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DISPENSARIES ON CRIME: EVIDENCE FROM A  
LOTTERY EXPERIMENT

BY

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Working Paper No. 2021-1

March 25, 2021

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

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March 25, 2021

## 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 crime. Combining lottery data with detailed geocoded crime data, we estimate that the presence of a dispensary has no impact on average local crime rates. However, within low-income neighborhoods, we find an increase in property crime adjacent to new dispensaries.

**Keywords:** recreational marijuana dispensaries; crime; dispensary opening

**JEL classification:** R38, R50, K23, K42

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\*We thank Gary Engelhardt, Alfonso Flores-lagunes, Ross Jestrab, Jeffrey Kubik, David Neumark, Alex Rothenberg, Perry Singleton, and Emily Wiemers for their valuable suggestions and helpful comments. We appreciate the assistance of the Pierce County Sheriff Department, the City of Tacoma Police Department, the Seattle Police Department, and the Washington State Liquor Control Board for their data support. We would also like to thank David Hutchinson for the excellent data assistance. All errors are our own.

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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 from 30% in 2000 to 67% in 2018 (Geiger, 2018). 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, 15 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). This paper contributes to the policy debate by estimating the short-run causal impact of recreational marijuana dispensaries on local crime.

Whether dispensaries increase or decrease crime is an empirical question. Identifying the effect of dispensaries on crimes 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 crime rates 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 mari-

juana 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 first 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. Therefore, we propose using the lottery outcome as an instrumental variable 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 no significant impact on the overall rate of local crime. Additionally, we provide evidence over a broad range of crime types to assess the effect on property, violent, and drug crime. We find no evidence of an overall increase or decrease in any aggregated crime type adjacent to dispensaries. However, robberies experience a small statistically significant rise around the lottery-winning dispensaries within a 100 meters radius.

To provide evidence on 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 statistically significant evidence of an increase in property crime within low-income neighborhoods. The findings provide some evidence that dispensaries encourage local theft as a means to raise money for the purchase of marijuana. Overall, our results provide a crucial first step to designing policy for optimal dispensary locations.

The next section summarizes related literature on marijuana policy and its impact on crime. Section 3 presents additional background on the marijuana policies and the Washington recreational marijuana dispensary license lottery. Section 4 describes the data used. Section 5 shows the research design and the identification strategies. Section 6 presents 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 towards marijuana legalization is recent, the literature on the relationship between dispensaries and local crime is still developing. The majority of the previous literature has found that marijuana dispensaries are associated with reduced levels of 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 crime rates. 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 instrumental variable strategy. The authors note that to serve customers outside of Colorado, Colorado dispensaries have 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 lead to a reduction of 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 effort toward non-drug crime. Examining the marijuana market in Italy, [Carrieri et al. \(2019\)](#) provided some recent evidence that the liberalization of marijuana laws crowded out the income of organized crime.

We argue that without spatially random allocation of dispensaries, estimating the relationship between crime and dispensaries is difficult given the potential spatial endogeneity between the two. Our paper complements prior work in an important way, by accounting for the endogeneity of policy and the endogenous location of dispensaries across neighborhoods by utilizing a lottery experiment that randomly allocates recreational marijuana dispensaries to identify the causal impact of dispensaries on local crime. Additionally, we document the heterogeneous impacts of dispensaries that vary across economically and demographically different neighborhoods, which is a crucial first step to designing optimal dispensary location policy.

## 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 1938, 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 mari-

juana by doctor recommendation for patients with certain medical conditions. Furthermore, 15 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.<sup>1</sup>

### 3.2 Washington Recreational Marijuana Law

Initiative-502 (I-502) was approved on November 6<sup>th</sup>, 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<sup>th</sup>, 2012. This allows 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 Control Board (WSLCB) began establishing regulations for the new recreational cannabis industry, with a deadline of December 1<sup>st</sup>, 2013 set by the initiative. The law requires a business to hold a license, with separate licensing for producers, processors, and retailers.<sup>2</sup>

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, BOTECH Analysis Corporation,

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

<sup>2</sup>“Marijuana producer” means a person licensed by the state liquor control board to produce and sell marijuana at wholesale to marijuana processors and other marijuana producers. “Marijuana processor” means a person licensed by the state liquor control board 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 state liquor control board to sell usable marijuana and marijuana-infused products in a retail outlet.

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.<sup>3</sup>

### **3.3 Washington Marijuana Retail License Lottery**

On November 18<sup>th</sup>, 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 applicant(s) gets the retail license. There are 75 jurisdictions where a lottery was required. The remaining 47 jurisdictions did not require a lottery due to the number of qualified applicants being less or equal to the number of available licenses.

The license lotteries were held between April 21<sup>st</sup> and 25<sup>th</sup>, 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

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<sup>3</sup><https://lcb.wa.gov/pressreleases/board-approves-filing-proposed-rules-implement-initiative-502>.

being the total number of applicants within a jurisdiction. After that, Kraght-Snell decoded the rankings. If a rank was lower than 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<sup>nd</sup>, 2014. Recreational marijuana sales to the public began in July 8<sup>th</sup>, 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.<sup>4</sup> 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. Lottery results are presented as a number between one and the total number of applicants. The winners of the lottery are the applicant whose rank is lower than its jurisdiction’s dispensary allotment. We obtain weekly 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.

**Figure 1** shows maps of Seattle, Spokane, and Tacoma. Each dot represents a marijuana

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<sup>4</sup><https://lcb.wa.gov/mj2015/post-marijuana-retail-lottery-faqs>.

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 (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.

## 4.2 Crime Data

We obtain data that covers instances of crime in the three largest cities in Washington: Seattle, Tacoma, and Spokane. 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. [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. To do so, we draw circles with a specific radius around the locations of dispensary applicants. [Figure 2](#) shows an example of the concentric circles of 100, 200, and 500 meters around a dispensary. We take the sum of crimes committed within these rings as a measure of local 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 will also tally crimes within particular crime categories to investigate a possible heterogeneous effect of dispensaries on different

crime types.

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 should absorb any systematic differences in crime reporting practices across jurisdictions.

### 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 2](#) provides population and demographic information for the analysis cities, as well as national averages for comparison.

As shown in the table, Seattle is significantly larger than the other two jurisdictions, with a population is 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 they are 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 Winning the Lottery

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](#)). We first estimate the impact of winning a dispensary license on local crime using a difference-in-differences (DiD) design. The goal of this strategy is to estimate the ITT effect. [Equation 1](#) captures the regression strategy.

$$\ln(C_{it}^d) = \alpha_0 + \alpha_1 W_i * Post_t + \alpha_2 W_i + \alpha_3 Post_t + \Theta_i + \Lambda_t + \varepsilon_{it} \quad (1)$$

$\ln(C_{it}^d)$  indicates the log number of crimes occurring within a distance  $d$  of a dispensary applicant  $i$  during month  $t$ .  $W_i$  is a dummy variable that takes a value of 1 if applicant  $i$  won the lottery and 0 if applicant  $i$  lost the lottery.  $Post_t$  is equal to 1 after July 2014 when the recreational marijuana sales market opens in Washington, and 0 otherwise.  $\Theta_i$  represents a vector of applicant fixed effects. The inclusion of applicant fixed effects absorbs randomly occurring, time-invariant differences between applicant locations, such as average crime levels.  $\Lambda_t$  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.  $\varepsilon_{it}$  is the error term. The coefficient of interest is  $\alpha_1$  and is equal to the effect of winning the lottery on local crime. Standard errors are clustered at the applicant level.

The identifying assumption of the DiD model is that the crime rates in areas close to lottery winners would not have changed relative to areas close to lottery losers, except due to the opening of marijuana dispensaries. In other words, a significant threat to the identification would be the presence of differential crime trends between treatment and control areas. To test this parallel trend assumption, we compare raw monthly crime trends around lottery winners and lottery losers. We find no evidence that overall crime was on a unique trajectory between “winner” and “loser” neighborhoods. Parallel trend graphs for a 300 meter treatment bandwidth are provided in [Figure A1](#) panel (a). This parallel trend also holds for different crime types, which are shown in [Figure A1](#) panels (b)-(d).

To further 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 a triple-difference model as follows:

$$\ln(C_{it}^d) = \alpha_0 + \alpha_1 W_i * Post_t + \alpha_2 W_i + \alpha_3 Post_t + \alpha_4 T_i * Post_t + \beta_1 T_i * W_i * Post_t + \Theta_i + \Lambda_t + \varepsilon_{it} \quad (2)$$

$T_i$  indicates a particular demographic measure that differs across applicant locations. The rest of the notation is consistent with [Equation 1](#).  $\alpha_1$  is equal to the effect of an applicant winning the lottery on local crime in neighborhoods that do not have the demographic characteristic  $T$ .  $\alpha_1 + \beta_1$  identifies the impact of winning the lottery on crime for locations that do meet the demographic condition. 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<sup>th</sup> percentile of the census tract-level household in-

come distribution in the sample, which is \$40,481. Similarly, we define high Hispanic/Black population share cutoffs as the 75<sup>th</sup> percentile of the Hispanic/Black population share distribution in the sample. In Appendix [Table A2](#) we also provide results for differing cutoffs in neighborhood type definitions.

## 5.2 The Effect of a Dispensary Opening

As mentioned earlier, not all lottery winners followed through with the opening of a dispensary. Additionally, there is a lag between the lottery drawing and the date when dispensaries actually opened, and this lag varies across the dispensaries. Both of these realities raise the imperfect compliance issue for the identification strategy and mean that the ITT estimate above may underestimate the effect of an actual operating dispensary. Therefore, we propose using the lottery outcome as an instrumental variable 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 3](#).

$$\ln(C_{it}^d) = \theta_0 + \theta_1 D_{it} + \Theta_i + \Lambda_t + \varepsilon_{it} \quad (3)$$

$D_{it}$  is a dummy variable that takes a value of 1 if there is an operating dispensary at applicant location  $i$  in month  $t$ , and 0 otherwise. Thus,  $\theta_1$  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 rates 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 area having an active dispensary ( $D_{it}$ ) with a variable for having won the lottery. [Equation 4](#) displays the first stage equation.  $W_{it}$  is a dummy variable that takes a value of 1 if the area held a winning lottery result at time  $t$ , and 0 otherwise. Therefore, the instrumental variable (IV) estimate for  $\theta_1$  corresponds to

the causal effect of a dispensary among the subsample of compliers, namely those locations that had an operating dispensary.

$$D_{it} = \gamma_0 + \gamma_1 W_{it} + \Theta_i + \Lambda_t + \varepsilon_{it} \quad (4)$$

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. Additionally, the statistical strength of the instrument can be demonstrated empirically, alleviating the “weak instrument” concern. [Table 3](#) shows the first stage regression result and demonstrates that the lottery is a strong predictor of actual dispensary locations. Winning the lottery is associated with a 20 percentage point increase in the likelihood of there being an operating dispensary at the applicant location in a post-treatment month.<sup>5</sup>

## 6 Results

### 6.1 Average Neighborhood Effects

We first present the impact of dispensaries on the frequency of local crimes in [Table 4](#). We provide results for treatment radii ranging from 100 to 500 meters. Column (1) lists the analysis radius. Column (2) presents the pre-lottery mean crime rate for the 100, 200, 300, 400, and 500 meters around lottery applicants. For example, approximately 3 crimes were occurring per month on average within 100 meters of an applicant location in the pretreatment period, and 33 crimes occurred per month on average within 500 meters of a dispensary.

[Table 4](#) shows both the ITT estimates from the DiD analysis in [Equation 1](#) (column 3) and the TOT estimates from the IV analysis in [Equation 3](#) (column 4). Our results indicate a dispensary has a null effect on the rate of local crime, though most point estimates suggest

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<sup>5</sup>The strength of the instrument is also demonstrated by an estimated value of the Cragg-Donald Wald F statistic of 3,439. This result strongly rejects the null hypothesis that the instrument is weak.

a marginal increase in crimes. For example, within 300 meters of an application location, the point estimates suggest that winning the lottery caused an increase in local crime of 0.051 log points, translating into approximately 5.2% ( $= (e^{0.051} - 1) * 100$ ), while an operating dispensary increased crime by 28.8% ( $= (e^{0.253} - 1) * 100$ ). The standard errors reported in these results are relatively small, allowing us to rule out the possibility of a drastic change in the crime rate occurring on account of new dispensaries. Nonetheless, these estimates are not statistically significant. [Figure 3](#) panel (a) shows the ITT effects graphically. The figure plots the estimated change in overall crimes, along with 95% confidence intervals and the chosen treatment bandwidth from 100 to 500 meters. Consistent with [Table 4](#), the range of estimates is very close to zero across the treatment bandwidths.

In contrast to our results, the majority of prior literature found dispensaries decrease local crime. Our results may differ from some past work due to our ability to make use of an instance of random spatial allocation. By using a lottery design, our results suggest that the overall impact of dispensaries on crime is innocuous, with treated and non-treated neighborhoods experiencing consistent crime trends during the period of dispensary openings. Our results are consistent with the recent evidence from [Chu and Townsend \(2019\)](#) and [Morris et al. \(2014\)](#), who find no causal effects of medical marijuana laws on crime. Our research suggests this is also true for recreational marijuana dispensaries.

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. Rape, which the FBI includes in violent crime, is omitted from this analysis as the City of Tacoma does not provide sex-related crime.<sup>6</sup>

For each crime type, [Table 5](#) shows the impact of dispensaries on crime both from the DiD analysis in [Equation 1](#) and from the IV analysis in [Equation 3](#). We do not find statistically

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<sup>6</sup>Rape incidents constitute only 0.2% of reported crimes within jurisdictions in our sample where data is available.

significant results for property, violent, or drug crime. This result holds for all distance bandwidths and estimation methods. [Figure 3](#) panels (b)-(d) show the equivalent ITT results by crime type and by treatment bandwidth. The figure indicates property, violent, and drug-related crime are not experiencing an increase or decrease in frequency around lottery-winning dispensaries.

[Table A1](#) takes a closer look at each crime type (i.e., motor vehicle theft, larceny, robbery, etc.) and shows the impact of dispensaries on crime by type using [Equation 1](#). We find some evidence that dispensaries increase robberies. At a 100 meter treatment bandwidth, the estimates show that winning the lottery led to a 1.6% rise in local robberies. At larger bandwidths, the causal estimates are less significant. This spatial pattern suggests that the increase may be related to robberies that occurred at, or directly adjacent to, the dispensaries. This robbery crime result is consistent with local news reporting in Washington, which suggested marijuana dispensaries have been the target of robberies for marijuana products and money.<sup>7</sup>

## 6.2 Heterogeneous Effects

While we generally find a null effect of dispensaries on overall local crime, the impact may differ across neighborhoods of differing demographics. 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. 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 triple-difference estimates

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<sup>7</sup>For example: *Surveillance video shows pot shop owner use bear spray to thwart armed robbery*, Q13 Fox, <https://q13fox.com/2020/02/17/surveillance-video-shows-pot-shop-owner-use-bear-spray-to-thwart-armed-robbery/>; *Violent pot shop robbers wanted in Seattle*, Q13 Fox, <https://www.q13fox.com/washingtons-most-wanted/violent-pot-shop-robbers-wanted-in-seattle>; *'They held a gun to my head': Armed robbers hit S. Seattle pot shop*, KOMO News, <https://www.q13fox.com/washingtons-most-wanted/violent-pot-shop-robbers-wanted-in-seattle>.

from [Equation 2](#). We estimate results for the total number of crimes, as well as show results corresponding to the three crime categories: property crime, violent crime, and drug crime.

[Table 6](#) shows the effect of lottery winning by crime type, by neighborhood characteristics, and by treatment bandwidth around dispensaries. While we do not find a significant effect on overall crime in any particular neighborhood type, panel B shows strong evidence of an increase in property crimes concentrated around marijuana dispensaries in low-income neighborhoods. The effect is strongest within 400 meters of the dispensary location and diminishes with distance. At 400 meters, we find that winning the lottery increases property crime in low-income neighborhoods by an additional 0.256 log points, or 29.2%, compared to the effect in non low-income neighborhoods. We estimate a null effect of dispensaries on property crime for non low-income neighborhoods at all treatment bandwidths.

We also examine heterogeneity in property crime for neighborhoods with high Black and Hispanic populations but find the heterogeneity in a neighborhood’s ethnic and racial makeup is not relevant to results. Panel C and D undertake a similar analysis for heterogeneous neighborhood effects for violent crime and drug crime. The point estimates suggest that the impacts of dispensaries on violent and drug crime types do not differ by neighborhood composition.

[Figure 4](#) graphically shows the property crime results by neighborhood characteristics. Consistent with [Table 6](#), the significant property crime effect for low-income neighborhoods can be seen in panel (b). We find that the racial and ethnic neighborhood composition is less relevant, as shown in panels (c) and (d).

## 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 the first evidence on this topic from a lottery setting.

Using data from the three largest cities in Washington state, we show that dispensaries have a null effect on overall local crime. When analyzing robbery crime rates at small distances from dispensaries we find some evidence of a crime increase. In low-income neighborhoods, we find evidence of a small increase in property crime. The finding suggests that recreational dispensaries may increase the level of local petty theft.

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 property crime we observe represents crimes that would not otherwise have occurred, or if these crimes would have occurred elsewhere and are redirected towards 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. are crucial to understanding the overall impact of recreational marijuana dispensary openings. For example, if police redirected patrols towards dispensaries because they anticipated crime occurring at those locations, this could bias estimates towards finding an increase in local crime around dispensaries.

Our findings have important policy implications for regulating recreational marijuana sales in the United States. We identify and quantify a small negative externality of dispensaries in low-income neighborhoods. However, the effect on local crime is only one social

consequence of dispensaries. Dispensaries in particular, and the legalization of marijuana in general, may hold numerous positive externalities. While we do not find evidence of crime reductions at the neighborhood level, it may be that marijuana legalization reduces crime rates 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, 2020](#)). The potential benefits of marijuana dispensaries must also be considered in conjunction with the small negative externalities identified in this paper.

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## Tables

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

Note: The table shows the number of reported crimes across crime type and jurisdiction.

Table 2: 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

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

Table 3: First Stage Results

<b>Variable</b>	
Lottery result (dummy)	.201*** (.052)
Year-month fixed effects?	Y
Applicant fixed effects?	Y
R <sup>2</sup>	0.352
N	24,696
Cragg-Donald Wald F statistic	3438.88

Note: The table reports the first stage estimate from Equation 4. The outcome variable is a dummy variable for an operating local dispensary. Standard errors are clustered at the applicant level in parenthesis. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 4: Effect of Dispensaries on Overall Number of Local Crime

Radius (meters)	Control Mean	Treatment Effects	
		ITT	TOT
100	2.634	0.021 (0.044)	0.104 (0.218)
200	7.712	0.055 (0.047)	0.275 (0.238)
300	13.996	0.051 (0.047)	0.253 (0.216)
400	23.204	0.038 (0.040)	0.188 (0.189)
500	32.785	0.026 (0.036)	0.129 (0.173)
N	15,876	24,696	24,696

Note: The table reports both the DiD analysis (Equation 1) and the IV analysis (Equation 3). The outcome variable is the log number of local crimes. Standard errors are clustered at the applicant level in parenthesis. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 5: Effect of Dispensaries on Local Crime by Crime Type

Radius (meters)	Property Crime		Violent Crime		Drug Crime	
	ITT	TOT	ITT	TOT	ITT	TOT
100	-0.024 (0.033)	-0.117 (0.168)	0.023 (0.017)	0.116 (0.092)	0.015 (0.010)	0.074 (0.054)
200	0.031 (0.045)	0.155 (0.217)	0.044 (0.029)	0.220 (0.162)	0.020 (0.014)	0.102 (0.080)
300	0.018 (0.055)	0.087 (0.265)	0.053 (0.033)	0.261 (0.161)	0.010 (0.019)	0.052 (0.095)
400	0.005 (0.049)	0.026 (0.240)	0.044 (0.032)	0.221 (0.155)	0.009 (0.021)	0.043 (0.101)
500	0.005 (0.044)	0.026 (0.214)	0.038 (0.030)	0.190 (0.151)	0.004 (0.022)	0.022 (0.106)
N	24,696	24,696	24,696	24,696	24,696	24,696

Note: The table reports both the DiD analysis in Equation 1 and the IV analysis in Equation 3. The outcome variable is the log number of local crimes for each crime type. Standard errors are clustered at the applicant level in parenthesis. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

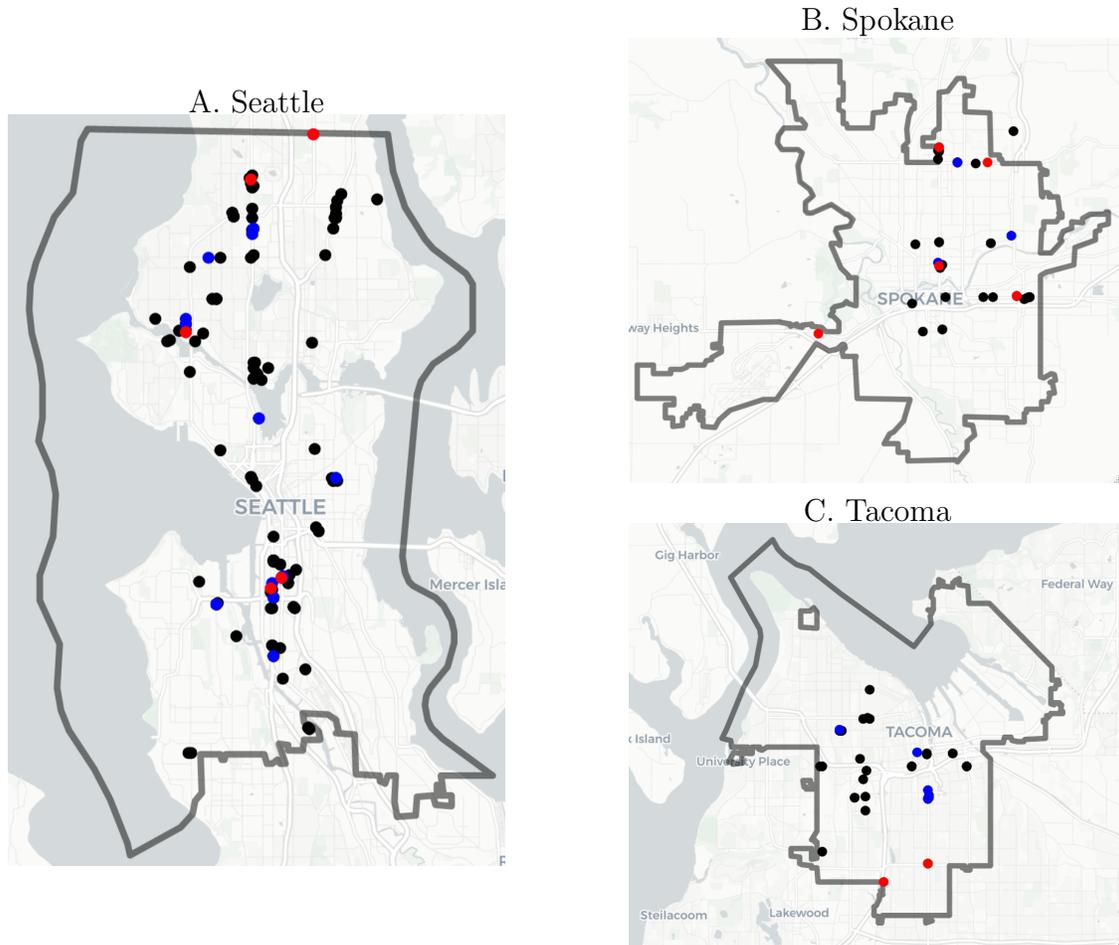
Table 6: Effect of Winning the Lottery on Local Crime by Crime Type and Neighborhood Characteristics

	Radius Around Dispensary (meters)				
	100	200	300	400	500
<i>Panel A: All Crime</i>					
Winner*Post*LowIncome	-0.037 (0.100)	-0.020 (0.125)	0.056 (0.106)	0.091 (0.097)	0.014 (0.084)
Winner*Post*HighHispanic	-0.067 (0.083)	0.082 (0.109)	-0.050 (0.133)	0.029 (0.118)	0.022 (0.104)
Winner*Post*HighBlack	0.072 (0.075)	0.169 (0.105)	0.175* (0.093)	0.114 (0.088)	0.078 (0.072)
<i>Panel B: Property Crime</i>					
Winner*Post*LowIncome	0.079 (0.066)	0.148 (0.108)	0.243** (0.117)	0.256** (0.114)	0.174 (0.107)
Winner*Post*HighHispanic	0.008 (0.062)	0.139 (0.106)	-0.016 (0.144)	0.044 (0.137)	0.041 (0.121)
Winner*Post*HighBlack	-0.002 (0.059)	0.030 (0.103)	-0.005 (0.108)	-0.003 (0.105)	-0.001 (0.088)
<i>Panel C: Violent Crime</i>					
Winner*Post*LowIncome	-0.014 (0.044)	-0.052 (0.068)	-0.019 (0.069)	0.023 (0.071)	-0.074 (0.065)
Winner*Post*HighHispanic	-0.019 (0.046)	0.038 (0.064)	0.030 (0.085)	0.086 (0.080)	0.086 (0.067)
Winner*Post*HighBlack	0.006 (0.034)	0.021 (0.053)	0.018 (0.059)	0.055 (0.069)	0.036 (0.059)
<i>Panel D: Drug Crime</i>					
Winner*Post*LowIncome	-0.002 (0.021)	-0.009 (0.033)	0.003 (0.044)	0.041 (0.051)	0.029 (0.052)
Winner*Post*HighHispanic	0.000 (0.020)	0.010 (0.029)	-0.002 (0.041)	-0.007 (0.047)	-0.021 (0.046)
Winner*Post*HighBlack	0.010 (0.018)	0.030 (0.027)	0.050 (0.037)	-0.010 (0.039)	-0.026 (0.046)
N	24,696	24,696	24,696	24,696	24,696

Note: The table reports the triple-difference analysis (Equation 2). The outcome variable is the log number of local crimes for each crime type. The low-income cutoff is the 25<sup>th</sup> 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<sup>th</sup> percentile of Hispanic and Black population shares in our sample, which are 9.4% and 18.5%, respectively. Standard errors are clustered at the applicant level and shown in parenthesis. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

# Figures

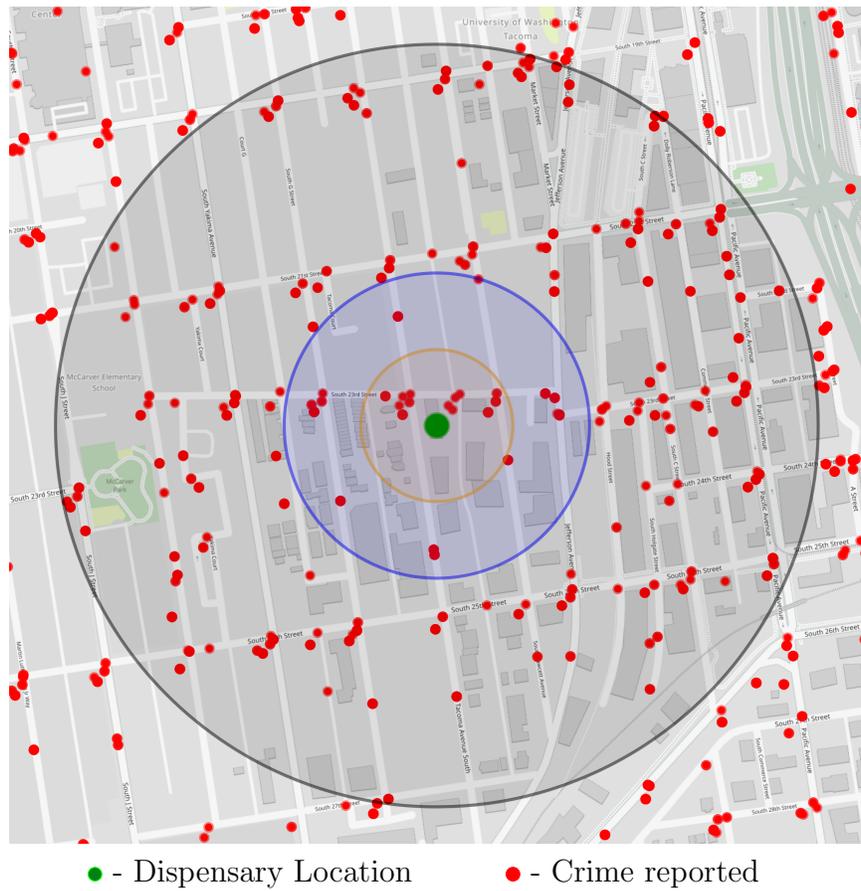
Figure 1: Dispensary Applicant Locations



- - Winning applicant, dispensary opened
- - Winning applicant, no dispensary opened
- - Losing applicant

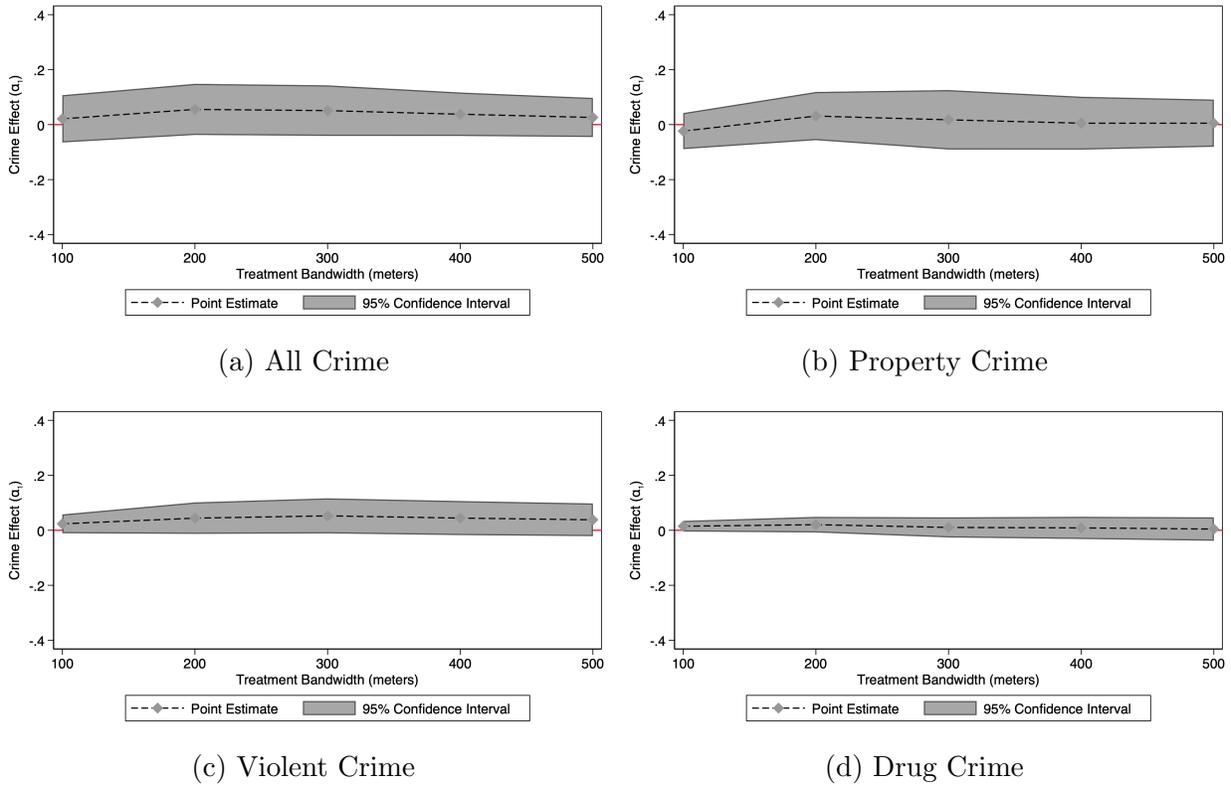
Note: The locations of all lottery applicants are displayed above, with the maps indicating the boundaries of each city. One applicant for the Spokane lottery proposed a location that was outside of the city limits. The applicant did not win the lottery. We rerun the analysis omitting this observation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

Figure 2: Dispensary Treatment Bandwidth Example



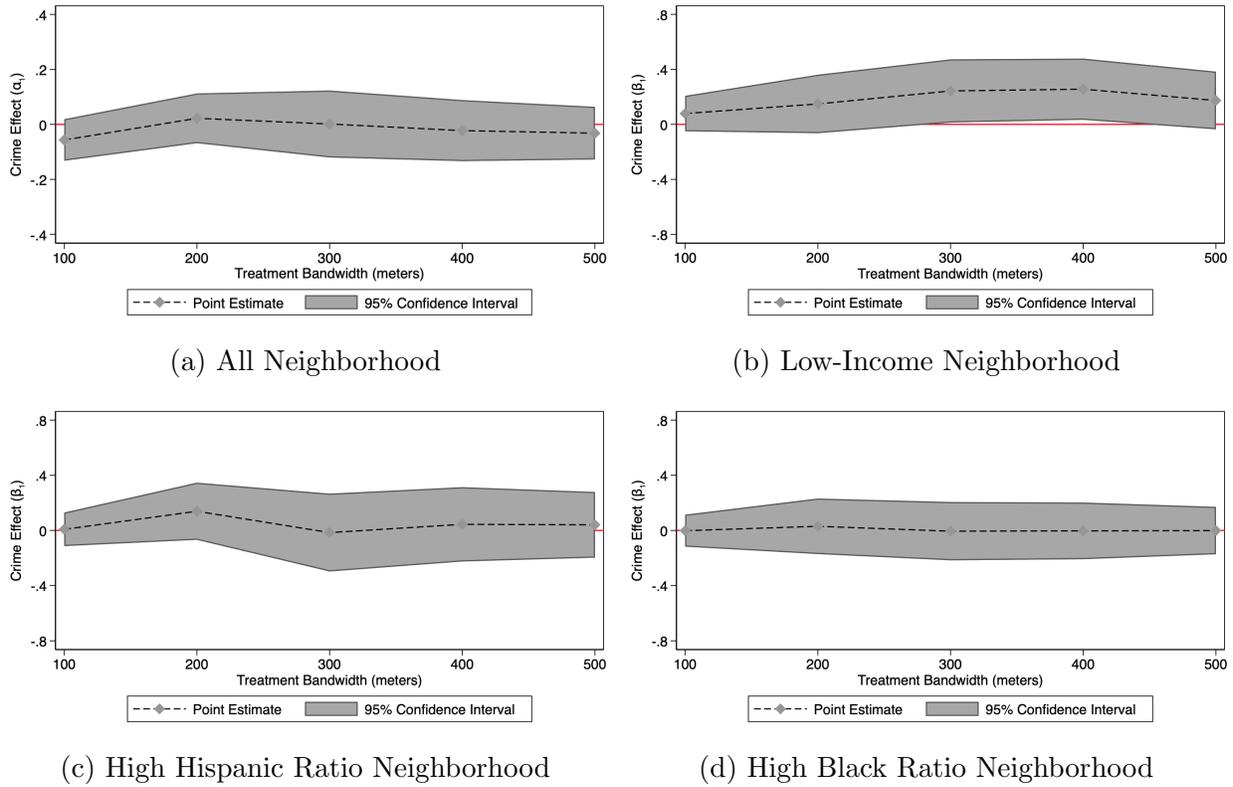
Note: The concentric circles show the 100 meter (orange), 200 meter (blue), and 500 meter (black) bandwidths. This example shows one dispensary location from the City of Tacoma.

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



Note: Each point estimate corresponds to a separate regression result ( $\alpha_1$ ). Regressions include year-month fixed effects and applicant fixed effects, as per Equation 1.

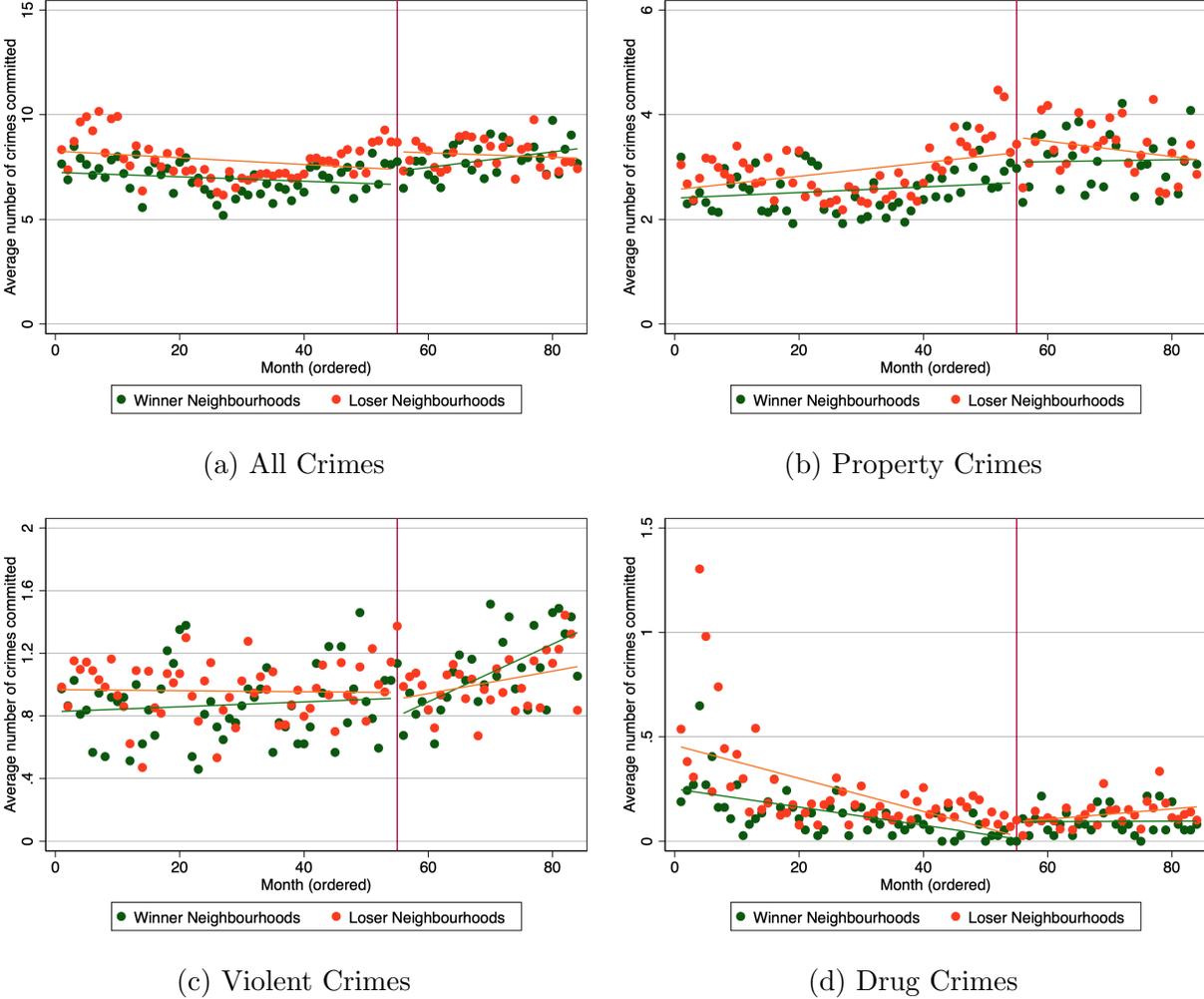
Figure 4: Estimated property crime effect as function of treatment bandwidth by neighborhood characteristics



Note: Each point estimate corresponds to a separate regression result ( $\beta_1$ ). Regressions include year-month fixed effects and applicant fixed effects, as per Equation 2.

# Appendix Figures

Figure A1: Mean Monthly Crime Counts by Lottery Status



Note: Mean monthly crime counts at 300 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.

## Appendix Tables

Table A1: Effect of Winning the Lottery on Local Crime by Disaggregated Crime Type

	Radius Around Dispensary (meters)				
	100	200	300	400	500
<i>All Property Crime</i>	-0.024 (0.033)	0.031 (0.045)	0.018 (0.055)	0.005 (0.049)	0.005 (0.044)
Motor Vehicle Theft	0.005 (0.008)	0.025 (0.019)	0.029 (0.024)	0.019 (0.029)	0.012 (0.027)
Larceny	-0.048* (0.027)	-0.005 (0.044)	-0.019 (0.061)	-0.012 (0.054)	-0.007 (0.050)
Burglary	0.013 (0.020)	0.027 (0.031)	0.030 (0.037)	0.009 (0.041)	0.015 (0.042)
Arson	0.001 (0.001)	0.003 (0.002)	0.005 (0.005)	0.005 (0.006)	0.008 (0.006)
<i>All Violent Crime</i>	0.023 (0.017)	0.044 (0.029)	0.053 (0.033)	0.044 (0.032)	0.038 (0.030)
Assault	0.009 (0.015)	0.034 (0.026)	0.034 (0.028)	0.031 (0.028)	0.024 (0.028)
Robbery	0.016** (0.006)	0.023 (0.017)	0.035 (0.024)	0.041 (0.028)	0.062* (0.031)
Homicide	-0.000 (0.001)	-0.001 (0.001)	-0.000 (0.003)	-0.003 (0.003)	-0.006 (0.004)
<i>All Drug Crime</i>	0.015 (0.010)	0.020 (0.014)	0.010 (0.019)	0.009 (0.021)	0.004 (0.022)
N	24,696	24,696	24,696	24,696	24,696

Note: The table reports the DiD analysis (Equation 1). The outcome variable is the log number of local crimes for each crime type. Standard errors are clustered at the applicant level in parenthesis.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table A2: 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
<i>Panel A: All Crime</i>					
Winner*Post*LowIncome	-0.032 (0.094)	-0.002 (0.114)	0.112 (0.103)	0.162* (0.096)	0.108 (0.087)
Winner*Post*HighHispanic	-0.065 (0.083)	0.085 (0.108)	-0.046 (0.133)	0.037 (0.118)	0.028 (0.104)
Winner*Post*HighBlack	0.075 (0.075)	0.132 (0.100)	0.147 (0.090)	0.071 (0.084)	0.042 (0.071)
<i>Panel B: Property Crime</i>					
Winner*Post*LowIncome	0.060 (0.063)	0.140 (0.098)	0.247** (0.109)	0.278*** (0.104)	0.229** (0.097)
Winner*Post*HighHispanic	0.010 (0.062)	0.143 (0.106)	-0.011 (0.144)	0.050 (0.137)	0.047 (0.121)
Winner*Post*HighBlack	0.022 (0.059)	-0.003 (0.098)	-0.018 (0.106)	-0.044 (0.101)	-0.040 (0.085)
<i>Panel C: Violent Crime</i>					
Winner*Post*LowIncome	-0.011 (0.041)	-0.051 (0.064)	0.028 (0.066)	0.058 (0.066)	-0.006 (0.062)
Winner*Post*HighHispanic	-0.019 (0.046)	0.039 (0.064)	0.031 (0.085)	0.086 (0.080)	0.085 (0.067)
Winner*Post*HighBlack	-0.003 (0.033)	0.001 (0.053)	-0.013 (0.058)	0.021 (0.067)	0.005 (0.060)
<i>Panel D: Drug Crime</i>					
Winner*Post*LowIncome	0.006 (0.022)	-0.028 (0.034)	-0.032 (0.043)	0.007 (0.048)	-0.004 (0.049)
Winner*Post*HighHispanic	-0.000 (0.020)	0.010 (0.029)	-0.003 (0.041)	-0.007 (0.047)	-0.022 (0.046)
Winner*Post*HighBlack	0.010 (0.018)	0.027 (0.027)	0.047 (0.036)	-0.005 (0.038)	-0.023 (0.044)
N	24,696	24,696	24,696	24,696	24,696

Note: The table reports the triple-difference analysis (Equation 2). The outcome variable is the log number of local crimes for each crime type. The low-income cutoff is the 33<sup>rd</sup> 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 66<sup>th</sup> percentile of Hispanic and Black population shares in our sample, which are 9.0% and 13.9%, respectively. Standard errors are clustered at the applicant level and shown in parenthesis. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.