Distance (t-3)						0.03852
t-statistic						(1.360)
Effect / Mean						10.4%
On-Premise Dist. (t)	-0.74798***	-0.17977	0.06970	0.07873	0.03001	-0.06323
t-statistic	(-13.035)	(-1.398)	(0.154)	(0.178)	(0.067)	(-0.157)
On-Premise Dist. (t-1)				-0.01008	-0.14392	-0.15861
t-statistic				(-0.038)	(-0.656)	(-0.766)
On-Premise Dist. (t-2)					-0.61812	-0.57595
t-statistic					(-1.575)	(-1.515)
On-Premise Dist. (t-3)						0.35278
t-statistic						(1.625)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,582	10,582	10,101	9,620	9,139	8,658
Within R-Squared	0.0416	0.0010	0.0127	0.0129	0.0132	0.0134

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 19: Regression Results for Census Block Group Panel Model (5 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Drug Crime	Drug Crime	Drug Crime	Drug Crime	Drug Crime	Drug Crime
Liquor Distance (t)	-0.21341***	0.00247	-0.25036**	-0.20872*	-0.22652*	-0.21407*
t-statistic	(-8.719)	(0.097)	(-2.239)	(-1.716)	(-1.897)	(-1.823)
Effect / Mean	-75.4%	0.9%	-88.5%	-73.8%	-80.1%	-75.7%
Liquor Distance (t-1)				0.15792**	0.11192	0.12880
t-statistic				(2.276)	(1.425)	(1.607)
Effect / Mean				55.8%	39.6%	45.5%
Liquor Distance (t-2)					-0.15624***	-0.13231**
t-statistic					(-2.612)	(-2.375)
Effect / Mean					-55.2%	-46.8%
Liquor Distance (t-3)						0.05156
t-statistic						(1.160)
Effect / Mean						18.2%
On-Premise Dist. (t)	-0.93417***	0.04676	-0.27353***	-0.20849*	-0.24061**	-0.22820**
t-statistic	(-21.157)	(0.655)	(-3.376)	(-1.923)	(-2.386)	(-2.018)
On-Premise Dist. (t-1)				0.32160**	0.25365	0.28193*
t-statistic				(2.018)	(1.559)	(1.692)
On-Premise Dist. (t-2)					-0.25115***	-0.20062***
t-statistic					(-3.270)	(-2.879)
On-Premise Dist. (t-3)						0.17197
t-statistic						(1.382)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,582	10,582	10,101	9,620	9,139	8,658
Within R-Squared	0.0156	0.0000	0.0055	0.0058	0.0061	0.0063

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

A.3.2 Results for Census Tract Panel

Figure 8: 2010 Census Tract Areas for Seattle ($N = 134$)



Source: Seattle Public Utilities GIS Unit.

Table 20: Regression Results for Census Tract Panel Model (1 of 5)

Variable	(1) Total Crime	(2) Total Crime	(3) Total Crime	(4) Total Crime	(5) Total Crime	(6) Total Crime
Liquor Distance (t)	-12.59758***	-5.41300**	-3.18696***	-3.46539***	-3.35341***	-3.33587***
t-statistic	(-10.540)	(-2.370)	(-4.232)	(-4.247)	(-4.119)	(-3.829)
Effect / Mean	-34.0%	-14.6%	-8.6%	-9.4%	-9.1%	-9.0%
Liquor Distance (t-1)				-1.10994	-0.95478	-0.92407
t-statistic				(-1.267)	(-1.010)	(-0.864)
Effect / Mean				-3.0%	-2.6%	-2.5%
Liquor Distance (t-2)					0.20774	0.30879
t-statistic					(0.169)	(0.246)
Effect / Mean					0.6%	0.8%
Liquor Distance (t-3)						0.44682
t-statistic						(0.343)
Effect / Mean						1.2%
On-Premise Dist. (t)	-52.82138***	0.33152	-0.82225	-0.60477	-1.26002	-0.43588
t-statistic	(-15.872)	(0.099)	(-0.100)	(-0.082)	(-0.167)	(-0.057)
On-Premise Dist. (t-1)				4.82003	1.57533	2.50446
t-statistic				(0.388)	(0.133)	(0.209)
On-Premise Dist. (t-2)					-24.67295**	-20.70122***
t-statistic					(-1.997)	(-2.894)
On-Premise Dist. (t-3)						32.10909
t-statistic						(0.798)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	2,948	2,948	2,814	2,680	2,546	2,412
Within R-Squared	0.1444	0.0131	0.2103	0.2135	0.2198	0.2246

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 21: Regression Results for Census Tract Panel Model (2 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Violent Crime	Violent Crime	Violent Crime	Violent Crime	Violent Crime	Violent Crime
Liquor Distance (t)	-4.95276***	-2.19264**	0.70409**	0.24312	0.35992	0.39398
t-statistic	(-10.241)	(-2.431)	(2.360)	(0.679)	(0.908)	(1.093)
Effect / Mean	-40.7%	-18.0%	5.8%	2.0%	3.0%	3.2%
Liquor Distance (t-1)				-1.64024***	-1.36879***	-1.29302**
t-statistic				(-3.730)	(-3.053)	(-2.470)
Effect / Mean				-13.5%	-11.3%	-10.6%
Liquor Distance (t-2)					0.85625	1.09611*
t-statistic					(1.211)	(1.722)
Effect / Mean					7.0%	9.0%
Liquor Distance (t-3)						0.95080***
t-statistic						(2.826)
Effect / Mean						7.8%
On-Premise Dist. (t)	-20.12985***	-4.55591**	-8.01739	-8.88752*	-8.87672*	-8.57838*
t-statistic	(-11.991)	(-2.428)	(-1.383)	(-1.843)	(-1.858)	(-1.680)
On-Premise Dist. (t-1)				-2.05680	-2.67137	-2.15909
t-statistic				(-0.211)	(-0.274)	(-0.221)
On-Premise Dist. (t-2)					-4.38148	-3.73242
t-statistic					(-0.619)	(-0.659)
On-Premise Dist. (t-3)						3.16831
t-statistic						(0.157)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	2,948	2,948	2,814	2,680	2,546	2,412
Within R-Squared	0.1192	0.0093	0.1155	0.1183	0.1215	0.1246

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 22: Regression Results for Census Tract Panel Model (3 of 5)

Variable	(1) Nonviolent Crime	(2) Nonviolent Crime	(3) Nonviolent Crime	(4) Nonviolent Crime	(5) Nonviolent Crime	(6) Nonviolent Crime
Liquor Distance (t)	-7.64482***	-3.22036**	-3.89105***	-3.70851***	-3.71334***	-3.72985***
t-statistic	(-9.813)	(-2.241)	(-4.353)	(-3.788)	(-3.781)	(-3.819)
Effect / Mean	-30.7%	-12.9%	-15.6%	-14.9%	-14.9%	-15.0%
Liquor Distance (t-1)				0.53030	0.41401	0.36895
t-statistic				(0.851)	(0.610)	(0.500)
Effect / Mean				2.1%	1.7%	1.5%
Liquor Distance (t-2)					-0.64851	-0.78732
t-statistic					(-0.817)	(-0.894)
Effect / Mean					-2.6%	-3.2%
Liquor Distance (t-3)						-0.50398
t-statistic						(-0.488)
Effect / Mean						-2.0%
On-Premise Dist. (t)	-32.69152***	4.88743	7.19514	8.28275	7.61669	8.14251
t-statistic	(-17.952)	(1.536)	(0.951)	(1.100)	(0.982)	(1.074)
On-Premise Dist. (t-1)				6.87683	4.24670	4.66354
t-statistic				(1.166)	(0.738)	(0.748)
On-Premise Dist. (t-2)					-20.29147**	-16.96880***
t-statistic					(-2.243)	(-2.796)
On-Premise Dist. (t-3)						28.94078
t-statistic						(1.210)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	2,948	2,948	2,814	2,680	2,546	2,412
Within R-Squared	0.1479	0.0089	0.1610	0.1647	0.1701	0.1752

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 23: Regression Results for Census Tract Panel Model (4 of 5)

Variable	(1) Shoplifting Crime	(2) Shoplifting Crime	(3) Shoplifting Crime	(4) Shoplifting Crime	(5) Shoplifting Crime	(6) Shoplifting Crime
Liquor Distance (t)	-1.32814***	-0.32379***	-0.02467	-0.01411	-0.02950	-0.04119
t-statistic	(-6.874)	(-3.049)	(-0.185)	(-0.106)	(-0.222)	(-0.309)
Effect / Mean	-99.8%	-24.3%	-1.9%	-1.1%	-2.2%	-3.1%
Liquor Distance (t-1)				-0.00806	-0.03705	-0.05671
t-statistic				(-0.074)	(-0.398)	(-0.538)
Effect / Mean				-0.6%	-2.8%	-4.3%
Liquor Distance (t-2)					-0.07924	-0.12140
t-statistic					(-0.517)	(-0.734)
Effect / Mean					-6.0%	-9.1%
Liquor Distance (t-3)						-0.13069
t-statistic						(-0.918)
Effect / Mean						-9.8%
On-Premise Dist. (t)	-1.78107***	0.94000**	-0.29223	-0.18973	-0.36853	-0.36002
t-statistic	(-10.465)	(2.295)	(-0.122)	(-0.082)	(-0.158)	(-0.159)
On-Premise Dist. (t-1)				0.76474	0.39393	0.45049
t-statistic				(0.599)	(0.371)	(0.359)
On-Premise Dist. (t-2)					-2.24596	-1.69528
t-statistic					(-1.453)	(-1.603)
On-Premise Dist. (t-3)						4.77470*
t-statistic						(1.922)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	2,948	2,948	2,814	2,680	2,546	2,412
Within R-Squared	0.0833	0.0026	0.0409	0.0414	0.0421	0.0427

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 24: Regression Results for Census Tract Panel Model (5 of 5)

Variable	(1) Drug Crime	(2) Drug Crime	(3) Drug Crime	(4) Drug Crime	(5) Drug Crime	(6) Drug Crime
Liquor Distance (t)	-0.65216***	0.03231	-0.97420***	-0.77100*	-0.83697**	-0.79809**
t-statistic	(-8.202)	(0.419)	(-2.733)	(-1.954)	(-2.168)	(-2.081)
Effect / Mean	-64.2%	3.2%	-95.9%	-75.9%	-82.4%	-78.6%
Liquor Distance (t-1)				0.77970***	0.60457*	0.66171*
t-statistic				(2.655)	(1.805)	(1.947)
Effect / Mean				76.8%	59.5%	65.2%
Liquor Distance (t-2)					-0.60845**	-0.50627**
t-statistic					(-2.505)	(-2.054)
Effect / Mean					-59.9%	-49.8%
Liquor Distance (t-3)						0.28638**
t-statistic						(2.143)
Effect / Mean						28.2%
On-Premise Dist. (t)	-3.12666***	0.97884***	0.04822	0.16294	0.04879	0.05349
t-statistic	(-23.536)	(3.041)	(0.089)	(0.303)	(0.103)	(0.105)
On-Premise Dist. (t-1)				0.55429	0.45382	0.41611
t-statistic				(0.911)	(0.674)	(0.739)
On-Premise Dist. (t-2)					-0.47161	-0.78573
t-statistic					(-0.407)	(-0.839)
On-Premise Dist. (t-3)						-2.43349
t-statistic						(-1.374)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	2,948	2,948	2,814	2,680	2,546	2,412
Within R-Squared	0.0411	0.0002	0.0203	0.0220	0.0232	0.0243

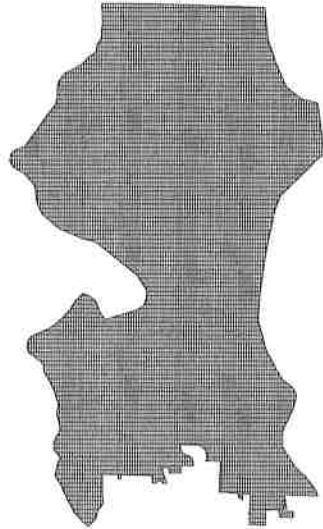
*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

A.3.3 Results for 120 x 120 Grid Panel

Figure 9: 120 x 120 Uniform Grid Areas for Seattle ($N = 9,586$)



Source: Author's calculations based on GIS boundary files provided by Seattle Public Utilities.

Table 25: Regression Results for 120 x 120 Grid Panel Model (1 of 5)

Variable	(1) Total Crime	(2) Total Crime	(3) Total Crime	(4) Total Crime	(5) Total Crime	(6) Total Crime
Liquor Distance (t)	-0.37688***	-0.07955**	-0.02697***	-0.03456***	-0.03328***	-0.03379***
t-statistic	(-6.409)	(-2.339)	(-4.189)	(-6.151)	(-5.916)	(-6.127)
Effect / Mean	-72.7%	-15.4%	-5.2%	-6.7%	-6.4%	-6.5%
Liquor Distance (t-1)				-0.02892***	-0.02695**	-0.02790**
t-statistic				(-2.858)	(-2.529)	(-2.563)
Effect / Mean				-5.6%	-5.2%	-5.4%
Liquor Distance (t-2)					0.00391	0.00149
t-statistic					(0.446)	(0.130)
Effect / Mean					0.8%	0.3%
Liquor Distance (t-3)						-0.00847
t-statistic						(-0.681)
Effect / Mean						-1.6%
On-Premise Dist. (t)	-0.83327***	-0.02288	-0.10727	-0.09693	-0.08763	-0.02912
t-statistic	(-21.974)	(-0.294)	(-0.684)	(-0.648)	(-0.614)	(-0.215)
On-Premise Dist. (t-1)				0.02532	0.02643	0.04154
t-statistic				(0.250)	(0.241)	(0.376)
On-Premise Dist. (t-2)					0.00724	0.03920
t-statistic					(0.105)	(0.482)
On-Premise Dist. (t-3)						0.10786
t-statistic						(1.043)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	210,892	210,892	201,306	191,720	182,134	172,548
Within R-Squared	0.0542	0.0005	0.0053	0.0055	0.0056	0.0058

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 26: Regression Results for 120 x 120 Grid Panel Model (2 of 5)

Variable	(1) Violent Crime	(2) Violent Crime	(3) Violent Crime	(4) Violent Crime	(5) Violent Crime	(6) Violent Crime
Liquor Distance (t)	-0.13182***	-0.03507***	0.00524***	-0.00227	-0.00046	-0.00209
t-statistic	(-6.550)	(-2.630)	(2.708)	(-0.772)	(-0.152)	(-0.646)
Effect / Mean	-77.5%	-20.6%	3.1%	-1.3%	-0.3%	-1.2%
Liquor Distance (t-1)				-0.02795***	-0.02426***	-0.02631***
t-statistic				(-5.665)	(-4.497)	(-4.511)
Effect / Mean				-16.4%	-14.3%	-15.5%
Liquor Distance (t-2)					0.01023	0.00745
t-statistic					(1.604)	(0.935)
Effect / Mean					6.0%	4.4%
Liquor Distance (t-3)						-0.00556
t-statistic						(-0.876)
Effect / Mean						-3.3%
On-Premise Dist. (t)	-0.29290***	-0.01538	-0.04859	-0.06728	-0.07098	-0.05402
t-statistic	(-25.427)	(-0.783)	(-0.816)	(-1.111)	(-1.162)	(-0.842)
On-Premise Dist. (t-1)				-0.06770	-0.07388	-0.05826
t-statistic				(-1.260)	(-1.391)	(-1.109)
On-Premise Dist. (t-2)					-0.00985	0.02577
t-statistic					(-0.201)	(0.496)
On-Premise Dist. (t-3)						0.10534
t-statistic						(1.293)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	210,892	210,892	201,306	191,720	182,134	172,548
Within R-Squared	0.0298	0.0003	0.0023	0.0023	0.0024	0.0025

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 27: Regression Results for 120 x 120 Grid Panel Model (3 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime
Liquor Distance (t)	-0.24506***	-0.04447**	-0.03221***	-0.03229***	-0.03282***	-0.03170***
t-statistic	(-6.298)	(-2.095)	(-4.438)	(-4.655)	(-4.695)	(-4.849)
Effect / Mean	-70.4%	-12.8%	-9.3%	-9.3%	-9.4%	-9.1%
Liquor Distance (t-1)				-0.00097	-0.00268	-0.00159
t-statistic				(-0.145)	(-0.361)	(-0.228)
Effect / Mean				-0.3%	-0.8%	-0.5%
Liquor Distance (t-2)					-0.00632	-0.00596
t-statistic					(-1.449)	(-1.137)
Effect / Mean					-1.8%	-1.7%
Liquor Distance (t-3)						-0.00291
t-statistic						(-0.419)
Effect / Mean						-0.8%
On-Premise Dist. (t)	-0.54037***	-0.00750	-0.05869	-0.02965	-0.01665	0.02490
t-statistic	(-18.948)	(-0.092)	(-0.420)	(-0.227)	(-0.137)	(0.208)
On-Premise Dist. (t-1)				0.09302	0.10031	0.09980
t-statistic				(1.021)	(1.047)	(1.070)
On-Premise Dist. (t-2)					0.01708	0.01343
t-statistic					(0.235)	(0.194)
On-Premise Dist. (t-3)						0.00252
t-statistic						(0.044)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	210,892	210,892	201,306	191,720	182,134	172,548
Within R-Squared	0.0539	0.0003	0.0036	0.0037	0.0038	0.0039

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 28: Regression Results for 120 x 120 Grid Panel Model (4 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime	Shoplifting Crime
Liquor Distance (t)	-0.02539***	-0.00642***	-0.00684***	-0.00642***	-0.00657***	-0.00653***
t-statistic	(-4.975)	(-3.319)	(-4.569)	(-3.504)	(-3.440)	(-3.331)
Effect / Mean	-136.4%	-34.5%	-36.8%	-34.5%	-35.3%	-35.1%
Liquor Distance (t-1)				0.00153	0.00147	0.00155
t-statistic				(1.225)	(0.962)	(0.908)
Effect / Mean				8.2%	7.9%	8.3%
Liquor Distance (t-2)					0.00040	0.00048
t-statistic					(0.230)	(0.226)
Effect / Mean					2.1%	2.6%
Liquor Distance (t-3)						0.00010
t-statistic						(0.055)
Effect / Mean						0.5%
On-Premise Dist. (t)	-0.03057***	-0.01098*	-0.00618	-0.00841	-0.00890	-0.01191
t-statistic	(-8.529)	(-1.660)	(-0.601)	(-0.831)	(-0.837)	(-1.212)
On-Premise Dist. (t-1)				-0.00791	-0.01026**	-0.01018**
t-statistic				(-1.448)	(-2.409)	(-2.419)
On-Premise Dist. (t-2)					-0.01639	-0.01148
t-statistic					(-1.102)	(-1.015)
On-Premise Dist. (t-3)						0.02205
t-statistic						(1.419)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	210,892	210,892	201,306	191,720	182,134	172,548
Within R-Squared	0.0067	0.0001	0.0006	0.0006	0.0007	0.0007

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 29: Regression Results for 120 x 120 Grid Panel Model (5 of 5)

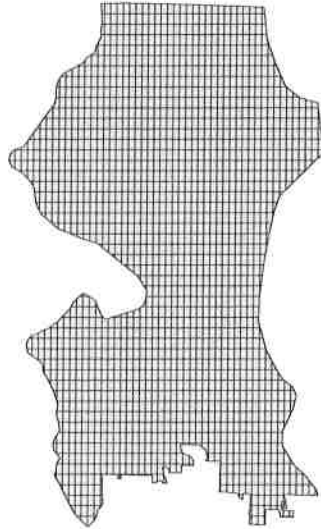
Variable	(1) Drug Crime	(2) Drug Crime	(3) Drug Crime	(4) Drug Crime	(5) Drug Crime	(6) Drug Crime
Liquor Distance (t)	-0.01304***	-0.00016	-0.00438**	-0.00338	-0.00355*	-0.00312
t-statistic	(-7.787)	(-0.139)	(-2.130)	(-1.547)	(-1.779)	(-1.580)
Effect / Mean	-91.7%	-1.1%	-30.8%	-23.8%	-25.0%	-21.9%
Liquor Distance (t-1)				0.00403*	0.00323	0.00381
t-statistic				(1.800)	(1.265)	(1.476)
Effect / Mean				28.3%	22.7%	26.8%
Liquor Distance (t-2)					-0.00336**	-0.00247**
t-statistic					(-2.331)	(-2.063)
Effect / Mean					-23.6%	-17.4%
Liquor Distance (t-3)						0.00211
t-statistic						(1.544)
Effect / Mean						14.8%
On-Premise Dist. (t)	-0.03005***	-0.00458	-0.01429	-0.01757	-0.01388	-0.01182
t-statistic	(-16.112)	(-0.568)	(-1.027)	(-0.993)	(-1.002)	(-0.727)
On-Premise Dist. (t-1)				-0.01757	-0.00374	-0.00452
t-statistic				(-0.601)	(-0.181)	(-0.218)
On-Premise Dist. (t-2)					0.05255	0.04799
t-statistic					(1.009)	(1.028)
On-Premise Dist. (t-3)						-0.01437
t-statistic						(-0.500)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	210,892	210,892	201,306	191,720	182,134	172,548
Within R-Squared	0.0033	0.0000	0.0003	0.0003	0.0003	0.0004

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

A.3.4 Results for 50 x 50 Grid Panel

Figure 10: 50 x 50 Uniform Grid Areas for Seattle ($N = 1,747$)



Source: Author's calculations.

Table 30: Regression Results for 50 x 50 Grid Panel Model (1 of 5)

Variable	(1) Total Crime	(2) Total Crime	(3) Total Crime	(4) Total Crime	(5) Total Crime	(6) Total Crime
Liquor Distance (t)	-2.14710***	-0.45159**	-0.11036**	-0.16431***	-0.15880***	-0.16057***
t-statistic	(-6.502)	(-2.399)	(-2.459)	(-4.358)	(-4.135)	(-4.557)
Effect / Mean	-75.5%	-15.9%	-3.9%	-5.8%	-5.6%	-5.6%
Liquor Distance (t-1)				-0.20060***	-0.18943***	-0.19539***
t-statistic				(-3.424)	(-2.927)	(-2.960)
Effect / Mean				-7.1%	-6.7%	-6.9%
Liquor Distance (t-2)					0.03050	0.01214
t-statistic					(0.540)	(0.165)
Effect / Mean					1.1%	0.4%
Liquor Distance (t-3)						-0.07015
t-statistic						(-0.961)
Effect / Mean						-2.5%
On-Premise Dist. (t)	-4.25246***	0.02422	-0.13207	-0.06884	-0.07855	0.11659
t-statistic	(-20.271)	(0.086)	(-0.223)	(-0.122)	(-0.150)	(0.220)
On-Premise Dist. (t-1)				0.38542	0.20113	0.20290
t-statistic				(0.866)	(0.423)	(0.437)
On-Premise Dist. (t-2)					-0.86092***	-0.88930**
t-statistic					(-3.056)	(-2.295)
On-Premise Dist. (t-3)						-0.25077
t-statistic						(-0.264)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	38,434	38,434	36,687	34,940	33,193	31,446
Within R-Squared	0.1039	0.0023	0.0228	0.0234	0.0241	0.0247

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 31: Regression Results for 50 x 50 Grid Panel Model (2 of 5)

Variable	(1) Violent Crime	(2) Violent Crime	(3) Violent Crime	(4) Violent Crime	(5) Violent Crime	(6) Violent Crime
Liquor Distance (t)	-0.75378***	-0.20063***	0.00714	-0.03313**	-0.02558*	-0.03106**
t-statistic	(-6.593)	(-2.737)	(0.583)	(-2.200)	(-1.661)	(-2.036)
Effect / Mean	-80.8%	-21.5%	0.8%	-3.5%	-2.7%	-3.3%
Liquor Distance (t-1)				-0.14842***	-0.13267***	-0.14010***
t-statistic				(-5.062)	(-4.338)	(-4.091)
Effect / Mean				-15.9%	-14.2%	-15.0%
Liquor Distance (t-2)					0.04493	0.03676
t-statistic					(1.105)	(0.776)
Effect / Mean					4.8%	3.9%
Liquor Distance (t-3)						-0.01014
t-statistic						(-0.305)
Effect / Mean						-1.1%
On-Premise Dist. (t)	-1.47337***	-0.04945	-0.25284	-0.32063	-0.34787	-0.28717
t-statistic	(-24.496)	(-0.461)	(-0.844)	(-1.104)	(-1.209)	(-0.875)
On-Premise Dist. (t-1)				-0.22365	-0.28438	-0.25888
t-statistic				(-1.035)	(-1.372)	(-1.541)
On-Premise Dist. (t-2)					-0.09800	-0.09186
t-statistic					(-0.361)	(-0.250)
On-Premise Dist. (t-3)						-0.29178
t-statistic						(-0.514)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	38,434	38,434	36,687	34,940	33,193	31,446
Within R-Squared	0.0654	0.0015	0.0099	0.0101	0.0104	0.0106

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 32: Regression Results for 50 x 50 Grid Panel Model (3 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime	Nonviolent Crime
Liquor Distance (t)	-1.39332***	-0.25095**	-0.11750**	-0.13119***	-0.13322***	-0.12951***
t-statistic	(-6.421)	(-2.125)	(-2.516)	(-2.979)	(-3.019)	(-3.330)
Effect / Mean	-73.0%	-13.1%	-6.2%	-6.9%	-7.0%	-6.8%
Liquor Distance (t-1)				-0.05218	-0.05676	-0.05529
t-statistic				(-1.357)	(-1.280)	(-1.307)
Effect / Mean				-2.7%	-3.0%	-2.9%
Liquor Distance (t-2)					-0.01443	-0.02462
t-statistic					(-0.519)	(-0.724)
Effect / Mean					-0.8%	-1.3%
Liquor Distance (t-3)						-0.06001
t-statistic						(-1.371)
Effect / Mean						-3.1%
On-Premise Dist. (t)	-2.77909***	0.07367	0.12076	0.25179	0.26932	0.40376
t-statistic	(-17.655)	(0.229)	(0.228)	(0.504)	(0.606)	(0.951)
On-Premise Dist. (t-1)				0.60907	0.48551	0.46177
t-statistic				(1.640)	(1.151)	(1.146)
On-Premise Dist. (t-2)					-0.76292***	-0.79744***
t-statistic					(-3.467)	(-3.668)
On-Premise Dist. (t-3)						0.04101
t-statistic						(0.062)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	38,434	38,434	36,687	34,940	33,193	31,446
Within R-Squared	0.1153	0.0012	0.0166	0.0171	0.0177	0.0182

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 33: Regression Results for 50 x 50 Grid Panel Model (4 of 5)

Variable	(1) Shoplifting Crime	(2) Shoplifting Crime	(3) Shoplifting Crime	(4) Shoplifting Crime	(5) Shoplifting Crime	(6) Shoplifting Crime
Liquor Distance (t)	-0.13728***	-0.03271***	-0.02896**	-0.02729*	-0.02876**	-0.02897**
t-statistic	(-5.439)	(-3.419)	(-2.254)	(-1.910)	(-2.019)	(-1.997)
Effect / Mean	-134.4%	-32.0%	-28.4%	-26.7%	-28.2%	-28.4%
Liquor Distance (t-1)				0.00552	0.00276	0.00280
t-statistic				(0.760)	(0.319)	(0.285)
Effect / Mean				5.4%	2.7%	2.7%
Liquor Distance (t-2)					-0.00708	-0.00689
t-statistic					(-0.815)	(-0.635)
Effect / Mean					-6.9%	-6.7%
Liquor Distance (t-3)						0.00065
t-statistic						(0.064)
Effect / Mean						0.6%
On-Premise Dist. (t)	-0.14942***	-0.00663	0.08635	0.07179	0.06873	0.04753
t-statistic	(-8.501)	(-0.191)	(1.361)	(1.173)	(1.080)	(1.030)
On-Premise Dist. (t-1)				-0.06286	-0.08365**	-0.08123*
t-statistic				(-1.358)	(-2.217)	(-1.778)
On-Premise Dist. (t-2)					-0.08811	-0.04859
t-statistic					(-1.106)	(-0.759)
On-Premise Dist. (t-3)						0.15473**
t-statistic						(2.111)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	38,434	38,434	36,687	34,940	33,193	31,446
Within R-Squared	0.0277	0.0004	0.0033	0.0033	0.0034	0.0035

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 34: Regression Results for 50 x 50 Grid Panel Model (5 of 5)

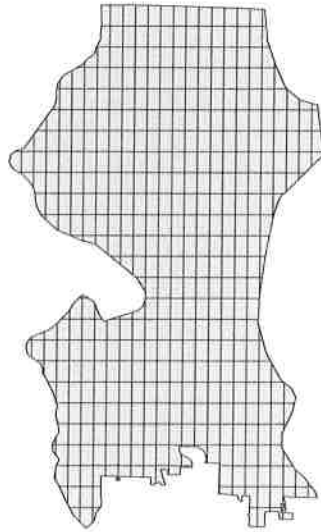
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Drug Crime	Drug Crime	Drug Crime	Drug Crime	Drug Crime	Drug Crime
Liquor Distance (t)	-0.07644***	-0.00121	-0.01286	-0.00912	-0.00883	-0.00755
t-statistic	(-7.217)	(-0.199)	(-1.249)	(-0.874)	(-0.912)	(-0.795)
Effect / Mean	-98.0%	-1.6%	-16.5%	-11.7%	-11.3%	-9.7%
Liquor Distance (t-1)				0.01513	0.01413	0.01527
t-statistic				(1.265)	(1.080)	(1.133)
Effect / Mean				19.4%	18.1%	19.6%
Liquor Distance (t-2)					-0.00688	-0.00608
t-statistic					(-0.808)	(-0.832)
Effect / Mean					-8.8%	-7.8%
Liquor Distance (t-3)						-0.00081
t-statistic						(-0.120)
Effect / Mean						-1.0%
On-Premise Dist. (t)	-0.14343***	-0.04994	-0.07487	-0.10193	-0.09246	-0.12993
t-statistic	(-12.989)	(-1.356)	(-1.013)	(-1.052)	(-1.193)	(-1.391)
On-Premise Dist. (t-1)				-0.13252	-0.06946	-0.08608
t-statistic				(-0.822)	(-0.701)	(-0.740)
On-Premise Dist. (t-2)					0.29932	0.23832
t-statistic					(1.001)	(1.083)
On-Premise Dist. (t-3)						-0.28131
t-statistic						(-0.962)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	38,434	38,434	36,687	34,940	33,193	31,446
Within R-Squared	0.0085	0.0000	0.0013	0.0013	0.0014	0.0014

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

A.3.5 Results for 25 x 25 Grid Panel

Figure 11: 25 x 25 Uniform Grid Areas for Seattle ($N = 465$)



Source: Author's calculations.

Table 35: Regression Results for 25 x 25 Grid Panel Model (1 of 5)

Variable	(1) Total Crime	(2) Total Crime	(3) Total Crime	(4) Total Crime	(5) Total Crime	(6) Total Crime
Liquor Distance (t)	-8.62876***	-1.73416**	-0.63203***	-0.77262***	-0.74151***	-0.74981***
t-statistic	(-6.642)	(-2.497)	(-3.092)	(-3.742)	(-3.722)	(-3.837)
Effect / Mean	-80.8%	-16.2%	-5.9%	-7.2%	-6.9%	-7.0%
Liquor Distance (t-1)				-0.51095*	-0.45533*	-0.47240*
t-statistic				(-1.945)	(-1.673)	(-1.655)
Effect / Mean				-4.8%	-4.3%	-4.4%
Liquor Distance (t-2)					0.12556	0.08430
t-statistic					(0.453)	(0.262)
Effect / Mean					1.2%	0.8%
Liquor Distance (t-3)						-0.14301
t-statistic						(-0.427)
Effect / Mean						-1.3%
On-Premise Dist. (t)	-14.74164***	-0.75987	-0.21847	0.31265	0.34897	1.08817
t-statistic	(-17.085)	(-0.476)	(-0.078)	(0.111)	(0.132)	(0.452)
On-Premise Dist. (t-1)				2.74785	2.31463	2.47994
t-statistic				(1.087)	(0.876)	(0.981)
On-Premise Dist. (t-2)					-2.46031	-2.42493
t-statistic					(-0.792)	(-0.766)
On-Premise Dist. (t-3)						-0.07237
t-statistic						(-0.023)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,230	10,230	9,765	9,300	8,835	8,370
Within R-Squared	0.1527	0.0063	0.0648	0.0663	0.0682	0.0696

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 36: Regression Results for 25 x 25 Grid Panel Model (2 of 5)

Variable	(1) Violent Crime	(2) Violent Crime	(3) Violent Crime	(4) Violent Crime	(5) Violent Crime	(6) Violent Crime
Liquor Distance (t)	-3.05834***	-0.72275***	0.03898	-0.08132	-0.05119	-0.07353
t-statistic	(-6.655)	(-2.666)	(0.687)	(-1.541)	(-0.846)	(-1.074)
Effect / Mean	-87.2%	-20.6%	1.1%	-2.3%	-1.5%	-2.1%
Liquor Distance (t-1)				-0.45734***	-0.39590***	-0.42407***
t-statistic				(-3.810)	(-3.256)	(-3.099)
Effect / Mean				-13.0%	-11.3%	-12.1%
Liquor Distance (t-2)					0.17264	0.14760
t-statistic					(1.283)	(0.931)
Effect / Mean					4.9%	4.2%
Liquor Distance (t-3)						-0.00803
t-statistic						(-0.061)
Effect / Mean						-0.2%
On-Premise Dist. (t)	-5.03821***	0.05251	-0.08388	-0.10772	-0.19305	0.07679
t-statistic	(-21.383)	(0.194)	(-0.078)	(-0.095)	(-0.170)	(0.073)
On-Premise Dist. (t-1)				0.15578	0.02227	0.20447
t-statistic				(0.155)	(0.018)	(0.176)
On-Premise Dist. (t-2)					-0.11951	-0.09895
t-statistic					(-0.068)	(-0.053)
On-Premise Dist. (t-3)						-0.62796
t-statistic						(-0.501)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,230	10,230	9,765	9,300	8,835	8,370
Within R-Squared	0.1063	0.0040	0.0316	0.0324	0.0330	0.0338

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 37: Regression Results for 25 x 25 Grid Panel Model (3 of 5)

Variable	(1) Nonviolent Crime	(2) Nonviolent Crime	(3) Nonviolent Crime	(4) Nonviolent Crime	(5) Nonviolent Crime	(6) Nonviolent Crime
Liquor Distance (t)	-5.57042***	-1.01141**	-0.67101***	-0.69130***	-0.69033***	-0.67628***
t-statistic	(-6.600)	(-2.321)	(-3.909)	(-3.947)	(-4.091)	(-4.263)
Effect / Mean	-77.6%	-14.1%	-9.4%	-9.6%	-9.6%	-9.4%
Liquor Distance (t-1)				-0.05361	-0.05944	-0.04832
t-statistic				(-0.328)	(-0.334)	(-0.279)
Effect / Mean				-0.7%	-0.8%	-0.7%
Liquor Distance (t-2)					-0.04707	-0.06331
t-statistic					(-0.281)	(-0.327)
Effect / Mean					-0.7%	-0.9%
Liquor Distance (t-3)						-0.13498
t-statistic						(-0.581)
Effect / Mean						-1.9%
On-Premise Dist. (t)	-9.70343***	-0.81238	-0.13458	0.42037	0.54202	1.01138
t-statistic	(-15.149)	(-0.544)	(-0.067)	(0.215)	(0.312)	(0.618)
On-Premise Dist. (t-1)				2.59207	2.29236	2.27547
t-statistic				(1.449)	(1.329)	(1.357)
On-Premise Dist. (t-2)					-2.34079	-2.32598
t-statistic					(-1.142)	(-1.190)
On-Premise Dist. (t-3)						0.55559
t-statistic						(0.232)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,230	10,230	9,765	9,300	8,835	8,370
Within R-Squared	0.1752	0.0041	0.0505	0.0520	0.0538	0.0551

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 38: Regression Results for 25 x 25 Grid Panel Model (4 of 5)

Variable	(1) Shoplifting Crime	(2) Shoplifting Crime	(3) Shoplifting Crime	(4) Shoplifting Crime	(5) Shoplifting Crime	(6) Shoplifting Crime
Liquor Distance (t)	-0.47254***	-0.10884***	-0.08687**	-0.07932*	-0.08137*	-0.08010*
t-statistic	(-6.000)	(-3.254)	(-2.047)	(-1.760)	(-1.790)	(-1.725)
Effect / Mean	-123.2%	-28.4%	-22.6%	-20.7%	-21.2%	-20.9%
Liquor Distance (t-1)				0.02827	0.02290	0.02626
t-statistic				(1.244)	(0.819)	(0.807)
Effect / Mean				7.4%	6.0%	6.8%
Liquor Distance (t-2)					-0.01952	-0.01165
t-statistic					(-0.530)	(-0.262)
Effect / Mean					-5.1%	-3.0%
Liquor Distance (t-3)						0.02720
t-statistic						(0.764)
Effect / Mean						7.1%
On-Premise Dist. (t)	-0.52461***	-0.22385*	0.00459	0.01053	-0.00463	-0.02176
t-statistic	(-10.228)	(-1.698)	(0.018)	(0.047)	(-0.020)	(-0.078)
On-Premise Dist. (t-1)				0.06576	-0.01628	-0.00401
t-statistic				(0.207)	(-0.060)	(-0.014)
On-Premise Dist. (t-2)					-0.32881	-0.21685
t-statistic					(-1.271)	(-0.974)
On-Premise Dist. (t-3)						0.36795
t-statistic						(1.041)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,230	10,230	9,765	9,300	8,835	8,370
Within R-Squared	0.0792	0.0012	0.0117	0.0119	0.0122	0.0123

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences.

Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 39: Regression Results for 25 x 25 Grid Panel Model (5 of 5)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Drug Crime	Drug Crime	Drug Crime	Drug Crime	Drug Crime	Drug Crime
Liquor Distance (t)	-0.31557***	-0.00405	-0.03853	-0.02661	-0.02661	-0.02266
t-statistic	(-7.472)	(-0.193)	(-0.952)	(-0.663)	(-0.710)	(-0.643)
Effect / Mean	-107.6%	-1.4%	-13.1%	-9.1%	-9.1%	-7.7%
Liquor Distance (t-1)				0.04530	0.04184	0.04609
t-statistic				(0.992)	(0.826)	(0.863)
Effect / Mean				15.5%	14.3%	15.7%
Liquor Distance (t-2)					-0.01930	-0.01990
t-statistic					(-0.770)	(-0.768)
Effect / Mean					-6.6%	-6.8%
Liquor Distance (t-3)						-0.02136
t-statistic						(-0.850)
Effect / Mean						-7.3%
On-Premise Dist. (t)	-0.49453***	-0.05633	-0.06881	-0.01699	0.00578	0.05037
t-statistic	(-12.309)	(-0.573)	(-0.220)	(-0.057)	(0.020)	(0.162)
On-Premise Dist. (t-1)				0.22631	0.33295	0.34496
t-statistic				(0.990)	(1.438)	(1.558)
On-Premise Dist. (t-2)					0.12718	0.14446
t-statistic					(0.556)	(0.711)
On-Premise Dist. (t-3)						0.27349
t-statistic						(1.065)
Area Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	Yes	Yes
Area Time Trends	No	No	Yes	Yes	Yes	Yes
n	10,230	10,230	9,765	9,300	8,835	8,370
Within R-Squared	0.0207	0.0000	0.0047	0.0047	0.0048	0.0049

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Note: Columns (1) and (2) are estimated in levels; columns (3)–(6) are estimated in first differences. Robust t-statistics are reported in parentheses based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

A.4 Crime Classifications

Table 40 provides a crosswalk between individual offense codes from Seattle Police Department incident reports and the crime categories used in the empirical estimation. All incident report data are available for download at <https://data.seattle.gov/>.

Table 40: Crosswalk of Seattle Police Department Offense Codes into Crime Categories

Violent Crime (Including Alcohol-Related)		
ASSLT-AGG-BODYFORCE	HOMICIDE-JUST-GUN	ROBBERY-OTHER
ASSLT-AGG-GUN	HOMICIDE-NEG-MANS-BODYFORCE	ROBBERY-RESIDENCE-BODYFORCE
ASSLT-AGG-POLICE-BODYFORCE	HOMICIDE-NEG-MANS-VEHICLE	ROBBERY-RESIDENCE-GUN
ASSLT-AGG-POLICE-GUN	HOMICIDE-PREMEDITATED-BODYFORC	ROBBERY-RESIDENCE-WEAPON
ASSLT-AGG-POLICE-WEAPON	HOMICIDE-PREMEDITATED-GUN	ROBBERY-STREET-BODYFORCE
ASSLT-AGG-WEAPON	HOMICIDE-PREMEDITATED-WEAPON	ROBBERY-STREET-GUN
ASSLT-NONAGG	INJURY - ACCIDENTAL	ROBBERY-STREET-WEAPON
ASSLT-NONAGG-POLICE	INJURY - OTHER	THREATS-DIGNITARY
ASSLT-OTHER	LIQUOR LAW VIOLATION	THREATS-KILL
DISORDERLY CONDUCT	LOITERING	THREATS-OTHER
DISPUTE-CIVIL PROPERTY (AUTO)	MALICIOUS HARASSMENT	THREATS-WEAPON
DISPUTE-CIVIL PROPERTY (NON AU	PROPERTY DAMAGE - GRAFFITI	TRAFFIC
DISPUTE-OTH	PROPERTY DAMAGE-NON RESIDENTIA	TRESPASS
DISTURBANCE-NOISE	PROPERTY DAMAGE-RESIDENTIAL	URINATING/DEFECATING-IN PUBLIC
DISTURBANCE-OTH	RECKLESS BURNING	VIOL-COURT ORDER
DRIVE-BY	ROBBERY-BANK-BODYFORCE	WARRANT-FUGITIVE
DUI-LIQUOR	ROBBERY-BANK-BODYFORCE	WARRARR-FELONY
ELUDING-FELONY FLIGHT	ROBBERY-BANK-GUN	WARRARR-MISDEMEANOR
ENDANGER	ROBBERY-BANK-GUN	WEAPON-CONCEALED
ENDANGERMENT	ROBBERY-BANK-OTHER	WEAPON-DISCHARGE
ESCAPE	ROBBERY-BANK-WEAPON	WEAPON-POSSESSION
HARASSMENT	ROBBERY-BUSINESS-BODYFORCE	WEAPON-SURRENDER-EXCLUDING FIR
HARASSMENT	ROBBERY-BUSINESS-GUN	WEAPON-UNLAWFUL USE
HARBOR - BOATING UNDER INFLUEN	ROBBERY-BUSINESS-WEAPON	
Nonviolent Crime		
ANIMAL-BITE	FRAUD-WIRE-ELECTRONIC	THEFT OF SERVICES
ANIMAL-CRUELTY	GAMBLE-BETTING	THEFT-AUTO PARTS
ANIMAL-OTH	ILLEGAL DUMPING	THEFT-AUTOACC
BIAS INCIDENT	NARC-FORGERY-PRESCRIPTION	THEFT-BICYCLE
BURGLARY-FORCE-NONRES	NARC-FRAUD-PRESCRIPTION	THEFT-BOAT
BURGLARY-FORCE-RES	OBSTRUCT	THEFT-BUILDING
BURGLARY-NOFORCE-NONRES	PORNOGRAPHY-OBSCENE MATERIAL	
BURGLARY-NOFORCE-RES	PROP RECOVERED-OTHER AGENCY	
BURGLARY-SECURE PARKING-NONRES	PROPERTY FOUND	THEFT-CARPROWL
BURGLARY-SECURE PARKING-RES	PROPERTY LOST	THEFT-COINOP

Continued on next page

Table 40 - Continued from previous page

Nonviolent Crime	
COUNTERFEIT	THEFT-LICENSE PLATE
DUI-DRUGS	THEFT-MAIL
EMBEZZLE	THEFT-OTH
EXTORTION	THEFT-PKPOCKET
FALSE REPORT	THEFT-PRSNATCH
FIREWORK-POSSESS	THEFT-UNLAWFUL ISSUANCE OF BAN
FIREWORK-USE	VEH-RCVD-FOR OTHAGY
FORGERY-CHECK	VEH-RCVD-FOR OTHER AGENCY
FORGERY-CREDIT CARD	VEH-THEFT-AUTO
FORGERY-OTH	VEH-THEFT-BUS
FRAUD-CHECK	VEH-THEFT-HVYEQUIP
FRAUD-COMPUTER	VEH-THEFT-MTRCYCLE
FRAUD-CREDIT CARD	VEH-THEFT-OTHVEH
FRAUD-IDENTITY THEFT	VEH-THEFT-RECREATION VEH
FRAUD-IDENTITY THEFT	VEH-THEFT-TRAILER
FRAUD-OTHER	VEH-THEFT-TRUCK
FRAUD-WELFARE	WEAPON-SELLING
Shoplifting Crime	
THEFT-SHOPLIFT	
Drug Crime	
NARC-DISTRIBUTE-HALLUCINOGEN	NARC-SELL-COCAINE
NARC-DRUG TRAFFIC LOITERING	NARC-SELL-HALLUCINOGEN
NARC-EQUIPMENT/PARAPHENALIA	NARC-SELL-HEROIN
NARC-FOUND-AMPHETAMINE	NARC-SELL-MARIJU
NARC-FOUND-COCAINE	NARC-SELL-METH
NARC-FOUND-HALLUCINOGEN	NARC-SELL-OPIMUM
NARC-FOUND-HEROIN	NARC-SELL-OTHER
NARC-FOUND-MARIJU	NARC-SELL-PILL/TABLET
NARC-FOUND-METH	NARC-SELL-PRESCRIPTION
NARC-FOUND-OPIMUM	NARC-SELL-SYNTHETIC
NARC-FOUND-OTHER	NARC-SMUGGLE-COCAINE
NARC-FOUND-PILL/TABLET	NARC-SMUGGLE-MARIJU
NARC-MANUFACTURE-HALLUCINOGEN	NARC-SMUGGLE-METH
NARC-MANUFACTURE-OTHER	
NARC-POSSESS-AMPHETAMINE	
NARC-POSSESS-BARBITUATE	
NARC-POSSESS-COCAINE	
NARC-POSSESS-HALLUCINOGEN	
NARC-POSSESS-HEROIN	
NARC-POSSESS-MARIJU	
NARC-POSSESS-METH	
NARC-POSSESS-OPIMUM	
NARC-POSSESS-OTHER	
NARC-POSSESS-PILL/TABLET	
NARC-POSSESS-PRESCRIPTION	
NARC-POSSESS-SYNTHETIC	
NARC-PRODUCE-MARIJU	
NARC-SELL-AMPHETAMINE	

Alcohol Outlets and Community Levels of Interpersonal Violence: Spatial Density, Outlet Type, and Seriousness of Assault

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Abstract

This study examined the association between alcohol outlets and violence. Employing Cincinnati block groups as units of analysis, the authors estimated spatially lagged regression models to determine if the variation in spatial density of alcohol outlets is related to the spatial density of simple and aggravated assaults. The authors estimated separate models for off-premise outlets, bars, and restaurants. The results revealed a positive and significant association between outlet density and assault density. This association held for simple and aggravated assaults and for total outlet density and the density of each

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the data and must be interpreted with caution, computing and reporting AFs aids in (a) the accumulation of evidence via comparison of AFs from different studies and (b) assessing the plausibility of an estimated macro-level effect.⁴

Limitations of Current Study

Two main limitations in our study are associated with the dependent variable. First, we have no way of knowing which assaults included in our measure were alcohol-related (see Livingston 2008) or occurred at an alcohol outlet (see Block and Block 1995). Information about alcohol involvement is sometimes recorded as part of the police record of an event, though the absence of such information does not necessarily mean the event was not alcohol- and/or outlet-associated but only that police did not note it in the record. Second, our assault data depends on police records and thus the traditional limitations associated with them. Nevertheless, if reporting and recording procedures are similar across the units in our analysis, which is likely to be the case for serious violent crimes, then this limitation becomes less troublesome. Using National Crime Victimization Survey data, Baumer (2002) showed that neighborhood disadvantage is not significantly associated with reporting aggravated assault. Baumer did find an association between neighborhood disadvantage and reporting simple assault, however, which must be kept in mind when interpreting our results.

There may also be limitations associated with the set of independent variables included in our models. Most importantly, we were unable to control for actual alcohol sales or alcohol consumption within block groups.⁵ Similarly, we did not control for land use or other area characteristics that might be associated with heightened levels of violence, such as major intersections, public transportation nodes, illegal drug trade, and nighttime business centers (Block and Block 1995; Gruenewald et al. 2006; Roncek and Maier 1991).

General Policy Implications

Ecological explanations like collective efficacy, social disorganization, and social cohesion are consistently found to be associated with area violence rates. Yet most elements of these theories—poverty, ethnic heterogeneity, residential mobility, anonymity of community members, and willingness to intervene on others' behalf—are notoriously difficult to remedy via policy or other social mechanisms. Alcohol outlet density, on the other hand, is

more amenable to policy changes (Livingston, Chikritzhs, and Room 2007). The concentration of off-premise alcohol outlets can be reduced by limiting liquor permits, setting density thresholds, requiring new outlets to be outside some minimum distance from existing outlets, refusing to issue a new license when a former alcohol outlet has gone out of business (especially if the area already possesses problematic outlets or a high density of outlets), and limiting outlets in high risk areas such as socially disorganized communities and neighborhoods with a high concentration of college students. Liquor licensing boards can close outlets that have proven to be a public nuisance via repeatedly violating liquor laws or being a hot spot for crime. We know from the empirical literature on bars that alcohol-related problems are not distributed equally among bars and that management decisions and business practices are partly to blame. Similarly, we can identify the characteristics of high crime off-premise outlets and (a) encourage management to make more responsible decisions (Madensen and Eck 2008) and (b) target limited public resources on improving or eliminating these risky facilities (Eck, Clarke, and Guerette 2007).

Unlike other negative neighborhood characteristics that often seem intractable, regulating the density and management of alcohol outlets, especially off-premise outlets, can be more readily addressed with a mixture of policies by liquor licensing boards, police, and government agencies that regulate land use. These and other alcohol policies can promote responsible business practices and responsible drinking, and improve the quality of life in communities by limiting deviant places and reducing violence and other alcohol-related problems within neighborhoods. By doing so, such actions could even help promote local levels of social organization, social cohesion, and collective efficacy.

Avenues for Future Research by Criminologists on the Outlet-Violence Association

Our results, together with those of other criminologists (Nielsen and Martinez 2003; Parker, Luter, and Murphy 2007) and those from public health and epidemiology (e.g., Gorman et al. 2001; Gruenewald et al. 2006; Livingston 2008) suggest a prominent role for alcohol in the study of the social ecology of crime.

First, we must answer a more general question posed by Sherman et al. (1989:46) about hot spots of criminality. That is, do alcohol outlets “vary in their capacity to help *cause* crime, or merely in their frequency of *hosting* crime that was going to occur some place inevitably, regardless of the

Conclusion

Relative to abstract concepts like social disorganization and its variants, the mainstream criminological literature on social ecology and crime rates has paid little attention to tangible ecological characteristics that may influence violence rates. One characteristic that has been the topic of recent research in the epidemiology, public health, and geography literatures, however, is alcohol outlet density. We employed a more spatially appropriate measure of community alcohol outlet density, used smaller units of analysis that allow for greater resolution of community characteristics and thus are more theoretically and practically appropriate, controlled for spatial autocorrelation, examine various types of alcohol outlets to determine their differential effects on community violence, and computed AFs. Using Cincinnati block groups as our unit of analysis and simple and aggravated assaults as our dependent variables, we found a general pattern of association between outlet density and assault density. We also found that while the associations held for both simple and aggravated assaults, the association with simple assaults was stronger. Finally, for both simple and aggravated assaults, we found that the strength of the association with violence was significantly greater for off-premise outlets than for bars and restaurants.

In sum, alcohol outlet density appears to play an important role in community violence rates, and the strength of this association varies by outlet type. While alcohol consumption may have individual-level effects on violent offending and victimization, our results provide evidence of ecological effects. Our research has direct policy implications, reveals the promise of the application of geographic information system and spatial analysis to the study of alcohol and violence, and presents clear avenues for future analysis of the outlet-violence association. Although other disciplines have paid more empirical attention to this association, too often public health and epidemiological research is conducted independent of theoretical frameworks suitable for understanding the social processes that underlie violence, thus neglecting important theoretical concerns that could direct empirical inquiry. We believe criminology can be beneficial in this respect, and our findings should encourage further criminological and sociological investigation of the nature of the ecological association between alcohol and violence.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interests with respect to the authorship and/or publication of this article.