Hits from the Bong:

The Impact of Recreational Marijuana Dispensaries on Property Values

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Abstract

This paper studies the impact of local disamenities on property values, by focusing on the lega lization of recreational marijuana dispensaries in Washington State. Policymakers have long expressed concerns that the positive effects of the legalization—e.g., increases in tax revenue—are well spread spatially, but the negative effects are highly localized. We use changes in property values to measure individuals' willingness to pay to avoid the local negative externalities caused by the arrival of marijuana dispensaries. Our key identification strategy is to compare changes in housing sales around winners and losers in a lottery for recreational marijuana retail licenses; due to location restrictions, license applicants were required to provide an address of where they would like to locate. Hence, we have the locations of both actual entrants and potential entrants, which provide a natural difference-in-differences set-up. Based on our preliminary analysis using data from King County, Washington, we find a 1.7% decrease in the value of properties within a 0.5 mile radius of an entrant (or a $6,700 decline in property values).

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1 Introduction

While recreational marijuana laws have begun liberalizing across the United States and in other parts of the world, legalized cannabis remains a contentious issue.[1] Advocates maintain that legalization will benefit government coffers through cannabis taxes, decrease spending on the enforcement of marijuana laws, and relieve a stressed criminal justice system by killing the black market for cannabis.[2] Opponents, however, argue that in addition to negatively impacting on the health of consumers, marijuana adversely affects local neighborhoods. A commonly cited concern is that marijuana dispensaries cause crime. Because marijuana is still federally illegal, cannabis businesses typically do not have access to banks and, consequently, are cash-only businesses, making them targets for robbers.[3] Other proponents of cannabis prohibition cite concerns about normalizing the use of marijuana to children in neighborhoods where dispensaries are present.[4]

These arguments imply that the positive effects of legalization are relatively well spread from a spatial standpoint, but the negative effects are highly localized. If marijuana dispensaries are a disamenity, then residents may leave the neighborhood, and these responses will be observed in the housing market through depressed prices. Therefore, the change in property values is a useful measure of willingness to pay to avoid negative externalities.[5]

This paper studies how the arrival of cannabis dispensaries impacts property values. A number of papers in the public health and public policy literature have found an association between marijuana retailer density and child neglect, crime, and youth usage (Freisthler et al., 2015; Kepple and Freisthler,

[1] In addition to the District of Columbia, eight states have legalized recreational marijuana: Colorado, Washington, Maine, California, Oregon, Massachusetts, Nevada, and Alaska. Canada also has legalized recreational cannabis. Several other states in the U.S. have marijuana decriminalization laws or medicinal marijuana laws.

[2] The Los Angeles Times Editorial Board. "It's Time to Legalize and Regulate Marijuana in California. Yes on Proposition 64." *Los Angeles Times*, September 16, 2016. http://www.latimes.com/opinion/editorials/la-ed-proposition-64-20160918-snap-story.html.

[3] Abcarian, Robin. "Your Business is Legal, but You Can't Use Banks. Welcome to the Cannabis All-Cash Nightmare." *Los Angeles Times*, January 29, 2017. http://www.latimes.com/local/abcarian/la-me-abcarian-cannabis-cash-20170129-story.html

[4] Aregawi, Hermela. KRON4.com. "Residents Fighting to Keep Marijuana Dispensary out of Sunset District Neighborhood." May 3, 2017. http://kron4.com/2017/05/03/residents-fighting-to-keep-marijuana-dispensary-out-of-sunset-district-neighborhood/

[5] This approach to measuring the damages from externalities has been taken in a many papers. Linden and Rockoff (2008) study how the property values change when sex offenders move into a neighborhood. In the education literature, Figlio and Lucas (2004) study the impact of school report cards on housing markets. In the environmental economics literature, recent examples include Chay and Greenstone (2005) on the impact of the Clean Air Act, Currie et al. (2015) on toxic planting openings and closings, Davis (2005) on cancer clusters, Davis (2011) on power plants, and Greenstone and Gallagher (2008) on hazardous waste.

2012; Mair et al., 2015; Shi, 2016). However, store entry is endogenous. Dispensaries enter in areas that they feel are particularly profitable, and location profitability may be correlated with local characteristics such as crime or other unobservables.

To address the identification challenge, this paper uses a natural experiment from the Washington recreational marijuana market to determine causal relationships between dispensary entry and property values.[6] After legalization in Washington, the state capped the number of retailer licenses it would issue and invited firms to apply for licenses. Due to tight restrictions in where cannabis businesses could locate, all applicants had to provide an address for a store site, so the state could check that the store met site requirements. Moreover, because Washington had more licenses applicants than available licenses, the state distributed the licenses via a lottery. Hence, we have data available on not only the location of market entrants but also on credible counterfactual store locations: those locations that missed out on a dispensary due to the lottery.

Our empirical strategy is, therefore, to compare housing prices in areas around actual entrants and lottery losers to identify changes in property values due to a dispensary entry, motivating a difference-in-differences design. Using data from King County, Washington, we find an almost 1.7% decrease in the value of properties within a 0.5 mile radius of an entrant. This implies a $6,700 decline in property values based on the median home sales price of $400,000, a non-trivial decrease that may imply the need for land use laws.

The paper proceeds as follows. Section 2 discusses the analytical framework for our analysis. Section 3 offers details about the setting of our empirical exercise in Washington state. Our data is described in Section 4, and Section 5 presents our statistical analysis and results. Section 6 concludes.

2 Analytical Framework: The Incidence of Marijuana Retail Shop Openings

To motivate our empirical strategy, we outline a partial equilibrium model of incidence in the context of the opening of marijuana retail shops.[7]

[6] This paper is one of few that uses quasi-experimental variation to identify the causal impacts of marijuana. Another is Marie and Zölitz (2017) which uses a policy change in the Netherlands to study the effects of marijuana use on school performance. Papers such as Anderson et al. (2013) and Anderson et al. (2015) discuss the relationship between medical marijuana laws and traffic fatalities and teen usage.

[7] The partial equilibrium model generalizes into a model of general equilibrium found in Kline (2010) and Moretti (2011), which are generalizations of Rosen (1979) and Roback (1982)'s classic models of general equilibrium effects of locational amenities on wages and housing prices with mobile workers and firms.

A local economy consists of a continuum of agents of measure one. The economy is divided into D number of neighborhoods, indexed by $d = 1, 2...D$, which represent the average distance of the neighborhood to a marijuana retail shop. Agents choose to live in a location d to maximize her utility. For now, we assume that agents work in the a single local labor market, regardless of their residential locations. The indirect utility of worker i at a housing location d is

$$U_{id} = \tau + A(d) + e_{id}$$

where

- τ is the tax revenue generated by marijuana retail shops. All residents receive the same amount of transfers.
- $A(d)$ is a measure of local amenities net of housing costs. We assume $A'(d) \neq 0$, i.e. distance to a marijuana retail shop affects the level of local amenities.
- A random term, e_{id}, represents worker i's idiosyncratic preferences in the valuation of local amenities. The e_{id}'s are identically and independently distributed across individuals and locations, and assumed to follow a type I extreme value distribution.

A worker chooses location d that maximizes her indirect utility. Without heterogeneity in locational preferences, all individuals will locate in the neighborhood that offers the highest value of indirect utility, i.e.,

$$v(d) \equiv \tau - r(d) + A(d).$$

With heterogeneity in tastes, individuals in location d have:

$$e_{id} - e_{id'} > v_{d'} - v_d = A(d') - A(d).$$

Define the distribution function of $\eta_i \equiv e_{id} - e_{id'}$ as $G(\cdot)$. Then,

$$L(d) \equiv G(\eta_i > v_{d'} - v_d),$$

where $L(d)$ is the measure of individuals living in neighborhood d.

Finally note that the total welfare of workers in location all D neighborhoods is given by,

$$V = \mathbb{E}_i \left[\max_d \{v_d + e_{id}\} \right].$$

Now consider a positive fiscal shock generated by the opening of a marijuana retail shop in the economy. This is assumed to increase residents income equally. The shop, however, creates a negative externality for residents living near the marijuana shop through, for example, increased crime rates and other nuisance problems. Taking derivative of workers aggregate welfare with respect to the fiscal shock associated with the opening of a marijuana retail shock yields the expression:

$$\frac{dV}{d\theta} = \sum_{d=1}^{D} L(d) \cdot \left[\frac{\partial \tau}{\partial \theta} + \frac{\partial A(d)}{\partial \theta} \right] = \frac{\partial \tau}{\partial \theta} + \sum_{d=1}^{D} L(d) \cdot \frac{\partial A(d)}{\partial \theta} \tag{1}$$

where $d\theta$ represent the marginal effect of the opening of marijuana retail shop and $\frac{dV}{dv_d} = L(d)$. The latter follows directly from the assumption that preference shock follows a Type I Extreme Value distribution, and is i.i.d across individuals and neighborhoods.

From Equation 1, the incidence of the marijuana retail shop may be summarized by two terms. First is the total fiscal impact associated with the marijuana retail business. Since all residents work in the same local jurisdiction, the fiscal impact is the same for all residents regardless of their distance to the marijuana retail shop. The second term consists of the non-wage changes in amenities associated with a marijuana retailer. Since negative externalities in the form of increased crime rates or other nuisances are arguably highly localized, these costs only accrue to the residents living near the retail shop.

For a 'marginal' worker living in location d, the following relationship holds (assume $d < d'$):

$$e_{id} - e_{id'} = v_{d'} - v_d = A(d') - A(d)$$

After the marijuana shop opens, if $A(d') - A(d) > 0$, the worker is better off moving further away. However, since workers are optimizing with respect to location decisions, a simple envelop result suggests that workers who switch locations in response to a change in local amenities are to *first order* indifferent about doing so. Therefore, the incidence of the marijuana retailer opening may be approximated simply by the change in prices experienced by the immobile population.

In the case of non-marginal changes in tax revenue or local amenities, the envelop theorem no longer holds, and taste-based sorting may also have first-order implication for welfare. However, in the case of localized disamenities, Bartik (1987) and Palmquist (1992) show that the slope of the hedonic price function is an approximation of the willingness to pay for a non-marginal change.[8]

3 The Washington Recreational Marijuana Market

3.1 Initiative-502

On November 6, 2012, Voters approved Initiative-502 (I-502), which not only legalized recreational marijuana possession and consumption for adults over the age of twenty-one, but also gave the state authority to tax, license, and regulate marijuana firms. In order for firms to participate in the recreational marijuana market, the law stipulated that a firm must hold a license. Three licenses classes were created: producer (marijuana farmers), processor (creators of joints, edibles, vapor products, etc.), and retailer. While producer and processors could be vertically integrated, retailers could not be integrated with upstream firms.

I-502 also instructed regulators to create license quotas. While the Washington Liquor Cannabis Board (WLCB) opted not to limit the number of licenses issued to upstream firms, it capped the number of retail licenses state-wide at 334. It then divided up these licenses among counties using a formula that found "the number of stores...[by] minimiz[ing] the population-weighted average" distance from the user to the marijuana retailer.[9][10] The licenses were then split across the county's incorporated cities according to the proportion of the county's population within the city. Remaining licenses were assigned to the county's rural areas.

Figure 1 displays a map of King County's jurisdictions. King County was allocated sixty-one retail licenses. Table A1 lists how licenses were allocated across all cities in King County. For example, Bellevue, which has about 6.3% of King County's population, was assigned four licenses, and Seattle,

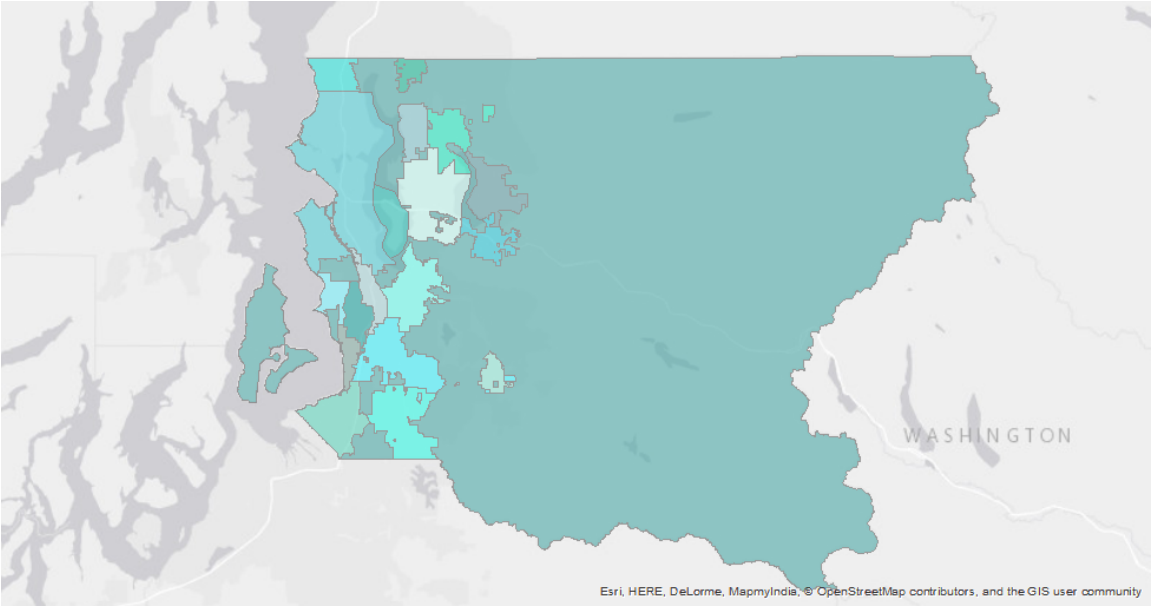
[8] Greenstone and Gallagher (2008) give an excellent discussion on the welfare effects of non-marginal changes in the context of local disamenities; whereas Kuminoff et al. (2013) provide a comprehensive review on equilibrium sorting models that also yield insights into the welfare effects of non-marginal changes in the context of local disamenities.

[9] Caulkins, Jonathan P. and Linden Dahlkemper, "Retail Store Allocation," BOTEC Analysis Corporation, Jun. 28, 2013, available from Washington Liquor Cannabis Board.

[10] To calculate this average distance, the formula assumes users are spread uniformly across the state and that "stores are placed... to maximize convenience." Hence, the "proxy" for distance is the area of a county divided by the number of stores in the county.

which has around one-third of the county's population, was assigned twenty-one licenses. Rural King County has almost 17% of the county's population and, therefore, was assigned eleven licenses.

Figure 1: Jurisdictions in King County, Washington



3.2 The Washington Marijuana Retail License Lottery

In November 2013, the WLCB opened a thirty day window in which those interested in becoming marijuana retailers could apply for a retailer license. Applicants were subject to background checks to determine if they were eligible for licenses. Furthermore, as stores were banned from locating within 1000 feet of a "school, playground, ... child care center, public park, public transit center, or library," the license applications required a potential store address so that regulators could determine compliance with the location restrictions.

In total, though only 334 retail licenses were available, almost 1,200 applications were submitted. King County had a total of 370 applicants for 61 licenses. In particular, Seattle had 191 applicants for 21 licenses. Firms could submit multiple applications for licenses; however, the state had additional restrictions on the number of licenses a firm could obtain: Firms could not have more than three licenses and no more than one-third of all licenses in a jurisdiction. While the application fee was

only $250, applicants tended not to submit several applications. In fact, 99% turned in less than three applications with 47% submitting a single application. Furthermore, 52% of firms that handed in multiple applications were not petitioning for licenses in the same jurisdiction.

Seventy-five jurisdictions—incorporated cities and rural county areas—had more applicants than licenses. Of which, King County had sixteen of these jurisdictions. For those jurisdictions with binding license quotas, the WLCB decided to distribute licenses via a lottery. The license lotteries were held April 21-25, 2014. Each applicant was randomly assigned a number by accounting firm Kraght-Snell. The numbers—without any identifying information—were then sent to Washington State University's Social and Economic Sciences Research Center, who ranked the numbers from 1-n, n being the number of applicants within a jurisdiction provided. Then Kraght-Snell decoded the rankings. If a ranking was higher than the number of licenses allocated to a jurisdiction, the firm was a lottery "winner." The results of the lottery were made public on May 2, 2014.

3.3 Entry in the Recreational Marijuana Market

Contingent on receiving a license, licensees could begin selling marijuana as early as July 2014. 70% of lottery winners entered the market, and half of those that did not enter (i.e., 15% of the lottery winners) were kept from opening due to local bans on marijuana businesses. We cannot account for the other half of lottery winners that did not enter the market though one possibility may be that these firms have failed subsequent background checks.

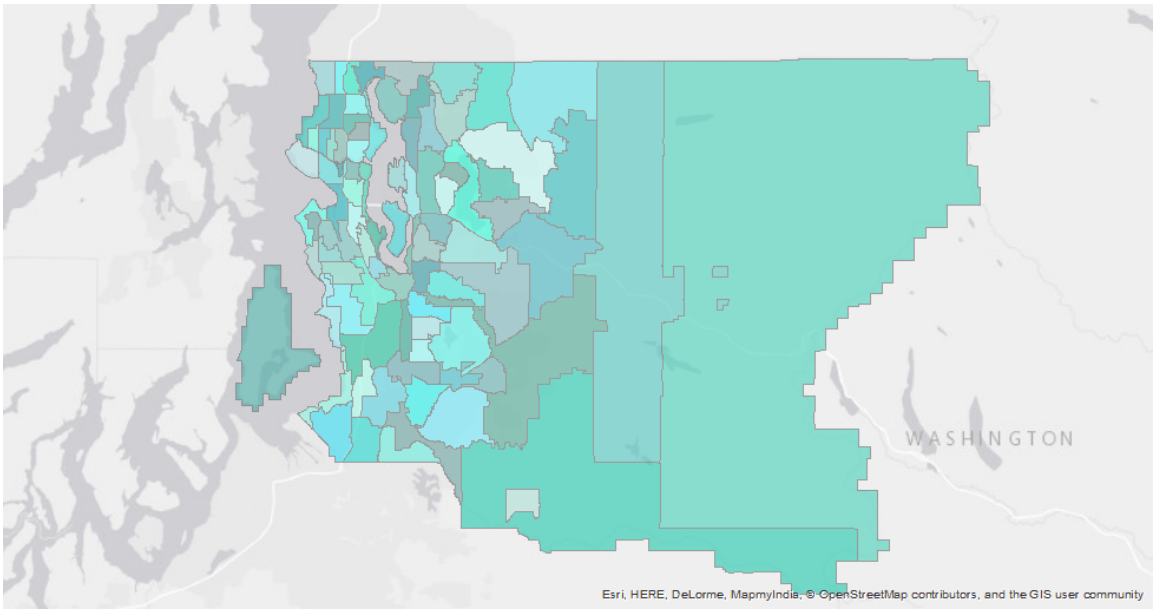
Entrants tended to locate at or near the address listed on their license applications even though addresses were not binding, with 47% locating in the exact address and 28% locating within one-third of a mile from the listed address.

4 Data

4.1 WLCB Data

The main data set from the WLCB is the results of the marijuana retail license lotteries. The results include the tradename of the applicant, an application number, an address for the potential store's location, and the applicant's lottery rank. Lottery addresses are geocoded using Texas A&M

Figure 2: Residential Areas in King County, Washington



University Geoservices. We merge this data with data on entrants (from July 2014 to November 2015) to see which lottery winners eventually entered the market. Entrant data include the retailer's geocoded location and address. As not all entrants began selling as of July 2014, we construct the firms' entry dates using retailer tax data, defining the month of firm entry as the month in which the firm first pays taxes. Panel A of Table 1 provides a summary of the lottery and entrant data, there are thirty-seven marijuana dispensaries seen in the data with 102 lottery losers.

4.2 King County Tax Assessor Data

Our second data source is from the King County Tax Assessor Office which includes all home sales from January 2012 to November 2015. Included is the sales price and sales date as well as the address. After geocoding the properties, we then measure the distance between properties and dispensaries and between properties and the lottery "losers" described above. We then keep property sales less than r meters from either a dispensary or license loser.

Moreover, the data provide property characteristics like the number of bedrooms, number of bathrooms, square footage and the residential area—an official definition determined by the Tax

Assessor's Office through "natural dividing lines, parcel counts, and area complexity/similarities." Figure 2 displays a map of county's residential areas. Also available is a tax assessor's measure of the quality–a grade from 4 ("low") to 12 ("luxury") and condition of the property—a grade from 1 ("poor") to 5 ("very good").

Panel B of Table 1 provides summary statistics of the property data. Prices of properties within 800 meters (approximately one-third of a mile) of entrants are slightly higher than properties close to lottery losers. However, property characteristics between properties near entrants and losers are similar: the mean number of bedrooms and bathrooms are nearly the same. In addition, though the condition and quality of homes near entrants is similar to homes near losers, properties near losing addresses are slightly larger than homes near entrants.

5 Estimation and Results

5.1 Identification Strategy

As discussed in Section 2, the choice of residence location reveals preferences not only about housing characteristics but the choice of neighborhood amenities. Therefore, if a recreational marijuana retailer is a disamenity—i.e., a neighborhood amenity that creates negative externalities to the residents—then it will be capitalized in property values. However, the retailer's choice of location may be correlated with neighborhood unobservables; hence, we cannot simply compare neighborhoods with retailers to those without retailers.

We overcome this difficulty by utilizing the Washington retail license lottery as a natural experiment. We know where the losing applicants wished to locate. Therefore, we have areas that would likely have a marijuana dispensary had the applicant won the recreational license lottery. We can then measure willingness to pay to avoid negative externalities from dispensaries by comparing home prices in areas close to active retailers with neighborhoods that missed getting a marijuana dispensary, motivating a difference-in-differences (DD) design.

A challenge to our DD estimation is that although we know where losing applicants may have located, we do not know the counterfactual entry dates. To resolve this issue, we examine only those home sales that occur within the same residential area as a marijuana retail entrant. We take the entry date of the first retail entrant in the residential area as the counterfactual entry date for the

Table 1: Summary Statistics

Panel A: Lottery and Entrant Data (King County)	
# of lottery losers	102
# of entrants	37
number of months	46

Panel B: Property Data			
	All Properties	Near Entrants	Near Losers
	Mean (*Standard Deviation*)		
mean sale price	$431,089.50 (285,253.60)	$433,290.40 (227,579.40)	$427,761.50 (355,113.70)
bedrooms	3.192 (0.964)	3.190 (0.993)	3.197 (0.918)
bathrooms	1.974 (0.776)	1.995 (0.767)	1.941 (0.790)
square footage (1,000 sqft.)	1,749.372 (716.758)	1,725.138 (682.015)	1,786.018 (764.957)
	Percentages		
quality rating			
6	13.79	12.75	15.37
7	46.30	47.48	44.50
8	29.49	32.31	25.36
other	10.42	7.46	14.77
condition rating			
1	0.17	0.08	0.30
2	1.12	1.04	1.25
3	64.39	65.86	62.15
4	23.40	22.23	25.18
5	10.92	10.78	11.12

lottery loser.

A caveat to our methodology, common to all papers that use house prices to measure disamenities, is that we observe only prices for houses that undergo changes in ownership. Therefore, if the dispensary causes changes in the composition of home buyers and/or sellers, we may not be observing the average willingness to pay to avoid externalities. For example, the property sellers may be those that find marijuana retailers particularly distasteful which would lower observed prices. On the other hand, buyers may be those more inured to the negative effects of dispensaries, meaning they are less willing to pay to avoid the externality than the average person, thereby increasing prices. It is unclear which direction this would bias estimates, and without information on buyers and sellers, it is not possible to examine the matter further.

5.2 Estimation

In a DD design, the primary identification assumption is parallel trends between the treatment and control groups. Figure 3 displays the trends in prices for the ten months around store or counterfactual store entry. Time trends in property values are netted out using a flexible polynomial regression. While pre-store entry prices do not seem to have systematic trends after controlling for cyclicality—which validates the parallel trend assumption—the post-period has a definite decrease in prices for the treatment group relative to control areas.

The DD estimating equation takes the following form:

$$ln(P_{ijt}) = \alpha_j + \alpha_t + X_i\beta + \gamma_1 T_{it} + \gamma_2 Post_{it} + \gamma_3 Post_{it} \times T_{it} + \varepsilon_{ijt} \tag{2}$$

where P_{ijt} is the sale price of home i in residential area j at time t. The term T_{it} denotes an indicator variable that equals one if the property is near a marijuana dispensary location, while $Post_{it} = 1$ after the dispensary enters or after the lottery losers' "entry date." In addition, X_i is a vector of property characteristics detailed in Table 1: building quality and condition, number of bedrooms and bathrooms, and square footage. The terms α_j and α_t are residential area and month-year fixed effects, respectively.

The parameter of interest is γ_3, the coefficient on the interaction between $Post_{it}$ and T_{it}. It captures the differential impact of a dispensary on home prices relative to areas that were "losers"

Table 2: Estimation Results

	(1)	(2)	(3)	(4)	(5)
$Post_{it} \times T_{it}$	-0.135***	-0.0344	-0.0202**	-0.0151	-0.0167**
	(0.0250)	(0.0474)	(0.0105)	(0.0135)	(0.00799)
$Post_{it}$	0.299***	-0.0958	0.232***	-0.0574	-0.0349
	(0.0352)	(0.114)	(0.00781)	(0.0444)	(0.0383)
T_{it}	0.0591	0.104	0.00969	-0.0177	-0.0174
	(0.0866)	(0.110)	(0.0406)	(0.0374)	(0.0310)
Area FE	N	N	Y	Y	Y
Month FE	N	Y	N	Y	Y
Property Char.	N	N	N	N	Y
N	8270	8270	8270	8270	8270
adj. R^2	0.029	0.062	0.323	0.358	0.486

Standard errors in parentheses are clustered at the residential area level.
* ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

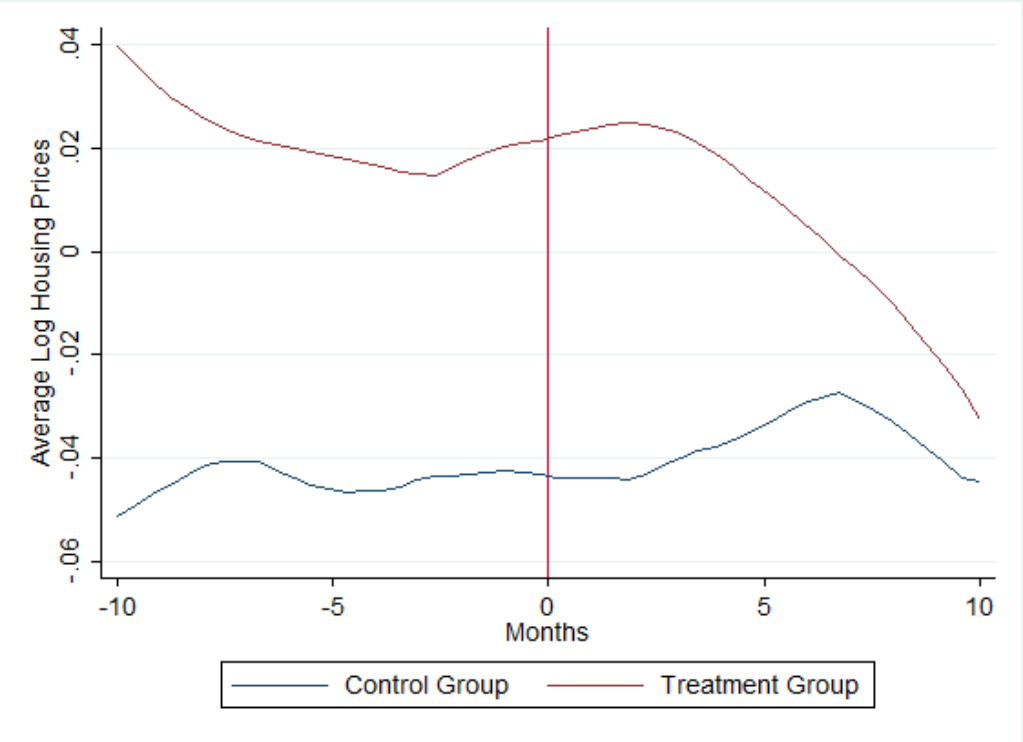
in the marijuana retail license lottery. As the model includes month-year and area fixed effects, identification is based on within-time and within-residential-area comparisons between areas near a dispensary and losing address.

We restrict our analysis to properties within 800 meters (approximately 0.5 miles) from dispensary or a lottery loser. As shown in Figure 4, price differences are highly localized, so choosing 0.5 miles balances the tradeoff between detecting price decreases from dispensary entry and sacrificing statistical power. In other words, making the distance from the store too large makes it difficult to find effects from store entry; however, decreasing the radius below 0.5 may make the sample size too small. This is discussed further in Section A.2 of the Appendix.

5.3 Results

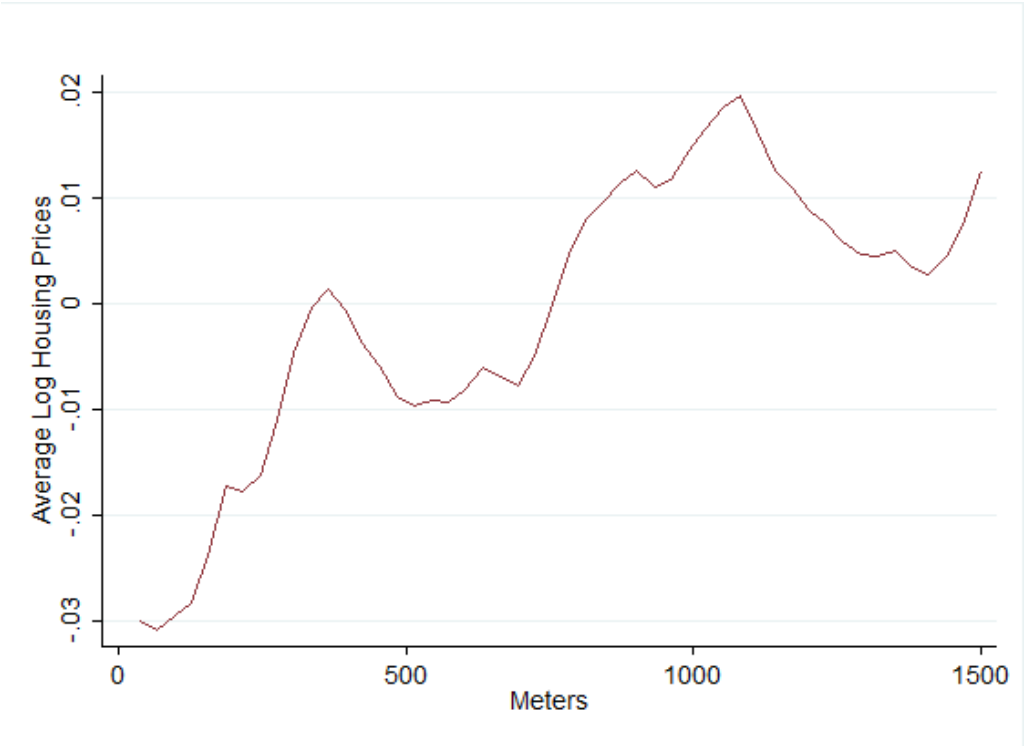
The estimation results are presented in Table 2. Column (1) reports a specification without month-year or area fixed effects or property characteristics. Here the DD estimate is 13.5. Adding fixed effects as in columns (2)-(4), considerably lowers the DD estimate. However, with month-year and area fixed effects, the DD coefficient is no longer significant at the 0.05 significance level.

Figure 3: Trends in Prices



Note: Results of polynomial regressions (bandwidth = 3 months) of sale price after netting out time trends.

Figure 4: Price Gradient of Distance from Dispensary



Note: Results of polynomial regressions (bandwidth = 100 meters) of sale price after dispensary entry.

Hence, our preferred specification is found in column (5). After controlling for residential area and month fixed effects, and house characteristics, we find a 1.67% drop in the sales price in response to a marijuana dispensary opening within 0.5 miles of a property. Given the median home price of $400,000, this implies a decline of $6,680, a non trivial amount. Households are willing to pay a high cost for policies that keep dispensaries out of neighborhoods, suggesting that policies such as marijuana zoning may be appropriate and welfare improving. Additional robustness checks such as falsification tests are discussed in Section A.3 of the Appendix.

These estimates, though slightly smaller, are comparable in magnitude to recent studies on the impact of disamenties on property values found in the public finance and environmental economics literature. Linden and Rockoff (2008) finds a 4.1% drop in property values after the arrival of a sex offender in neighborhoods, an implied decrease of $5,500 given median home prices in their area of study: Mecklenberg County, North Carolina. Chay and Greenstone (2005) calculates an elasticity of housing prices with respect to air particulates concentrations of -0.2 to -0.35. In Davis (2011), neighborhoods within two miles of a power plant experience a 3-7% decreases in housing values and rents while toxic plants lead to declines in property values by 11% for homes within 0.5 miles of the plants in Currie et al. (2015).

6 Conclusion

We use study the impact of disamenities from cannabis dispensaries on property values. A recreational marijuana retail license lottery held in Washington state provides plausibly exogenous variation to neighborhoods that were affected by a marijuana retailer. Because participants in the license lottery were required to submit potential addresses due to location restrictions, we have data on both actual entrants' addresses and the addresses for lottery losers. Using a difference-in-differences set-up, we are then able to compare the property values around the locations of entrants and those that failed to receive a license.

We find that in King County, Washington, a marijuana dispensary decreases property values by almost 1.7% for homes within 0.5 miles of the retailer, a decline of almost $6,700 based on median home values. These results imply a high willingness to pay to avoid the local negative externalities, suggesting the need for localized policies such as land use or zoning ordinances to mitigate the localized impact marijuana retailers on neighborhoods.

Given the public policy implications, the impact of dispensaries on neighborhoods remains an important area of research. Using the Washington retail license lottery as a source of quasi-experimental variation, future work will focus on determining causal relationships between retail store locations and neighborhood outcomes such as crime rates, marijuana-related hospitalizations, and the entry of complementary businesses.

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A Appendix

A.1 Licenses Distribution Across King County

Table A1: Changes in Distance from a Dispensary

City/Locality	Population	# of Licenses
Unincorporated	325,000	11
Auburn	62,761	2
Bellevue	122,363	4
Burien	33,313	1
Des Moines	29,673	1
Federal Way	89,306	3
Issaquah	30,434	1
Kent	92,411	3
Kirkland	48,787	2
Maple Valley	22,684	1
Mercer Island	22,699	1
Redmond	54,144	2
Renton	90,927	3
Sammamish	45,780	1
SeaTac	26,909	1
Seattle	608,660	21
Shoreline	53,007	2
Tukwila	19,107	1
King County	1,931,249	61

A.2 Varying the Radius from a Dispensary

As discussed in Section 5.2, changing the radius we use in our analysis involves trading off detecting effects and statistical power. To check whether 800 meters balances these two issues, I estimate equation 2 while varying the distance from dispensaries. Table A2 reports results for radii of 300 meters, 450 meters (approximately 0.25 miles), and 1250 meters (approximately 0.75 miles). Each specification has month-year and residential area fixed effects and property characteristics.

At a radius of 450 meters, the number of observations decreases by over 5,000. The difference-in-differences estimate is close to the DD estimate reported in Table 2. However, the DD estimate is not statistically significant. Expanding the radius to 1250 meters increases the number of observations by over 12,000, but the magnitude of the estimate decreases by almost 50% and the coefficient is no longer significant. Hence, 800 meters may provide the best radii to detect effects on property values from dispensaries.

Table A2: Changes in Distance from a Dispensary

	300 meters	450 meters	1250 meters
$Post_{it} \times T_{it}$	-0.0800	-0.0171	-0.0091
	(0.0529)	(0.0243)	(0.00845)
$Post_{it}$	-0.0877**	-0.0720	0.0000150
	(0.0237)	(0.0616)	(0.0320)
T_{it}	0.0498	-0.0384	-0.0482*
	(0.0237)	(0.0279)	(0.0223)
Area FE	Y	Y	Y
Month FE	Y	Y	Y
Property Char.	Y	Y	Y
N	993	2554	20,352
adj. R^2	0.406	0.465	0.454

Standard errors in parentheses are clustered at the area-level.
* ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$)

A.3 Robustness Checks

While the graphical analysis does not reveal differential trends in prices between treatment and control group, we still investigate the possibility that the results are driven by trends in areas where dispensaries locate. To do this we estimate equation 2 using false entry dates equal to 3 months, 6 months and 12 months prior to the true entry dates of the stores. The results of these placebo tests are presented in Table A3. We find no evidence of spurious effects.

Table A3: Falsification Test Results

	3 months	6 months	1 year
$Post_{it} \times T_{it}$	-0.0154	-0.0330	-0.0335
	(0.0150)	(0.0199)	(0.0243)
$Post_{it}$	-0.0207	0.0274	0.0257
	(0.0259)	(0.0199)	(0.0220)
T_{it}	-0.0187	-0.0131	-0.0136
	(0.0131)	(0.0137)	(0.0136)
Area FE	Y	Y	Y
Month FE	Y	Y	Y
Property Char.	Y	Y	Y
N	8270	8270	
adj. R^2	0.486	0.486	0.486

Standard errors in parentheses are clustered at the area-level.
* $(p < 0.05)$, ** $(p < 0.01)$, *** $(p < 0.001)$