The Impact of Recreational Marijuana Dispensaries on Crime: Evidence from a Lottery Experiment

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Abstract

Many North American jurisdictions have legalized the operation of recreational marijuana dispensaries. A common concern is that dispensaries may contribute to local crime. Identifying the effect of dispensaries on crime is confounded by the spatial endogeneity of dispensary locations. Washington State allocated dispensary licenses through a lottery, providing a natural experiment to estimate the causal effect of dispensaries on neighborhood-level crime. Combining lottery data with detailed geocoded crime data, we estimate that the presence of a dispensary has no significant impact on local crime in the average neighborhood. We estimate a small rise in property crime in low-income neighborhoods specifically.

Keywords: marijuana; crime; dispensaries; legalization
JEL classification: R14, R38, R52, K23, K42

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1 Introduction

Public opinion has shifted drastically over the past 20 years in support of marijuana legalization. The share of U.S. adults who support marijuana legalization has increased to 91%, representing a doubling of support since 2000 (Green, 2021). This growth in public support has coincided with a growing number of states legalizing the possession and sale of marijuana. Starting with Washington and Colorado, 18 states and the District of Columbia have passed recreational marijuana laws since 2012. The legalization wave has led to a heated discussion of recreational marijuana's impact on social, economic, and public health outcomes (Anderson and Rees, 2014; Hansen et al., 2017, 2020; Tyndall, 2019; Nicholas and Maclean, 2019; Dong, 2022). This paper contributes to the policy debate by estimating the short-run causal impact of recreational marijuana dispensaries on local crime.

The opening of recreational marijuana dispensaries could affect criminal activity through several potential mechanisms. First, people could commit crimes as a means to obtain money to buy drugs. If so, we might expect an increase in the availability of drugs to result in a rise in the local rate of property crime or robberies. Second, the illegality of marijuana at the federal level limits the legal recourse to settling financial or customer disputes, potentially leading to coercion through violence at dispensary sites. Because most dispensaries can only accept cash, this fact could also increase robberies at dispensaries. On the other hand, Becker and Murphy (2013) claim that legalizing drug markets would "reduce the role of criminals in producing and selling drugs". If so, we may expect legal dispensaries to crowd out illegal drug trafficking. Additionally, dispensaries may employ security systems such as personnel and cameras to protect their financial assets and products, which could discourage local crime (Cook and MacDonald, 2011; Chang and Jacobson, 2017). This study will focus specifically on local, neighborhood-level crime effects, which may come from overall changes in crime levels, or from a spatial redistribution of crime.

Whether dispensaries increase or decrease crime is an empirical question. Identifying the effect of dispensaries on crime has been confounded by the spatial endogeneity of dispensary locations. In other words, dispensary location choice may correlate with local characteristics such as crime or other unobservables. While differences in the level of local crime could be controlled for in fixed-effect models, dispensaries may also select locations with particular socioeconomic trends. For example, dispensary owners may selectively place dispensaries in areas they see as likely to experience economic or population growth in the future. Such endogenous selection would bias attempts to compare the number of crimes between neighborhoods with and without dispensaries. To address the above identification challenges, we utilize a natural experiment from the Washington State recreational marijuana market.

After recreational marijuana legalization in Washington, the state capped the number of retail licenses it would issue and invited businesses to apply. Due to tight restrictions on where marijuana businesses could locate, all applicants had to provide an exact address for the prospective dispensary so the state officials could check whether the dispensary location met site requirements. After collecting a pool of eligible business applicants, the state distributed the licenses by drawing a lottery. We obtain data on the recreational marijuana retail license lottery results. The data includes the location of lottery winners and the credible counterfactual dispensary locations: lottery losers.

To identify the causal impact of dispensaries on local crime, we compare crimes in areas around the lottery winners and lottery losers. However, this intent-to-treat (ITT) estimate will not be equal to the effect of an actual dispensary opening because not all lottery winners followed through with opening a dispensary at the proposed location. Therefore, we propose using the lottery outcome as an instrumental variable (IV) for dispensary market entry in a standard two-stage least squares approach.

Using data from the three largest cities in Washington, our results show that dispensaries have a null effect on average local crime. Additionally, we present evidence over a broad range of crime types to assess the effect on property, violent, and drug crime. To show how the impact of dispensaries varies across economically and demographically different neighborhoods, we combine data on the location of dispensary applicants, lottery results, and US Census tract-level neighborhood characteristics to estimate heterogeneous effects of dispensaries on local crime across different neighborhood types. We find a small crime increase in low-income neighborhoods, driven by property crime. The findings help address widespread public safety concerns regarding legalized marijuana sales. We find some supporting evidence for concerns specific to property crime in low-income neighborhoods in the areas immediately surrounding dispensary sites. Overall, our results provide crucial evidence for designing policy for optimal dispensary locations.

The next section summarizes related literature on marijuana policy and its impact on crime. Section 3 presents the historical background of marijuana policy and the Washington recreational marijuana dispensary license lottery. Section 4 describes the data used. Section 5 lays out the research design and the identification strategies. Section 6 presents the results, and section 7 concludes.

2 Related Studies

This section summarises the previous studies on marijuana policy and its impact on crime, with most of the evidence focused on the medical marijuana market. Given that the trend toward marijuana legalization is recent, the literature on the relationship between dispensaries and local crime is still developing. The majority of the previous studies have found that marijuana dispensaries decreased or have no effect on local crime.

Chang and Jacobson (2017) studied the effect of medical marijuana dispensaries on neighborhood crime in Los Angeles, California, by exploiting a change in policy that led to the closing of dispensaries. The authors found an immediate increase in crime around dispensaries ordered to close relative to those allowed to remain open. The authors suggest that the closures led to vacant storefronts, which may have attracted criminal activity. Huber III et al. (2016) examined the relationship between medical marijuana legalization, depenalization of marijuana possession, and the incidence of non-drug crimes. Using cross-sectional variation in state policies from 1970 to 2012, they found a 4 to 12% reduction in robberies, larcenies, and burglaries due to the legalization of medical marijuana. Depenalization, on the other hand, had little effect and may have marginally increased the number of crimes. Using both regression analysis and a synthetic control method, Chu and Townsend (2019) found no causal effect of medical marijuana laws on violent or property crime at the national level.

Dragone et al. (2019) exploited the staggered legalization of recreational marijuana enacted by the adjacent states of Washington (2012) and Oregon (2014) and found a drop in property crime and rapes on the Washington side of the border once marijuana was legalized. Brinkman and Mok-Lamme (2019) estimated a causal effect of dispensaries on crime in Denver, Colorado, by relying on an IV strategy. The authors note that to serve customers outside of Denver, dispensaries had an incentive to locate close to the city border, which generates variation in dispensary location that is exogenous to local neighborhood conditions. Their results imply that dispensaries led to a reduction in crimes. Burkhardt and Goemans (2019) find that the opening of dispensaries in Denver, Colorado, decreases violent crime rates in above median income neighborhoods, but increases car break-ins within a one-mile radius of dispensaries. Thomas and Tian (2021) examined the local effects of marijuana dispensaries in Washington State. Similar to the current study, the authors made use of random variation from the state licensing lottery to identify causal effects. The authors found that home values around new dispensaries declined. Looking at Seattle specifically, the authors found dispensaries lead to an increase in local nuisance crimes. Outside of the US, Adda et al. (2014) studied the effects of a marijuana policy change in a borough of London. They found that a marijuana decriminalization policy decreased crime at the aggregate level, and caused the police to reallocate efforts toward non-drug crime. Examining the marijuana market in Italy, Carrieri et al. (2019) provided evidence that the liberalization of marijuana laws crowded out the income of organized crime.

Among related studies, our study is most similar to Thomas and Tian (2021). We contribute new results from proprietary, detailed crime data across the three largest cities in Washington State. We leverage the spatially precise data with a unique spatial, empirical approach and identify differing results across unique crime types. Additionally, we document the heterogeneous impacts of dispensaries across economically and demographically different neighborhoods, which is important for designing optimal dispensary location policy. While we identify the effect of a dispensary on crime within its local neighborhood, we do not attempt to estimate the society-wide crime effects of dispensaries.

3 Background

3.1 US Marijuana Laws

Marijuana was entered into the United States Pharmacopeia in 1850 as a treatment for pain, some infectious diseases, bleeding, and other conditions. Before the passage of the Marijuana Taxation Act of 1937, the consumption of marijuana for both recreational and medical purposes was legal. The Controlled Substance Act of 1970 re-classified marijuana as a Schedule I substance along with heroin and methamphetamine, as a drug with "high potential for abuse and little known medical benefit".

Oregon became the first state to decriminalize the possession of small amounts of marijuana in 1973, although the cultivation and distribution of the drug remained felony offenses. In 1996, California became the first state to legalize marijuana for medical use. Currently, 36 states and the District of Columbia allow the cultivation, possession, and use of marijuana by doctor's recommendation for patients with certain medical conditions. Furthermore, 18 states and the District of Columbia have legalized personal recreational marijuana use since 2012. The rapid trend towards legalization in the US has increased the need for policy analysis of early-adopting states to inform legalization policies across the US. Despite the liberalization of marijuana laws, marijuana remains illegal in the majority of states and is still illegal under federal law.[1]

3.2 Washington Recreational Marijuana Law

Initiative-502 (I-502) was approved on November 6$^{\text{th}}$, 2012 by Washington voters with a vote of 55.7% to 44.3%. I-502 had two main components. The first component was "demand-side legalization", which took effect on December 6$^{\text{th}}$, 2012. Demand-side legalization allows

[1] The federal government regulates drugs through the Controlled Substances Act (21 U.S.C. §811), which does not recognize the difference between the medical and recreational use of marijuana.

possession of up to 1 ounce (28 grams) of marijuana by adults over the age of 21. The second component was "supply-side legalization", which pertains to the legalization and regulation of marijuana production and sales and allows for the manufacture and sale of marijuana by/to adults, subject to state licensing, regulations, and taxation. After I-502 went into effect, the Washington State Liquor and Cannabis Board (WSLCB) began establishing regulations for the new recreational cannabis industry, with a deadline of December 1st, 2013 set by the initiative. The law requires a business to hold a license, with separate licensing for producers, processors, and retailers.[2]

Important to the identification strategy of our study, I-502 also directed the WSLCB to limit the number of retail licenses according to quotas. The WSLCB received information on marijuana consumption patterns from a consultancy firm, BOTEC Analysis Corporation, and determined that a total of 334 retail dispensaries would be allocated throughout the state. Allocations were broken down by county. The most populous cities within each county were allocated a proportionate number of dispensaries, and the remaining licenses were assigned to the unincorporated land within counties.

3.3 Washington Marijuana Retail License Lottery

On November 18th, 2013, the state began accepting applicants for marijuana producers, processors, and retailers. During a 30-day window, the WSLCB received over 2,000 applications for marijuana retailers. Applicants were subjected to the verification requirements to determine if they were eligible for licenses. The requirements included: a personal and criminal history statement; verification that the applicant was above 21 years old; verification of residency; verification that the business entity was formed in Washington State; and verification of a location address and right to the property. The dispensary location could not be within 1,000 feet of any elementary or secondary school, playground, recreation center, child care center, public park, public transit center, library, or game arcade that allows minors to enter.

After the pre-screening process, 1,174 applicants were left to be considered for a total quota of 334 retail licenses. In the situation where retail applications exceed the allocated amount for a given city or county, the WSLCB would conduct a lottery to decide which applicants received licenses. There were 75 jurisdictions where a lottery was required. The remaining 47 jurisdictions did not require a lottery due to the number of qualified applicants

[2] "Marijuana producer" means a person licensed by the WSLCB to produce and sell marijuana at wholesale to marijuana processors and other marijuana producers. "Marijuana processor" means a person licensed by the WSLCB to process marijuana into usable marijuana and marijuana-infused products, package and label usable marijuana and marijuana-infused products for sale in retail outlets, and sell usable marijuana and marijuana-infused products at wholesale to marijuana retailers. "Marijuana retailer" means a person licensed by the WSLCB to sell usable marijuana and marijuana-infused products in a retail outlet.

being less or equal to the number of available licenses.

The license lotteries were held between April 21^{st} and 25^{th}, 2014. The lotteries were run by Washington State University's Social and Economics Research Center. A representative of the Washington State Treasurer's Office verified the results. Each applicant was randomly assigned a number by the accounting firm Kraght-Snell. The Washington State University's Social and Economic Sciences Research Center ranked the numbers from 1-n, n being the total number of applicants within a jurisdiction. After that, Kraght-Snell decoded the rankings. If a rank was below or equal to the number of licenses allocated to a jurisdiction, the applicant was a lottery winner. The results of the lottery were made public on May 2^{nd}, 2014. Recreational marijuana sales to the public began on July 8^{th}, 2014.

At the local level, some jurisdictions implemented temporary moratoriums on marijuana sales within their boundaries. Hence, the dispensary opening dates of lottery winners vary. For instance, in Spokane, the earliest recreational marijuana dispensary opened in August 2014, while Seattle's earliest opening was in August 2015. Moreover, not all lottery winners open the dispensaries at their application addresses. There are strict limits on circumstances when an applicant may move locations. For example, after winning the lottery, if the property owner decided they no longer wished to allow a dispensary to operate on the property, the lottery winner would have an opportunity to find a new dispensary address. We will return to this "imperfect compliance" issue in the empirical strategy section.

4 Data

4.1 Lottery Data

The marijuana retail license lottery data is from the WSLCB. For each applicant, it includes a proposed dispensary name, a precise address for the proposed dispensary, a unique identification number, and the applicant's lottery result. If the applicant was successful, it also includes the precise address where the dispensary opened. Lottery results are presented as a number between one and the total number of applicants. The winners of the lottery are the applicants whose rank is lower or equal to their jurisdiction's dispensary allotment. We obtain monthly data from May 2014, when the lottery results were made public, to December 2016 on license issue status from the WSLCB and use the license issue date as the proxy for the dispensary opening date. The license issue date is unique from the lottery win date. Individual licenses were not issued until, in addition to winning the lottery, the applicant had met the regulatory conditions, and the applicant's municipality had approved the opening of the marijuana market.

Figure 1 shows maps of Seattle, Spokane, and Tacoma. Each dot represents a marijuana dispensary application location. The figure shows the dispensary license lottery winners that opened dispensaries (red dots), winners that did not end up opening a dispensary at their application address (blue dots), and lottery losers (black dots) within each city. The WSLCB received 192 applicants from Seattle for 21 licenses, Spokane had a total of 58 applicants for 8 licenses, and Tacoma had 44 applicants for 8 licenses. We only observe two instances where a lottery winner simply chose not to follow through with opening a dispensary. However, we observe 22 instances where a lottery winner opened a dispensary at a location that was different from the address on their original application. These include minor location changes, such as moving to a neighboring unit within the same building, as well as more substantial moves within the city. We account for the presence of these relocated dispensaries in our analysis, as discussed in the identification strategy section. We also observe four instances where an applicant won the lottery, but upon further vetting by the WSLCB, it was discovered that their application did not conform to regulations, so they were disqualified. Within each lottery group, these four licenses were subsequently offered to the next highest-ranking applicant in the lottery.

4.2 Crime Data

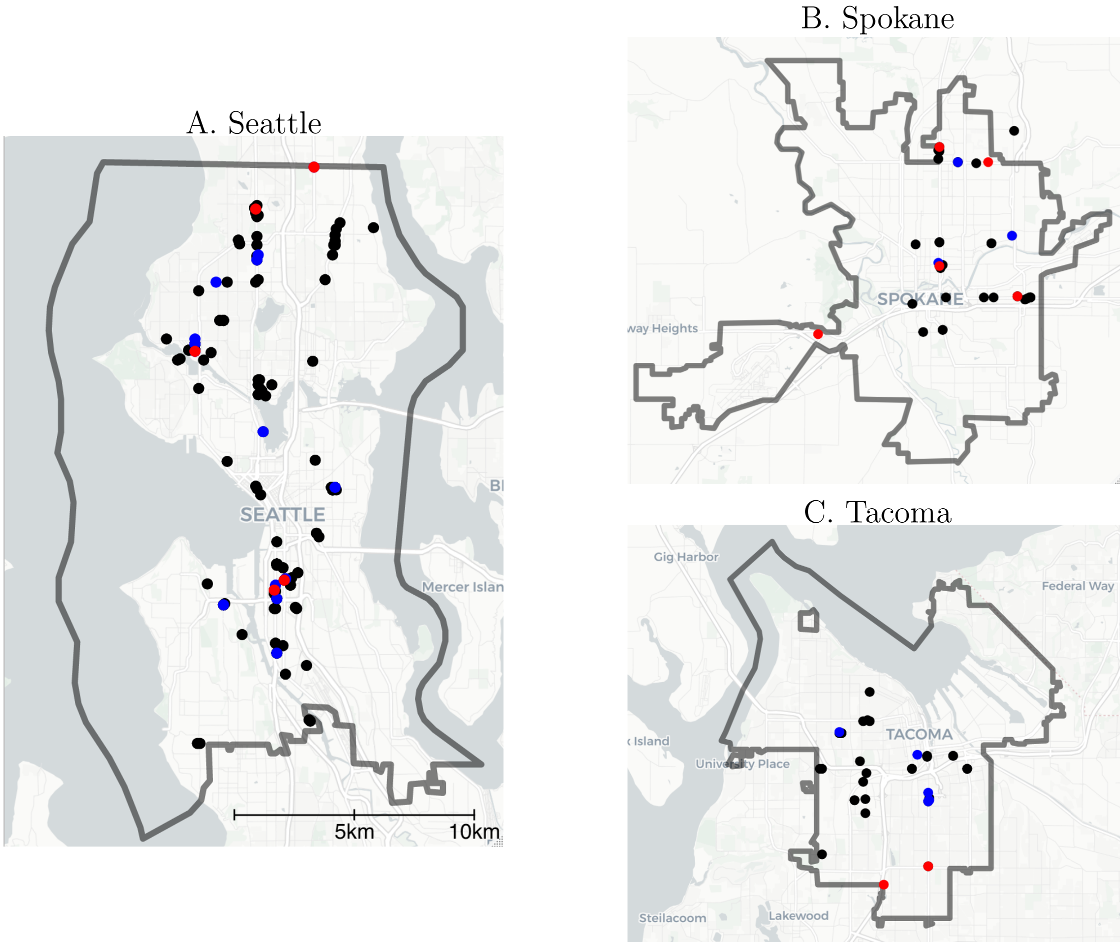
We obtain data that covers instances of crime in the three largest cities in Washington: Seattle, Spokane, and Tacoma. The data was provided directly to us by the Seattle Police Department, the City of Tacoma Police Department, and the City of Spokane Police Department. For each crime incident, the data from all three sources include the date, time, geocoded location, and type of crime committed from 2010-2016. The geocoded crime locations allow us to measure the distance between crime incidents and lottery applicants.

All three police departments report and classify crimes under the Federal Bureau of Investigations (FBI) Uniform Crime Reporting Program, making the data sets comparable across cities. The data provided by the Tacoma Police Department omitted incidents of rape, so we dropped such instances from the Seattle and Spokane samples for consistency.[3] Table 1 presents the number of crimes that occurred across crime type and location in the analysis sample.

Our analysis focuses on the local neighborhoods surrounding dispensary applicants. We draw circles with a specific radius around the locations of dispensary applicants. Figure 2 shows an example of concentric circles with radii of 100, 200, and 500 meters around a dispensary. We take the sum of crimes committed within these rings as a measure of local

[3] Rape incidents constitute only 0.2% of reported crimes within jurisdictions in our sample where data is available.

Figure 1: Dispensary Applicant Locations



● - Winning applicant, dispensary opened
● - Winning applicant, no dispensary opened at application address
● - Losing applicant

> The locations of all lottery applicants are displayed above, with the maps indicating the boundaries of each city. One applicant for the Spokane lottery proposed a location that was outside of the city limits. The applicant did not win the lottery. We rerun the analysis omitting this observation and the results are essentially unchanged. All cities are shown at the same scale.

criminal activity. We tally crimes for each month of the study period to compare changes in crime over time that may be related to the timing of dispensary openings. In addition to looking at total crime counts within the rings, we also tally crimes within particular crime categories to investigate a possible heterogeneous effect of dispensaries on different crime types. Table 2 presents the average number of crimes reported within a local circle drawn

Table 1: Number of Crimes Recorded Across Cities, 2010-2016

	Seattle	Spokane	Tacoma	Total
Arson	652	472	462	1,586
Assault	58,921	40,662	9,363	108,946
Burglary	48,700	33,953	17,917	100,570
Drug related	9,017	5,563	1,811	16,391
Homicide	173	291	43	507
Larceny	173,843	62,123	48,914	284,880
Motor vehicle theft	29,305	5,151	11,949	46,405
Robbery	10,513	4,232	3,076	17,821
Others	241,135	233,315	25,127	499,577
	572,259	385,762	118,662	1,076,683

The table shows the number of reported crimes across crime types and jurisdictions.

around an applicant, per month. By focusing only on areas around dispensary applicants, the methodology will ignore any areas of the cities that are more than 500 meters from an applicant. We keep all months for all dispensary areas, generating a balanced panel at the applicant-month level.

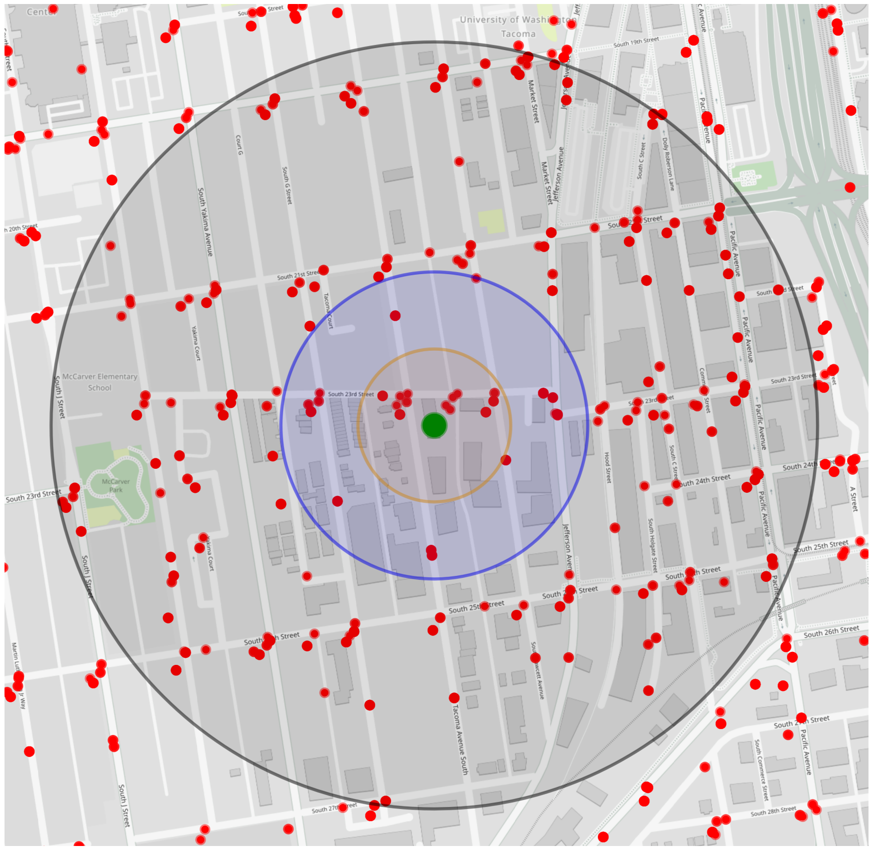
Table 2: Average Monthly Number of Crimes Recorded Within Treatment Radii

	100m	200m	300m	400m	500m
Arson	0.004	0.009	0.016	0.027	0.040
Assault	0.295	0.814	1.419	2.338	3.251
Burglary	0.160	0.509	1.041	1.803	2.657
Drug related	0.073	0.191	0.331	0.481	0.608
Homicide	0.001	0.004	0.008	0.010	0.016
Larceny	0.680	2.213	4.000	6.659	9.411
Motor vehicle theft	0.096	0.302	0.572	0.956	1.365
Robbery	0.059	0.160	0.274	0.419	0.575
Others	1.244	3.634	6.662	10.969	15.433
	2.612	7.838	14.322	23.663	33.355

The table shows the number of reported crimes that occurred within the average applicant's treatment area each month for the various treatment bandwidths.

As an initial check on whether crimes were spatially correlated with dispensary applicant locations, we provide heat maps of crime activity surrounding dispensary applicant locations in Figure A2. We do not find a strong spatial correlation between applicant sites and the pre-lottery distribution of local crimes.

Figure 2: Dispensary Treatment Bandwidth Example



● - Dispensary Location ● - Crime reported

The concentric circles show the 100 meter (orange), 200 meter (blue), and 500 meter (black) bandwidths. This example shows one dispensary location in the City of Tacoma.

One limitation of our analysis is that we can only observe the crimes reported to the police departments. Crimes that may have occurred but were not recorded by the police will be outside of our analysis. Despite all jurisdictions abiding by the FBI reporting standards, it is plausible that there may be differences in reporting practices across jurisdictions. In our identification strategy, we control for time-invariant spatial differences in crimes, which will absorb any systematic differences in crime reporting practices across jurisdictions. Additionally, while prior studies used publicly available crime incidents, we have access to restricted crime data with high precision. For example, Seattle and Tacoma observations have latitude/longitude information that is precise up to at least six decimal places, and the Spokane data is precise up to seven decimal places. Measurement error could still be introduced if the officer incorrectly recorded the crime's location.

4.3 Study Area and Neighborhood Characteristics Data

The analysis spans the three largest cities in Washington State. Using the American Community Survey (ACS) 2006-2010 five-year estimates, Table 5 provides population and demographic information for the analysis cities, as well as national averages for comparison.

Table 3: Demographic Characteristics of Cities

	Seattle	Spokane	Tacoma	USA
Population	668,849	212,078	205,602	-
Median household income ($)	74,458	43,274	53,553	55,322
Population share with a college degree	.604	.288	.267	.303
Median home value	484,600	160,800	212,400	184,700
Median age	35.8	35.8	36.0	37.7
White population share	.692	.860	.653	.734
Black population share	.071	.023	.101	.126
Hispanic population share	.066	.061	.113	.173

Data is from the 2010 5-year American Community Survey.

As shown in the table, Seattle is significantly larger than the other two jurisdictions, with a population of nearly 700,000, while Tacoma and Spokane each have a population of just over 200,000. Seattle also has a significantly higher median income ($74,000) than the other two cities in the sample. Spokane ($43,000) and Tacoma ($54,000) both have median incomes that are below the national median ($55,000). Similarly, the population share with a college degree in Seattle (60%) is significantly above the national average (30%), while Spokane (29%) and Tacoma (27%) have lower rates of college education. While median home values in Spokane and Tacoma are relatively representative of the national market, home prices in Seattle are higher than the national average. The median home value in Seattle ($484,600) is more than twice that of Tacoma ($212,400) and roughly three times that of Spokane ($160,800). Finally, Spokane is relatively racially homogeneous, with 86% of the population identifying as white, while Seattle and Tacoma have white population shares of 69% and 65%, respectively.

In addition to providing estimates of the average effects of dispensaries, we also test whether the impacts differ across neighborhoods with different demographic characteristics. We collect neighborhood characteristics from the ACS 2006-2010 five-year estimates at the census tract level. The data provides information on the median income levels and racial and ethnic population shares. We then match each dispensary applicant to demographic data based on the census tract it is located in. Overall, our sample spans a diverse array of neighborhoods. However, care should be taken in generalizing our results to other settings. For example, our analysis does not include rural areas, where the impacts of dispensaries on crime may be different.

5 Identification Strategy

5.1 The Effect of a Dispensary Opening

Washington's retail license lottery provides a natural experiment that allows for the causal identification of local dispensary effects. Our research design follows literature that utilizes lotteries for identification (Angrist, 1990; Jacob and Ludwig, 2012). To estimate the effect of a dispensary opening on local crime, we propose using the lottery outcome as an IV for dispensary opening in a standard two-stage least-squares approach to estimate the effect of treatment on the treated (TOT) of having an operating local dispensary. The estimation equation is shown in Equation 1.

$$C_{it}^{d} = \beta_0 + \beta_1 D_{it}^{d} + \Theta_i + \Lambda_t + \varepsilon_{it} \tag{1}$$

C_{it}^{d} indicates the number of crimes occurring within a circle of radius d, centered at dispensary applicant i during month t. D_{it}^{d} is a variable capturing the presence of an operating local dispensary. If the local treatment circle of radius d does not overlap the treatment circle of other open dispensaries, D_{it} takes a value of 1 when dispensary i is operating, and 0 otherwise. However, in some cases, applicants have treatment rings that are near the location of other operating dispensaries. To account for overlapping treatment areas, we calculate D_{it}^{d} as the total area within treatment ring i that is treated by *any* open dispensary at time t, as a share of the area within the ring. For example, if applicant i was not open at time t but a second dispensary was operating nearby, and a circle drawn with radius d around the second dispensary overlapped 50% of applicant i's treatment circle, then D_{it}^{d} would equal 0.5. For cases where the treatment circles of several dispensaries overlap, we intersect all circles, calculate the area of resulting polygons, and calculate the sum of all treated polygons within distance d of a dispensary at time t, as a share of local treatment circle i's area. The value of D ranges from zero, when none of the local circle's area is near an operating dispensary, and can exceed one when multiple open dispensaries are operating nearby. For example, at a 300 meter treatment bandwidth, D_{it}^{d} ranges from 0 to 2.0 in the data, with an average value of 0.15. Allowing D_{it}^{d} to exceed one allows us to recover partial effects that account for some areas being treated by multiple dispensaries simultaneously.

Θ_i in Equation 1 represents a vector of applicant fixed effects. The inclusion of applicant fixed effects absorbs time-invariant differences between applicant locations, such as average crime levels. Λ_t takes a unique value for every year-month in the data and represents a vector of time fixed effects. The inclusion of time fixed effects absorbs variation through time in overall crimes that occurred across the study area. ε_{it} is the error term. β_1 is the estimate of the effect of an operating dispensary on the number of local crimes. While the analysis is limited to areas adjacent to lottery applicants, the above specification may still suffer from bias. Areas with particular crime levels or other characteristics may be more (or less) likely to follow through with a dispensary opening, conditional on having won the lottery.

To address the above bias we instrument the share of the local area near an operating dispensary (D^d_{it}) with a variable for the share of the local area that is near a lottery winner (W^d_{it}). When discussing "local areas" we are referring to the circular area within distance d of the applicant location. W^d_{it} is calculated with the same procedure as D^d_{it}, but using whether the locations held a winning lottery license at time t, rather than whether the location was operating. If a treatment circle of radius d for dispensary applicant i does not overlap other applicant treatment circles, W^d_{it} takes a value of 1 if the applicant held a winning lottery result at time t, and 0 otherwise. For instances where neighboring applicants have overlapping treatment circles, we calculate the sum of the area treated by a lottery winner at time t as a share of the local area. W^d_{it} is continuous and can exceed one in instances where multiple lottery winners overlap.[4] For example, the value of W^d_{it} using a 300 meter treatment bandwidth ranges from 0 to 3.9 in the data, with an average value of 0.68.[5]

After applying the instrument, the IV estimate for β_1 corresponds to the causal effect of a dispensary among the subsample of compliers, namely those locations that had an operating dispensary. Equation 2 displays the first stage equation. Using a lottery as an instrument fulfills the "exclusion restriction" because the drawing of the lottery does not affect crime trends, other than through its role in dispensary allocation.

$$D^d_{it} = \gamma_0 + \gamma_1 W^d_{it} + \Theta_i + \Lambda_t + \varepsilon_{it} \tag{2}$$

Table 4 shows the first-stage regression results and demonstrates that the lottery is a strong predictor of actual dispensary locations. For example, using the 300-meter treatment bandwidth ($d = 300$), if the local area around applicant i is entirely within 300 meters of a lottery winner ($W^d_{it} = 1$), the share of the circle around i that is within 300 meters of an active recreational marijuana dispensary in a post-lottery month is increased by 0.115, on average.[6]

[4] To further clarify the calculation of D^d_{it} and W^d_{it} in cases where treatment circles overlap, we provide an example in Figure A3.

[5] We allow D^d_{it} and W^d_{it} to exceed one in order to capture treatment intensity. The choice implies that the partial effect of being treated by two dispensaries is twice that of being treated by a single dispensary. We test robustness to alternate constructions of D^d_{it} and W^d_{it} in Table A6 and find results are consistent.

[6] We test for finite sample bias by estimating the Cragg-Donald Wald F statistic. We estimate the F

A threat to identification would be if the treated and control areas had different characteristics before the lottery occurred. Table 5 presents results from a balance test on pre-treatment covariates, dividing the sample by applicants that ultimately won or lost the lottery. As shown in the table, demographic characteristics and pre-treatment crime rates are not significantly different between the areas around lottery-winning and losing applicants.

Table 4: First Stage Results

	Radius Around Dispensary (meters)				
	100	200	300	400	500
Lottery result	0.104	0.092**	0.115***	0.111***	0.100***
	(0.070)	(0.046)	(0.031)	(0.025)	(0.026)
Year-month fixed effects?	Y	Y	Y	Y	Y
Applicant fixed effects?	Y	Y	Y	Y	Y
Partial R^2	0.268	0.277	0.305	0.313	0.314
R^2	0.495	0.535	0.571	0.585	0.596
Observations	24,696	24,696	24,696	24,696	24,696
Clusters	177	156	139	127	125
Cragg-Donald Wald F statistic	582.31	619.61	1051.34	1104.84	980.99

The table reports the first stage estimate from Equation 2. The outcome variable is the share of the local area within the defined radius of an operating dispensary. Standard errors are spatially clustered by the local area and shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

When estimating standard errors, our primary concern is that the error structure may be correlated among applicants who are spatially near to one another. In a standard setting with spatial panel data, it is common to cluster errors at the spatial unit at which treatment is assigned (Abadie et al., 2017; Barrios et al., 2012). Our setting has an additional level of complexity due to some spatial treatment areas overlapping one another. Overlapped observations have mechanically correlated errors because a crime committed in the overlapped section impacts the crime count in both observations. We, therefore, assign standard error clusters at the applicant level, but group applicants whose local treatment areas overlap into a single cluster. Using 100 meter radius treatment circles, the method generates 177 local area clusters across the 294 unique applicants. At larger treatment areas the number of clusters shrinks as additional units overlap. For example, when using 500 meter radius treatment circles we estimate models with 125 unique clusters. We will provide a robustness test where we collapse spatial units to avoid the issue of overlapping units entirely.

statistic at over 500 for all treatment radii, strongly rejecting the presence of significant bias.

Table 5: Pre-treatment Balancing Test

	Mean of Lottery Winners	Mean of Lottery Losers	P-value of t-test $Pr(\|T\| > \|t\|)$
Median household income ($)	48,583	52,065	0.190
Unemployment (%)	4.889	5.205	0.528
Median age	39.270	37.893	0.271
Population with a high-school diploma (%)	90.700	90.616	0.935
Population with a college degree (%)	33.949	40.805	0.057
Black population (%)	11.373	10.961	0.803
Hispanic population (%)	8.046	8.212	0.877
Average monthly crimes occurring			
within 100 meters	2.377	2.671	0.600
within 200 meters	6.955	7.821	0.593
within 300 meters	12.734	14.177	0.638
within 400 meters	20.620	23.576	0.537
within 500 meters	30.395	33.129	0.674
Observations	37	257	.

The sample is limited to only the pre-lottery period. Each observation corresponds to one unique applicant. Winning and losing applicants are defined dichotomously based on the applicant's own lottery result, rather than using the continuous variable W^d_{it}.

5.2 The Effect of Winning the Lottery

In addition to estimating the causal effect of an open dispensary, we also provide estimates of the impact of winning a dispensary license on local crime, utilizing a difference-in-differences (DiD) design. The goal of this strategy is to estimate the ITT effect. In our context, the ITT effect is the partial effect of an areal unit being treated by the presence of a lottery winner, irrespective of where dispensaries actually ended up being located. The approach will also be extended to estimate differential effects based on neighborhood demographic conditions, which was not possible in the IV specification. Equation 3 captures the regression strategy.

$$C^d_{it} = \alpha_0 + \alpha_1 W^d_{it} + \Theta_i + \Lambda_t + \varepsilon_{it} \tag{3}$$

Variables in Equation 3 are defined identically to Equation 1 and Equation 2. We make use of the same sample of applicant locations, allowing us to contrast areas that had a lottery winner ($W^d_{it} > 0$) with a control group of locations without a lottery winner ($W^d_{it} = 0$). The coefficient of interest is α_1 and is equal to the effect of a local treatment circle being fully treated by a lottery winner. An areal unit that is fully treated by a lottery winner ($W^d_{it} = 1$) will experience α_1 additional crimes relative to an areal unit that was not treated by a lottery winner ($W_{it}^d = 0$). For instances where treatment circles overlap we adopt the partial treatment calculations described in Section 5.1.

The identifying assumption of the DiD model is that the number of crimes in areas close to lottery winners would not have changed relative to areas close to lottery losers, except due to winning the lottery. Although there is no statistical test for the parallel trends assumption, visual inspection is useful since we have observations over many points in time. We provide figures exploring the parallel trends assumption in Figure A1.

Recent developments in difference-in-difference methodology have yielded improved estimators for cases with staggered treatment (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). However, our setting is one of uniform treatment timing, as we estimate the ITT effect of winning the lottery itself, which occurs at a uniform time. Related recent literature concerns cases where their may be heterogeneity in treatment effect within the treated group (De Chaisemartin and d'Haultfoeuille, 2020), or in cases where the treatment designation is represented as a continuous variable (De Chaisemartin and d'Haultfoeuille, 2018; Callaway et al., 2021). While our method fits a conventional two-period difference-in-difference design, some concerns raised in this literature could apply. As a robustness check, we apply the estimation method proposed in De Chaisemartin and d'Haultfoeuille (2020) to our difference-in-difference design. We find our results are broadly consistent under this alternative estimation strategy.

To explore how the impact varies across economically and demographically different neighborhoods, we combine the location of dispensary applicants, lottery results, and census tract-level neighborhood characteristics data and use the following specification:

$$C_{it}^d = \alpha_0 + \alpha_1 W_{it}^d + \alpha_2 (T_i \times P_t) + \alpha_3 (W_{it}^d \times T_i) + \Theta_i + \Lambda_t + \varepsilon_{it} \tag{4}$$

T_i is a dummy variable indicating whether a demographic criteria is met. For example, when looking at low-income neighborhoods, $T = 1$ if the neighborhood is low-income and $T = 0$ if it is not. P_t is equal to 1 during or after July 2014, when the recreational marijuana sales market was open in Washington, and 0 otherwise. The remainder of the variables in Equation 4 are defined identically to Equation 3. α_1 is equal to the effect of an applicant winning the lottery on local crime in neighborhoods where $T = 0$. $\alpha_1 + \alpha_3$ identifies the impact of winning the lottery on crime for locations where $T = 1$. While we assume winning the lottery only affects crime through the presence of dispensaries, the effect of a dispensary could be different across neighborhood types. We examine the potential for differential effects for low-income neighborhoods and neighborhoods with high Black and Hispanic population shares. We define the low-income cutoff as the 25$^{\text{th}}$ percentile of the census tract-level household income distribution in the sample, which is \$40,481. Similarly, we define high Hispanic/Black population share cutoffs as the 75$^{\text{th}}$ percentile of the Hispanic/Black population share distribution in the sample. As a robustness check, we also provide results for alternative cutoff values.

6 Results

6.1 Average Neighborhood Effects

We first present the impact of dispensaries on the number of local crimes in Table 6. We provide results for treatment radii ranging from 100 to 500 meters. The first column lists the analysis radius. The second column shows the TOT estimates from the IV analysis (Equation 1), and the third column shows ITT estimates from the DiD analysis (Equation 3). Overall, our results indicate a dispensary has a null effect on the number of local crimes, though most point estimates suggest an increase in crimes. For the 100 meter treatment bandwidth, we find an operating dispensary (TOT) increases the number of monthly crimes by 2.18, but the estimate is statistically insignificant. However, we do estimate a small, statistically significant effect of winning the lottery (ITT) of 0.23 additional local crimes. For context, the average monthly number of crimes reported within a 100 meter treatment area was 2.6.

When expanding the treatment radii, we find the effect magnitudes dissipate as a portion of pre-treatment crime levels. The reduced effect at greater distances is consistent with a spatial decay in the effect of dispensaries on local crime. Figure 3 panel (a) and Figure 4 panel (a) show the TOT and ITT effects graphically. The figures plot the estimated change in overall crimes with 95% confidence intervals, ranging from 100 to 500 meter treatment bandwidths. Our results are consistent with the recent evidence from Morris et al. (2014), Chu and Townsend (2019), and Thomas and Tian (2021), who find no causal effects of medical marijuana laws on overall crime.

As discussed in the methodology section, our empirical setting includes instances where the areal units overlap, introducing correlation across spatial units. As a robustness test, we provide alternative results where overlapping areal units are collapsed into a single unit. We execute the analysis in the same way as above but calculate treatment status across the union of the combined areal units. This approach creates discrete treatment units that do not overlap. In Table A1 we provide the results of this alternative methodology. We find results are very similar to the main results. Specially, we find positive and statistically insignificant effects with comparable magnitudes per unit area.

We elect to measure crimes as a count variable, rather than a rate per local population.

Table 6: Effect of Dispensaries on Overall Number of Local Crimes

	Treatment Effects	
Radius (meters)	TOT	ITT
100	2.182	0.227**
	(1.789)	(0.098)
200	4.480	0.411*
	(3.900)	(0.247)
300	3.293	0.378
	(4.687)	(0.505)
400	2.271	0.252
	(4.745)	(0.514)
500	1.218	0.121
	(5.526)	(0.549)
Observations	24,696	24,696

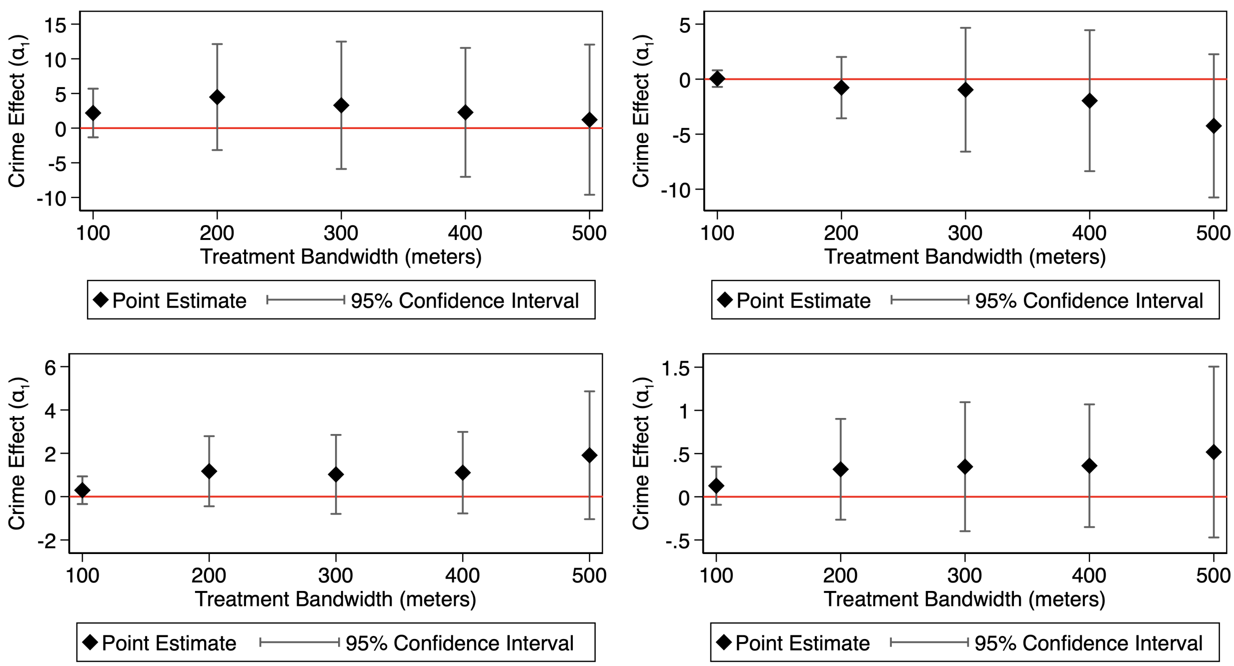
The table reports both the IV analysis of Equation 1 and the DiD analysis of Equation 3. The outcome variable is the number of local crimes. Standard errors are spatially clustered by the local area and shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

As our treatment areas are small and don't align with census geographies, we cannot recover exact population figures. Additionally, because many applicants are from commercial areas, the true population of local residents may be low or even zero. Nevertheless, we provide additional results in Table A2 where the outcome is expressed in crimes per 10,000 local residents. We approximate local population numbers by crosswalking census block group population estimate to our treatment ring geographies by assuming block group populations are distributed uniformly within the block group. We find results that are positive, and more statistically significant than our main estimates. However, the magnitude of the estimates relative to pre-treatment crime levels are very similar to our main estimates.

Next, we analyze the impact of dispensaries on different crime types. We follow the standard FBI crime type definitions and estimate our model separately for the following crime types: property, violent, and drug crime. Specifically, property crime is defined as motor vehicle theft, larceny, burglary, and arson. Violent crime is defined as aggravated assault, robbery, and homicide.

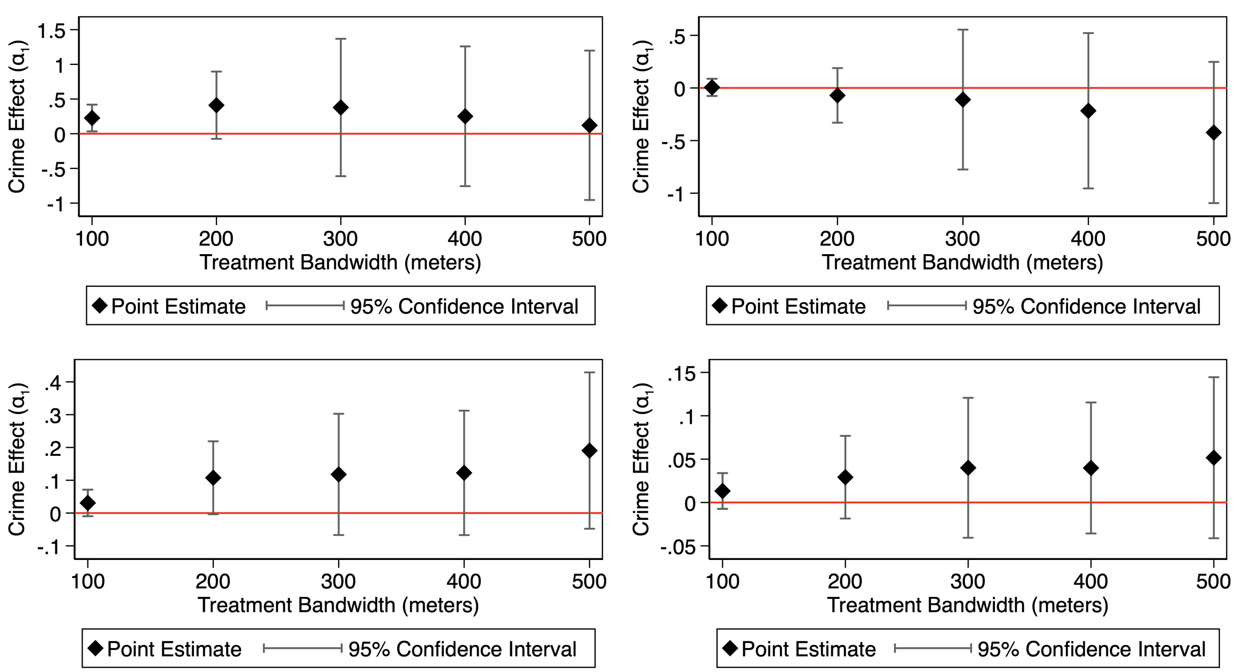
Table 7 shows the impact of dispensaries on each crime type, both from the IV analysis of Equation 1 and from the DiD analysis of Equation 3. Similar to the overall crime effect, we do not detect any statistically significant evidence of an operating dispensary effect (TOT) on

Figure 3: Estimated TOT Effect as Function of Treatment Bandwidth and Crime Type



Each point estimate corresponds to a separate regression result (β_1), as per Equation 1.

Figure 4: Estimated ITT Effect as Function of Treatment Bandwidth and Crime Type



Each point estimate corresponds to a separate regression result (α_1), as per Equation 3.

any of the three crime types. We do find some evidence that winning a license lottery (ITT) leads to increased violent crime using a 200-meter treatment bandwidth. However, given the statistically insignificant effects from the IV estimates and the other treatment bandwidths, we interpret this result with caution. Figure 3 panels (b)-(d) and Figure 4 panels (b)-(d) show the TOT and ITT effects graphically. The figures indicate property, violent, and drug-related crimes are generally not increasing by statistically significant margins around dispensaries.

Table 7: Effect of Dispensaries on Local Crime by Crime Type

	Property Crime		Violent Crime		Drug Crime	
Radius (meters)	TOT	ITT	TOT	ITT	TOT	ITT
100	0.052	0.005	0.296	0.031	0.128	0.013
	(0.384)	(0.042)	(0.326)	(0.021)	(0.113)	(0.011)
200	-0.770	-0.071	1.173	0.108*	0.318	0.029
	(1.422)	(0.132)	(0.826)	(0.057)	(0.298)	(0.024)
300	-0.961	-0.110	1.026	0.118	0.348	0.040
	(2.870)	(0.339)	(0.930)	(0.094)	(0.381)	(0.041)
400	-1.955	-0.217	1.106	0.123	0.359	0.040
	(3.268)	(0.377)	(0.960)	(0.097)	(0.362)	(0.039)
500	-4.244	-0.423	1.910	0.190	0.518	0.052
	(3.320)	(0.342)	(1.505)	(0.122)	(0.504)	(0.047)
Observations	24,696	24,696	24,696	24,696	24,696	24,696

The table reports both the IV analysis of Equation 1 and the DiD analysis of Equation 3. The outcome variable is the number of local crimes for each crime type. Standard errors are spatially clustered by the local area and shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

In the appendix, we provide additional evidence on the impact of dispensaries on local crime. We show results at finer levels of disaggregation (i.e., motor vehicle theft, larceny, robbery, etc.) for both TOT and the ITT effects in Table A3. We find some evidence that winning the lottery (ITT) increased robberies. At a 100-meter treatment bandwidth, the estimates show that winning the lottery increased robberies by 0.015 incidents. Additionally, at a 200-meter treatment bandwidth, we find that winning the lottery increased assault crimes by 0.083 incidents. This small result is consistent with local news reporting in Washington, which suggested marijuana dispensaries have been the target of robberies for marijuana products and money.[7] Our results are also consistent with the recent evidence from Thomas and Tian (2021), who argue that crimes near marijuana dispensaries were

[7]For example: *Surveillance video shows pot shop owner use bear spray to thwart armed robbery*, Fox 13, Seattle, 02/17/2020; *Violent pot shop robbers wanted in Seattle*, Fox 13, Seattle, 02/07/2020; *'They held a gun to my head': Armed robbers hit S. Seattle pot shop*, KOMO News, 11/19/2019.

partially to blame for a decline in nearby home prices.

In our main model specification, we use the number of local crimes occurring as the outcome variable. Because this count measure is bound at zero, the distribution of crimes across observations is rightward skewed. Using a logged outcome variable may correct for this skew, but introduces an issue with instances where the crime count is zero. In Appendix Table A4 we reestimate main results using the log of the number of crimes plus one, or $ln(C_{it}^{d}+1)$, as a measure of local crime rates. We show results that are similar to the main specification. Table A5 shows results that utilize a Poisson model. Due to our dependent variable being count data, a Poisson model may provide a more parsimonious estimation of effects. We again find results are generally consistent under this alternative regression specification. Table Table A6 provides results for alternative constructions of D_{it}^{d} and W_{it}^{d}, where their upper bound is capped at one. The alternative construction assumes that the effect of multiple dispensaries is not cumulative. We find similar results under the alternative definitions.

6.2 Heterogeneous Effects

The local impact of a dispensary on crime may differ across neighborhoods of differing demographics and income levels. The heterogeneous effects of a place-based public policy on crime is a topic of perennial interest in public and urban economics. A similar question has been investigated for the case of public housing (Rephann, 2009). For example, Freedman and Owens (2011) find that low-income housing development in the poorest neighborhoods brings significant reductions in violent crime. Our paper contributes to the literature by exploring the heterogeneous impact of dispensaries across neighborhood types. Specifically, we present the differential effect estimates from Equation 4. We estimate results for the total number of crimes, as well as show results corresponding to the three crime categories.

Table 8 shows how the effect of winning the lottery differs across neighborhoods of different demographic characteristics and income levels. We provide results for the three main crime types across five treatment bandwidths. We find evidence that the crime effects of dispensaries are stronger in low-income neighborhoods. Neighborhoods below the 25^{th} percentile of household income ($40,481) experienced a far greater increase in crime than did similarly treated neighborhoods with higher income. Using the 300 meters radius treatment definition, we find that a winning lottery applicant in a low-income neighborhood contributes an additional 3.15 monthly crimes relative to the effect in a higher-income neighborhood. We find the difference is driven by an increase in property crime in low-income neighborhoods relative to higher-income neighborhoods. Winning the dispensary lottery in a low-income neighborhood contributed 2.52 additional monthly property crimes within a 300 meter radius relative to the effect in a higher-income neighborhood.

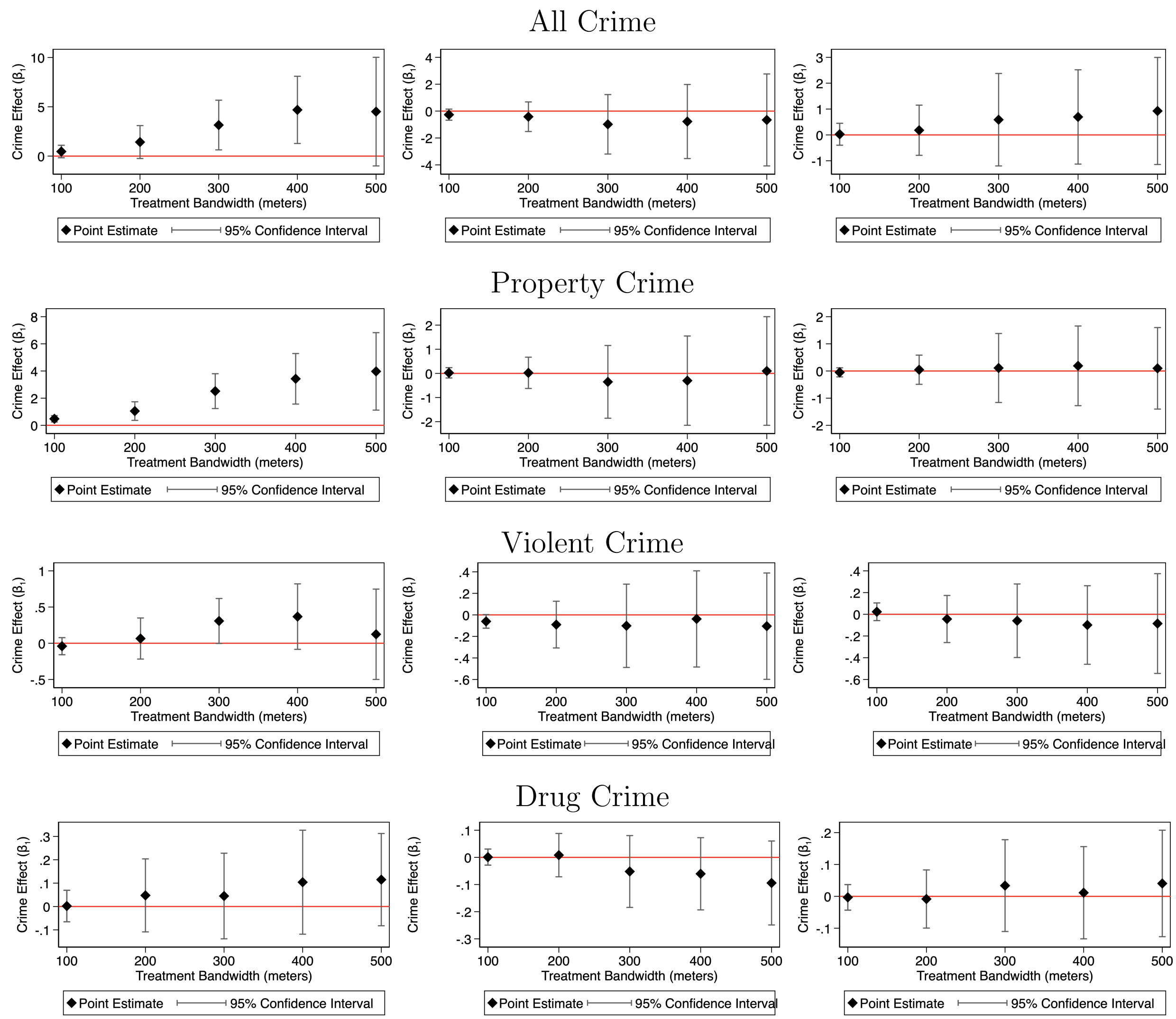
Table 8: Effect of Winning the Lottery on Local Crime by Crime Type and Neighborhood Characteristics

	Radius Around Dispensary (meters)				
	100	200	300	400	500
Panel A: All Crime					
Low Income	0.464	1.424*	3.149**	4.688***	4.511
	(0.323)	(0.852)	(1.286).	(1.740)	(2.811)
High Hispanic Ratio	-0.266	-0.418	-0.982	-0.775	-0.658
	(0.210)	(0.561)	(1.128)	(1.406)	(1.745)
High Black Ratio	0.026	0.181	0.588	0.695	0.926
	(0.216)	(0.495)	(0.912)	(0.930)	(1.056)
Panel B: Property Crime					
Low Income	0.476***	1.049***	2.517***	3.426***	3.972***
	(0.120)	(0.349)	(0.654)	(0.950)	(1.455)
High Hispanic Ratio	0.025	0.024	-0.351	-0.300	0.099
	(0.109)	(0.330)	(0.768)	(0.943)	(1.147)
High Black Ratio	-0.050	0.047	0.111	0.190	0.099
	(0.085)	(0.274)	(0.648)	(0.748)	(0.766)
Panel C: Violent Crime					
Low Income	-0.041	0.065	0.308*	0.368	0.124
	(0.060)	(0.145)	(0.158)	(0.231)	(0.318)
High Hispanic Ratio	-0.061*	-0.090	-0.101	-0.038	-0.105
	(0.032)	(0.111)	(0.197)	(0.228)	(0.252)
High Black Ratio	0.023	-0.043	-0.059	-0.099	-0.085
	(0.042)	(0.111)	(0.173)	(0.184)	(0.234)
Panel D: Drug Crime					
Low Income	0.002	0.048	0.045	0.104	0.115
	(0.034)	(0.080)	(0.094)	(0.114)	(0.101)
High Hispanic Ratio	0.001	0.008	-0.052	-0.060	-0.094
	(0.015)	(0.041)	(0.067)	(0.068)	(0.079)
High Black Ratio	-0.003	-0.008	0.034	0.011	0.040
	(0.020)	(0.047)	(0.073)	(0.074)	(0.085)
Observations	24,696	24,696	24,696	24,696	24,696

The table reports the Equation 4 heterogeneity analysis, reporting α_3 estimates. The outcome variable is the number of local crimes for each crime type. The low-income cutoff is the 25^{th} percentile of the household income distribution in our sample of tracts, which is $40,481. The high Hispanic and Black population share cutoffs are the 75^{th} percentiles of Hispanic and Black population shares in our sample, which are 9.4% and 18.5%, respectively. Standard errors are spatially clustered by local area and shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

We do not find statistically significant results showing a differential effect in high Black or Hispanic population neighborhoods, as shown in Table 8. Figure 5 shows the results of Table 8 graphically. The small and significant differential overall and property crime effect for low-income neighborhoods can be seen in panels (a) and (d). One caveat is that, although differential effects could be the result of different responses from different communities, because our data do not cover unreported crimes, results could also be driven by changes in police behavior regarding enforcement levels around dispensaries in different neighborhood types (Kau and Rubin, 1975).

Figure 5: Differential Effect of Winning the Lottery on Crime by Neighborhood Characteristics and Treatment Bandwidth



Panels (a)-(c) show overall crimes, (d)-(f) show property crimes, (g)-(i) show violent crimes, and (j)-(l) show drug crimes. Each point estimate corresponds to a separate regression result (α_3), as per Equation 4.

In Table A7 we provide results using a looser cutoff to define low-income, high Black, and high Hispanic neighborhoods. We find reduced estimates of a heterogeneous effect in low-income neighborhoods, consistent with the effect being strongest in the lowest income areas. We again find null effects when testing for a heterogeneous effect in high Black and Hispanic population ratio neighborhoods.

7 Conclusion

The random assignment of recreational marijuana retail licenses in Washington State provides a unique opportunity to identify the causal effect of dispensary openings on local crime. Existing studies have yielded ambiguous predictions about the effect of dispensaries on local crime, with a majority of the evidence pointing towards a crime reduction. We provide evidence on this topic from a lottery setting.

Using data from the three largest cities in Washington State, our results indicate a dispensary opening has a null effect on the number of local crimes in the average neighborhood. We identify a small increase in crimes in low-income neighborhoods, driven by a rise in property crime. Because marijuana is still illegal at the federal level, most dispensaries can only accept cash, which provides a possible explanation for the observed increase in robberies around dispensaries. Overall, our results provide a crucial first step to designing policy for optimal dispensary locations.

The roll-out of marijuana legalization has played out differently in different US states. While our results benefit from a plausible identification strategy that overcomes spatial endogeneity, there is some uncertainty regarding the external validity of findings to other locations. Future studies covering other regions are important in confirming the external validity of our findings and to better understand the overall impact of dispensaries on crime.

Another caveat is that our causal estimates assume that there are no spillover effects between dispensary locations of lottery winners and losers. Additionally, we cannot say whether the rise in low-income neighborhood property crime represents crimes that would not otherwise have occurred, or if these crimes would have occurred elsewhere and are redirected toward new dispensary locations. In other words, we estimate local and not aggregate crime effects.

It is also important to mention that the effects identified in this paper are short-run and may not capture general equilibrium effects. Based on our results, future research on the impact of dispensary openings on rent, local business establishment, police behavior, etc. is crucial to understanding the overall impact of recreational marijuana dispensaries. For example, if police redirected patrols toward dispensaries because they anticipated crime occurring at those locations, this could bias estimates toward finding an increase in local crime around dispensaries.

Our findings have important policy implications for regulating recreational marijuana sales in the United States. Increased local crime represents a negative externality of dispensaries. We find no evidence of such an effect for the average neighborhood. Local crime is only one social consequence of dispensaries. Dispensaries in particular, and the legalization of marijuana in general, may hold numerous positive effects. While we do not find evidence of crime reductions at the neighborhood level, it may be that marijuana legalization reduces crime at the aggregate national level. For example, legalization may reduce aggregate criminal activity pertaining to the marijuana market or reduce the size of criminal gangs by crowding out a source of revenue (Becker and Murphy, 2013). The opportunity to regulate the marijuana market is likely to yield safety benefits for marijuana users (Ghosh et al., 2016). Finally, the tax revenue raised through marijuana sales could be deployed for the benefit of society (Hollenbeck and Uetake, 2021). The potential benefits of marijuana dispensaries must also be considered in conjunction with the negative externality of local crime examined in this paper.

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Appendix Tables

Table A1: Effect of Dispensaries on Overall Number of Local Crimes, Combined Areal Unit Approach

	Sample Mean		Treatment Effects	
Radius (meters)	Crimes	Observations	TOT	ITT
100	2.779	14,868	1.325	0.228
			(1.021)	(0.152)
200	8.634	13,104	2.066	0.336
			(2.595)	(0.389)
300	14.165	11,676	1.822	0.216
			(3.464)	(0.406)
400	23.587	10,668	4.265	0.583
			(4.185)	(0.555)
500	31.797	10,500	3.273	0.490
			(3.851)	(0.572)

The table reports both the IV analysis of Equation 1 and the DiD analysis of Equation 3. The outcome variable is the number of local crimes. Areal units that overlapped in the original analysis are combined into single areal units in this table. Standard errors are spatially clustered by the local area and shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A2: Effect of Dispensaries on Overall Number of Local Crimes, Outcome in Crimes per 10,000 Residents

	Treatment Effects	
Radius (meters)	TOT	ITT
100	24.212	2.518***
	(21.440)	(0.910)
200	48.773	4.474**
	(42.771)	(1.980)
300	38.809	4.459**
	(24.286)	(2.169)
400	49.348*	5.466**
	(28.684)	(2.536)
500	31.671*	3.160*
	(18.545)	(1.605)

The table reports both the IV analysis of Equation 1 and the DiD analysis of Equation 3. The outcome variable is the number of local crimes per 10,000 residential population. Standard errors are spatially clustered by the local area and shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A3: Effect of Dispensaries on Local Crime by Disaggregated Crime Type

	Radius Around Dispensary (meters)									
	100		200		300		400		500	
Treatment Effects	TOT	ITT	TOT	ITT	TOT	ITT	TOT	ITT	TOT	ITT
All Property Crime	0.052	0.005	-0.770	-0.071	-0.961	-0.110	-1.955	-0.217	-4.244	-0.423
	(0.384)	(0.042)	(1.422)	(0.132)	(2.870)	(0.339)	(3.268)	(0.377)	(3.320)	(0.342)
Motor Vehicle Theft	0.120	0.012	-0.187	-0.017	-0.069	-0.008	-0.080	-0.009	0.103	0.010
	(0.119)	(0.008)	(0.515)	(0.049)	(0.444)	(0.052)	(0.428)	(0.048)	(0.474)	(0.047)
Larceny	-0.106	-0.011	-0.640	-0.059	-1.153	-0.132	-2.067	-0.229	-4.796	-0.479
	(0.313)	(0.030)	(1.013)	(0.093)	(2.133)	(0.249)	(2.427)	(0.276)	(3.398)	(0.301)
Burglary	0.037	0.004	0.058	0.005	0.194	0.022	0.114	0.013	0.358	0.036
	(0.141)	(0.016)	(0.428)	(0.040)	(0.948)	(0.108)	(1.282)	(0.143)	(1.923)	(0.189)
Arson	0.000	0.000	-0.001	-0.000	0.067	0.008	0.078	0.009	0.092	0.009
	(0.009)	(0.001)	(0.028)	(0.003)	(0.051)	(0.005)	(0.063)	(0.007)	(0.105)	(0.009)
All Violent Crime	0.296	0.031	1.173	0.108*	1.026	0.118	1.106	0.123	1.910	0.190
	(0.326)	(0.021)	(0.826)	(0.057)	(0.930)	(0.094)	(0.960)	(0.097)	(1.505)	(0.122)
Assault	0.151	0.016	0.901	0.083**	0.602	0.069	0.563	0.062	1.202	0.120
	(0.243)	(0.019)	(0.710)	(0.039)	(0.617)	(0.063)	(0.593)	(0.061)	(0.940)	(0.078)
Robbery	0.140	0.015***	0.271	0.025	0.394	0.045	0.539	0.060	0.737	0.074
	(0.091)	(0.005)	(0.269)	(0.029)	(0.375)	(0.040)	(0.476)	(0.049)	(0.637)	(0.052)
Homicide	0.005	0.001	0.001	0.000	0.029	0.003	0.005	0.001	-0.029	-0.003
	(0.007)	(0.001)	(0.013)	(0.001)	(0.040)	(0.005)	(0.040)	(0.005)	(0.042)	(0.004)
All Drug Crime	0.128	0.013	0.318	0.029	0.348	0.040	0.359	0.040	0.518	0.052
	(0.113)	(0.011)	(0.298)	(0.024)	(0.381)	(0.041)	(0.362)	(0.039)	(0.504)	(0.047)
Observations	24,696	24,696	24,696	24,696	24,696	24,696	24,696	24,696	24,696	24,696

The table reports the IV analysis of Equation 1 and the DiD analysis of Equation 3. The outcome variable is the number of local crimes for each disaggregated crime type. Standard errors are spatially clustered by the local area and shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table A4: Effect of Dispensaries on Local Crime by Crime Type, Using Log Transformed Crime Measure

	All Crime		Property Crime		Violent Crime		Drug Crime	
Radius (meters)	TOT	ITT	TOT	ITT	TOT	ITT	TOT	ITT
100	0.430	0.045**	-0.106	-0.011	0.103	0.011	0.046	0.005
	(0.418)	(0.022)	(0.196)	(0.016)	(0.141)	(0.011)	(0.048)	(0.005)
200	0.310	0.028	-0.092	-0.008	0.324	0.030*	0.087	0.008
	(0.406)	(0.028)	(0.284)	(0.026)	(0.297)	(0.022)	(0.109)	(0.010)
300	0.067	0.008	-0.144	-0.017	0.210	0.024	0.056	0.006
	(0.403)	(0.046)	(0.422)	(0.049)	(0.289)	(0.031)	(0.119)	(0.013)
400	0.045	0.005	-0.165	-0.018	0.147	0.016	0.059	0.006
	(0.271)	(0.030)	(0.300)	(0.034)	(0.207)	(0.022)	(0.123)	(0.013)
500	0.007	0.001	-0.234	-0.023	0.268	0.027	0.095	0.009
	(0.226)	(0.023)	(0.235)	(0.024)	(0.232)	(0.020)	(0.167)	(0.016)
Observations	24,696	24,696	24,696	24,696	24,696	24,696	24,696	24,696

The table reports both the IV analysis of Equation 1 and the DiD analysis of Equation 3. The outcome variable is the log number of local crimes plus one for each crime type. Standard errors are spatially clustered by the local area and shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table A5: Effect of Winning the Lottery on Local Crime, Poisson Regression

Radius (meters)	All Crime	Property Crime	Violent Crime	Drug Crime
100	0.108***	0.026	0.097*	0.023
	(0.039)	(0.067)	(0.055)	(0.233)
200	0.061**	-0.000	0.106*	0.050
	(0.031)	(0.052)	(0.056)	(0.291)
300	0.031	-0.008	0.071	N/A
	(0.033)	(0.060)	(0.045)	
400	0.014	-0.016	0.048*	N/A
	(0.021)	(0.035)	(0.029)	
500	0.004	-0.028	0.050**	N/A
	(0.016)	(0.022)	(0.025)	
Observations	24,696	24,696	24,696	24,696

The table reports the DiD analysis using a Poisson Model. The outcome variable is the number of local crimes for each crime type. We do not report some results for Drug Crimes as the limited statistical variation in the category prevents convergence of the Poisson model. Standard errors are spatially clustered by the local area and shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A6: Effect of Dispensaries on Overall Number of Local Crimes, Alternative Definitions of D and W

	Treatment Effects							
	Main Specification $0 \leq D$ $0 \leq W$		$0 \leq D \leq 1$ $0 \leq W$		$0 \leq D$ $0 \leq W \leq 1$		$0 \leq D \leq 1$ $0 \leq W \leq 1$	
Radius (meters)	TOT	ITT	TOT	ITT	TOT	ITT	TOT	ITT
100	2.182	0.227**	2.433	0.227**	1.962	0.446**	2.395	0.446**
	(1.789)	(0.098)	(2.077)	(0.098)	(1.280)	(0.214)	(1.633)	(0.214)
200	4.480	0.411*	4.431	0.411*	3.500	0.753	3.823	0.753
	(3.900)	(0.247)	(3.799)	(0.247)	(3.199)	(0.587)	(3.499)	(0.587)
300	3.293	0.378	4.256	0.378	4.715	1.458	6.324	1.458
	(4.687)	(0.505)	(6.454)	(0.505)	(3.390)	(1.011)	(4.871)	(1.011)
400	2.271	0.252	3.143	0.252	2.393	0.816	3.371	0.816
	(4.745)	(0.514)	(6.893)	(0.514)	(3.557)	(1.224)	(5.099)	(1.224)
500	1.218	0.121	1.829	0.121	-0.392	-0.124	-0.583	-0.124
	(5.526)	(0.549)	(8.490)	(0.549)	(5.051)	(1.611)	(7.525)	(1.611)
Observations	24,696	24,696	24,696	24,696	24,696	24,696	24,696	24,696

The table reports both the IV analysis of Equation 1 and the DiD analysis of Equation 3. The outcome variable is the number of local crimes. The first two columns show the main results (Table 6). The subsequent columns show results where D and/or W are capped at one. Capping the variables at one assumes local dispensary effects are not cumulative in a spatial unit. Standard errors are spatially clustered by the local area and shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

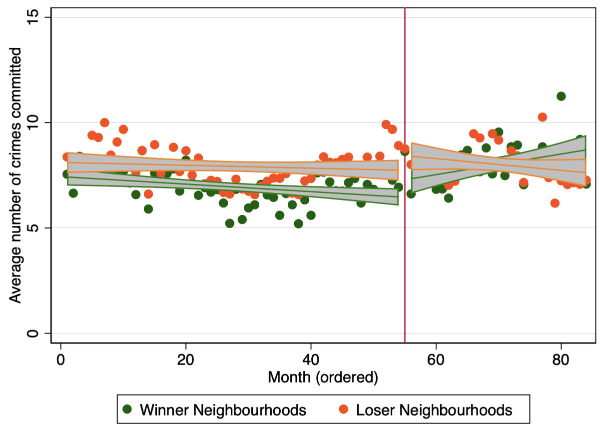
Table A7: Effect of Winning the Lottery on Local Crime by Crime Type and Neighborhood Characteristics, Alternative Neighborhood Type Definitions

	Radius Around Dispensary (meters)				
	100	200	300	400	500
Panel A: All Crime					
Low Income	0.424	1.168	2.346*	3.152*	2.680
	(0.353)	(0.911)	(1.276)	(1.744)	(2.708)
High Hispanic Ratio	-0.262	-0.405	-0.958	-0.736	-0.614
	(0.210)	(0.561)	(1.129)	(1.409)	(1.750)
High Black Ratio	0.020	0.048	0.316	0.399	0.438
	(0.219)	(0.520)	(0.960)	(0.991)	(1.163)
Panel B: Property Crime					
Low Income	0.344***	0.518	1.543**	2.036*	2.261
	(0.123)	(0.435)	(0.770)	(1.089)	(1.542)
High Hispanic Ratio	0.028	0.035	-0.332	-0.272	0.135
	(0.109)	(0.329)	(0.768)	(0.945)	(1.151)
High Black Ratio	-0.028	-0.025	-0.018	0.018	-0.222
	(0.086)	(0.278)	(0.659)	(0.760)	(0.806)
Panel C: Violent Crime					
Low Income	0.013	0.181	0.372**	0.404*	0.199
	(0.071)	(0.158)	(0.147)	(0.210)	(0.271)
High Hispanic Ratio	-0.061*	-0.089	-0.100	-0.036	-0.104
	(0.032)	(0.111)	(0.197)	(0.227)	(0.252)
High Black Ratio	0.013	-0.069	-0.099	-0.142	-0.145
	(0.042)	(0.113)	(0.180)	(0.192)	(0.243)
Panel D: Drug Crime					
Low Income	0.030	0.076	0.115	0.138	0.147
	(0.040)	(0.115)	(0.149)	(0.141)	(0.159)
High Hispanic Ratio	0.000	0.007	-0.053	-0.062	-0.096
	(0.015)	(0.041)	(0.068)	(0.068)	(0.079)
High Black Ratio	-0.004	-0.014	0.027	0.008	0.030
	(0.020)	(0.046)	(0.074)	(0.073)	(0.085)
Observations	24,696	24,696	24,696	24,696	24,696

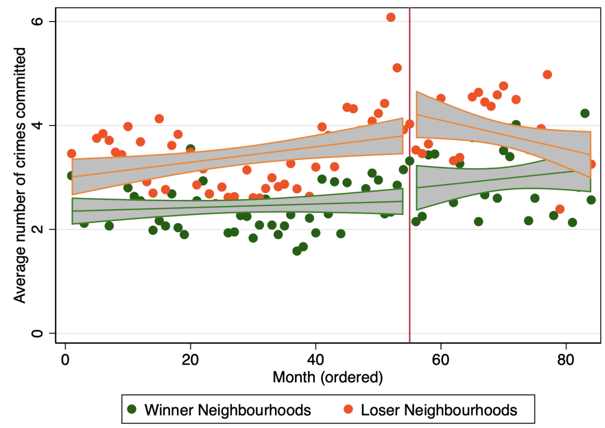
The table reports the Equation 4 heterogeneity analysis, reporting α_3 estimates. The outcome variable is the number of local crimes for each crime type. The low-income cutoff is the 33rd percentile of the household income distribution in our sample of tracts, which is $46,393. The high Hispanic and Black population share cutoffs are the 66th percentiles of Hispanic and Black population shares in our sample, which are 9.0% and 13.9%, respectively. Standard errors are spatially clustered by the local area and shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Appendix Figures

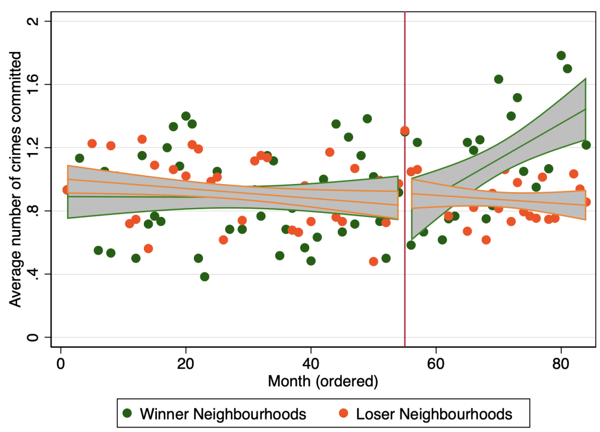
Figure A1: Mean Monthly Crime Counts by Lottery Status



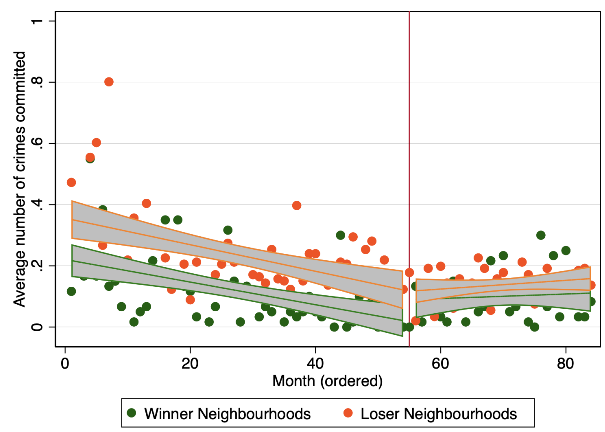
(a) All Crime



(b) Property Crimes



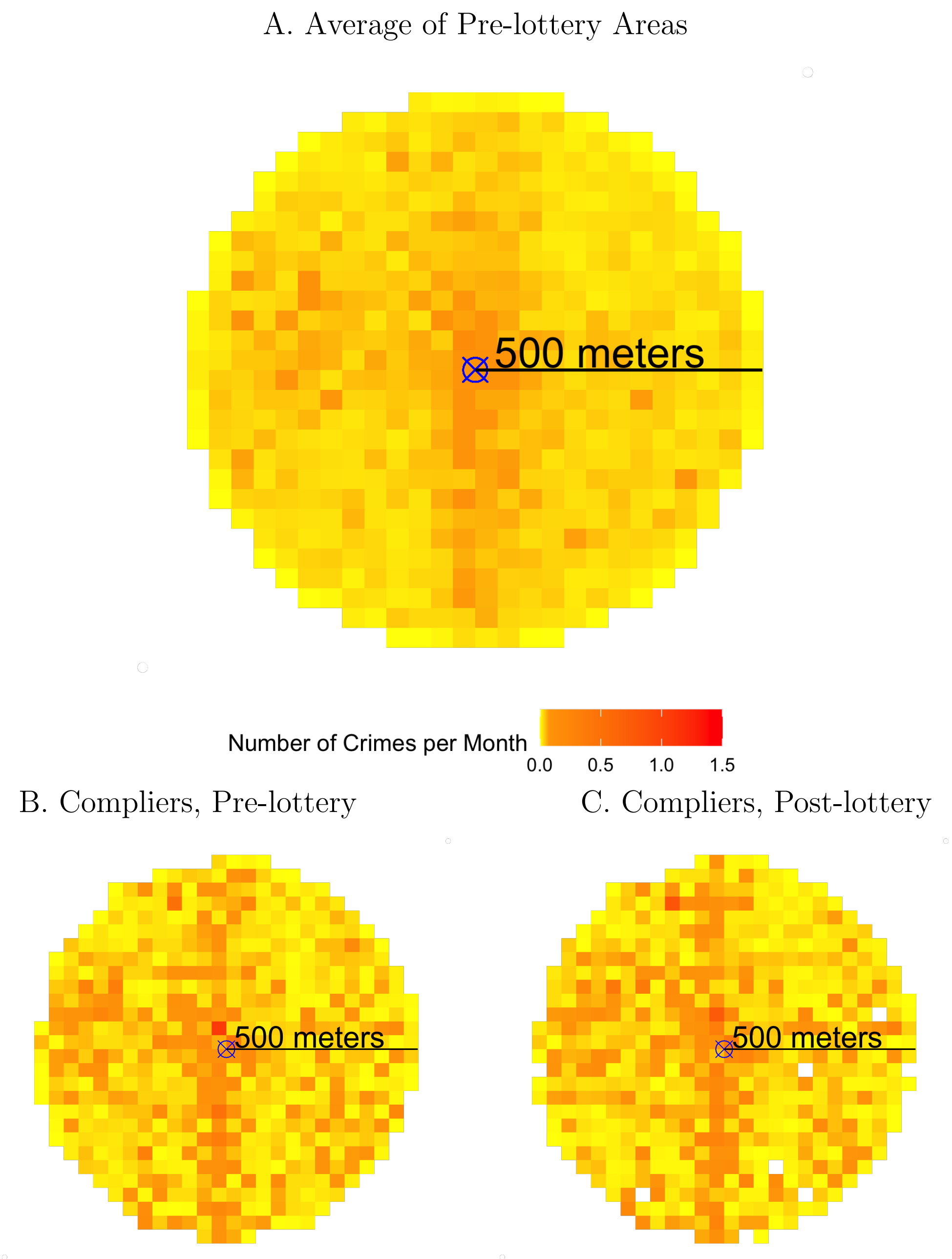
(c) Violent Crimes



(d) Drug Crimes

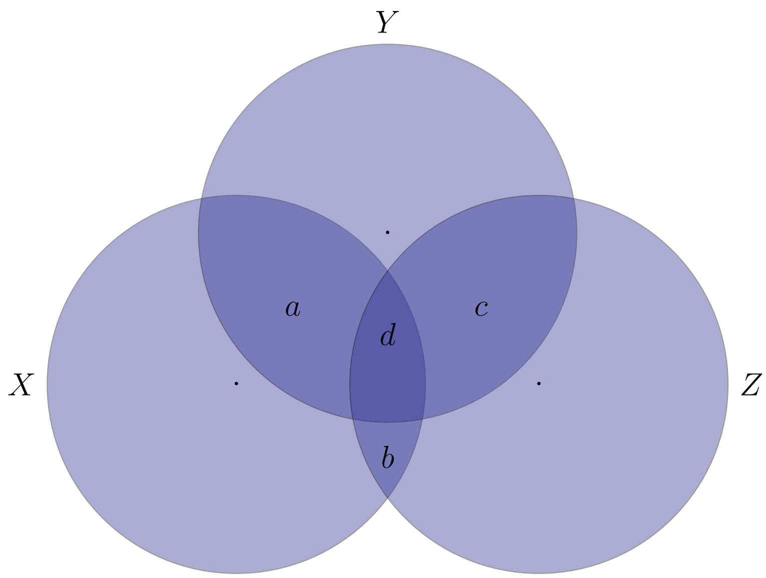
Mean monthly crime counts with a 95% confidence interval at 200 meters around dispensaries for (a) all crimes, (b) property crimes, (c) violent crimes, and (d) drug crimes by lottery result from 2010 to 2016. The vertical red line indicates the time of the lottery drawing. Month 0 is equal to January 2010. A significant threat to the identification would be the presence of differential crime trends between treatment and control areas. Visual inspection suggests the pre-treatment trends are parallel.

Figure A2: Crime Heat Maps



The figure displays the frequency of crime occurring in a particular square unit, within a month, relative to the location of a dispensary applicant, averaged across applicants. Panel A shows the average crime activity before the lottery event, across all applicant locations. We compare lottery compliers (those winners who opened a dispensary at their application address) before (B) and after (C) the lottery event. We do not find a strong spatial correlation between applicant sites and pre-lottery crime rates when examining the immediate areas.

Figure A3: Calculating W and D When Treatment Areas Overlap



Applicant	Lottery Outcome	Open Dispensary	W	D
X	Won	Open	$1 + a + d$	1
Y	Won	Not Open	$1 + a + d$	$a + d$
Z	Lost	Not Open	$b + c + 2 \times d$	$b + d$

The figure and table illustrate a hypothetical case of calculating values of W and D in a case where the treatment areas of three applicants overlap. In this example, at a specific time (t) lottery applicants X and Y have won the dispensary lottery but only applicant X is operating a dispensary. a-d represent areas as a share of a unit circle. For example, if a covers 20% of a circle, a=0.2.