The Price Effects of Greening Vacant Lots: How Neighborhood Attributes Matter

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Abstract

We identify the effects of greening vacant lots on nearby housing prices and show how neighborhood attributes matter to these outcomes. Using data from a longstanding program in Philadelphia, we find that prices for houses within 1,000 feet of a greened vacant lot rise by about 4%, consistent with the literature, with the effect size increasing over time. Using the extensive data available in Philadelphia, we show how these effects vary by the attributes of the neighborhood in which they occur, with larger effects in areas with a high share of vacant land and higher-than-average median household incomes, with peak responses estimated at 19% and 15%, respectively. We demonstrate the importance of sample selection bias adjustment for identification of the effect of vacant lot greening.

Keywords: vacant lot, green space, amenity, Philadelphia

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The appendix is available upon request from the authors.

1. Introduction

Vacant lot "cleaning and greening" is a simple but potentially effective strategy for mitigating negative effects of blighted land on surrounding property values. Philadelphia, long plagued by property abandonment, is a pioneer in remediation programs. In 1996, the Pennsylvania Horticulture Society (PHS) in cooperation with the New Kensington Community Development Corporation (NKCDC) initiated a plan to convert vacant lots into green spaces (NKCDC, 2021; MacDonald and Branas, 2019). PHS expanded the pilot and launched the Philadelphia LandCare Program (PLC) in 2004 with ongoing public and philanthropic support. In 2021, new legislation aimed at fighting blighted properties including unattended vacant lots became law throughout Pennsylvania.

Despite anecdotal evidence and early empirical findings that show an aggregate positive impact of treating vacant land on the value of adjacent properties, the existing literature is generally silent on where such policies are likely to succeed. For city officials making investment decisions with limited funds, it is helpful to know how neighborhood attributes matter to program outcomes. More generally, identifying where greening has positive impacts can improve our understanding of how neighborhood amenities affect housing prices. Studies in the existing literature using early PLC data find citywide positive effects, but they also find significantly negative and insignificant impacts in specific submarkets, suggesting that neighborhood attributes matter.

We investigate the large number of vacant lots treated in the Philadelphia LandCare program. Besides scale and duration, the data from the Philadelphia LandCare program have a unique advantage due to PLC's standardized approach to treating vacant lots. PLC has tracked their greening of vacant lots for over a decade. In addition, PLC follows a standard protocol. PLC selects lots, removes brush and trash, plants grass, installs a low picket-fence, and thereafter maintains the lot through seasonal care. It is PLC's relatively standard treatment protocol that enables tests for the impact of neighborhood varying attributes as well as the identification of PLC effects over time. While older industrial cities, including Cleveland and Detroit, have initiated vacant lot reuse programs, these are relatively new, smaller in scale, and not standardized. Hence, Philadelphia is an interesting case study for empirical analysis of a relatively simple cleaning and greening vacant land conversion program.

We exploit the availability of data on the installation of PLC lots by grouping geocoded housing sales into treatment and control groups based on their vicinity to greened or untreated vacant lots and their sale dates. We then test for impact over time and by distance to a treated lot, using a difference-in-difference (DID) methodology and a hybrid repeated-sales price model. Our analyses incorporate many attributes of the surrounding neighborhood, including income, vacant land share, crime occurrence, size and number of lots treated, and presence of neighborhood parks. We deal with non-random selection of vacant lots for the greening treatment by matching and propensity score weighting to achieve a covariate balance of neighborhood characteristics in the treatment-control group comparison.

In our city-wide results, we find a positive and significant impact of vacant land conversion on the value of nearby properties (within 1,000 feet), with a 4.3% rise in value after the first year, and 13% after 6 years (which then attenuates). The city's average effect of 4.3% is larger than the price effect of 3.6% in Voicu and Been (2008) on New York's community gardens and smaller than the price effect of 5.6% in the Heckert and Mennis (2012) evaluation of the earlier years of Philadelphia's LandCare program.

We show that adjacent property values increase more in specific types of neighborhoods, namely, areas with higher-than-average median income, higher-than-average vacant land share, and low-to-average crime occurrence. We find that in high-income neighborhoods (household income 40% above the median), the treatment effect decreases in the neighborhood household income. The opposite effect is found for low-income neighborhoods. We show that a higher share of vacant land (above 3%) increases the negative impact of land vacancy on nearby property values, and that greening in these neighborhoods effectively eliminates this negative impact. By relaxing the assumption of a constant greening effect, we estimate a 9% greening effect evaluated at the 5.8% city average level of the vacant land share, with the effect peaking at 19% for high-vacancy neighborhoods.[1] The positive effect of greening vacant lots is almost large enough to offset the negative pre-treatment price differential (-21.9%). We also find that concentrating the greening of vacant lots positively affects the impact on nearby property values. We demonstrate the importance of adjusting for the non-random selection of lots for the identification of these greening intervention effects.

The rest of the paper is organized as follows. Section 2 reviews the existing literature. Section 3 describes the LandCare program, and Section 4 describes the data used in our analyses. Section 5 discusses the methodology, the empirical model, and the results. Section 6 concludes.

2. Existing Literature

The literature on the impact of vacant lot conversion on surrounding property prices generally identifies the effect of greening initiatives through difference-in-difference (DID) methodologies that examine changes in prices of nearby houses, after an intervention, relative to changes in house prices near unimproved vacant lots. The study most directly related to our own, Heckert and Mennis (2012) (HM hereafter) examines the impact on nearby housing prices of vacant lot conversion for the early years of Philadelphia's LandCare program through 2006. Using data on the impact of 747 greened lots in the PHS LandCare program, HM develops global and local versions of spatial DID models. HM finds an overall 5.6% significant effect of vacant lot greening on house prices per square foot within 500 feet from school and commercial corridors. Local DID estimates, based on a geographically weighted regression model using a subset of observations, result in location-specific coefficients and show positive and significant effects in certain parts of Philadelphia (Eastern North, Southwest, West) but insignificant or negative effects elsewhere.

Using a similar DID approach, several studies examine the impact of other neighborhood greening initiatives including community gardens, green corridors, and tree planting, with varying results. In one of the few studies to include neighborhood attributes, Voicu and Been (2008) (VB hereafter) studies the impact of

[1] Voicu and Been (2008) test for differential impact by high- and low-income area, with similar results, as discussed further below.

community gardens on nearby property values in NYC and finds an overall positive and significant effect of 3.6% and an effect that is 5.7% higher in low-income neighborhoods relative to high-income neighborhoods.[2] Hobden, Laughton and Morgan (2004) (HLM hereafter) uses paired samples to investigate the effect greenways have on adjacent properties, finding that they increase housing prices by 2.8%. Greenways include pathways that widen at some points to small parks and HLM shows the latter increase the values of adjacent properties by 6.9%. Studies for tree planting programs find a range of outcomes, from no measurable impact (Wachter and Wong, 2008) to positive and significant effects (Franco and MacDonald, 2018). These studies vary in whether and how they adjust for selection bias, as discussed further below.[3]

A substantial body of literature also investigates the link between property values and proximity to permanently installed green spaces, including parks, greenbelts, and farmland. The most relevant studies for our research show the large positive effect parks have on nearby property values. A review of early studies (Compton, 2001) shows that the presence of a park results in an estimated single digit to 20% price premium on adjacent properties. Large parks with predominantly passive use generate higher adjacent property values than small parks with more active recreational use. Crompton and Nicholls (2020) reviews recent studies and generally confirms the earlier findings on park size and use, finding a price premium of 8-10% on properties adjacent to a passive park.

Greened lots differ from parks, even pocket parks, by their smaller size and the resulting limitation on amenities offered. Nonetheless, the cleaning and greening of a vacant lot removes a neighborhood disamenity and indicator of neighborhood disfunction. A growing literature, much of it using the PLC data, shows how the remediation of derelict and trash strewn lots has positive quality-of-life effects, specifically through crime

[2] VB defines low-income neighborhoods as those with income lower than 80% of MSA median household income. The effect in high-income neighborhoods (higher than 80% of MSA median income) is insignificant.

[3] Franco and MacDonald (2018) using remote sensing and spatial autoregressive model finds that tree canopy coverage is positively valued, with a square kilometer increase in the relative size of tree canopy valued at 0.20% of housing prices. See also Netusil et al. (2010) and Li and Saphores (2012).

reduction and mental health benefits.[4] A growing literature further examines the potential heat island mitigating effects of green spaces and their unequal distribution.[5] Pearsall (2017) using satellite thermal infrared sensor measures land surface temperature by socio-spatial neighborhood patterns. Kondo et al. (2020) uses remote sensing and aerial imagery data for Philadelphia to conduct a citywide resident health impact assessment of the city's tree canopy policy on premature mortality.[6]

Quality-of-life benefits, from stress or heat alleviation, may contribute to higher willingness to pay for locations near previously blighted lots. The focus of the LandCare program has been explicitly to overcome the neighborhood disamenity effects of vacant lots, while other city programs address the problem of blighted properties more generally. Business Improvement Districts (BIDs) have focused on the transformation of specific disinvested Philadelphia neighborhoods for several decades.[7] These placemaking programs typically include the cleaning and greening of vacant lots and removal of abandoned houses, along with the provision of commercial district amenities and additional funding for improved public safety and, in some cases, for schools (Rodin, 2005, 2015). The success of these neighborhood programs in Philadelphia, along with the revitalization of downtowns in legacy cities across the US, attests to the importance of placemaking in providing amenities (Fee and Hartley, 2013). Public (and private) amenities attract talent to cities, particularly young talent, although not without raising concerns over the resulting gentrification and

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[4] Branas et al. (2016) examines crime occurrence around vacant properties and finds that vacant lot remediation significantly reduces firearm violence but no effect on non-firearm violence. Kondo et al. (2015) use a quasi-experimental DID approach to estimate the citywide safety effect of green stormwater infrastructure installments and finds a significant reduction in burglaries and narcotics possession and manufacturing near the installments. Branas et al. (2018) using PLC data from 110 randomly selected vacant lots shows that gun violence decreases after PLC greening.

South et al. (2015) conducts a randomized controlled trial (RCT) for mental health impacts of vacant lot clusters by tracking the heart rate of participants and finds that remediating urban blight reduces stress. A related RCT study by South et al. (2018) finds a significant decrease in participants who feel depressed. Branas et al. (2011) examines the effects on health and safety outcomes and finds less reported stress and more exercise around PLC treated lots.

[5] The environmental and ecosystem benefits of green space while important go well beyond the scope of this study. See Rigolon (2016) for a literature review on the environmental inequities of urban park access across demographic groups.

[6] Pearsall (2017) finds that greened vacant lots have the potential to mitigate inequities in urban heating in socioeconomically vulnerable neighborhoods. Kondo et al. (2020) find that 3% of total mortality could be prevented annually if Philadelphia accomplished its 2025 goal of increasing tree canopy cover to 30%.

[7] For the introduction of BIDs in Philadelphia, see a comprehensive report by the City of Philadelphia Department of Commerce and Drexel University's Center for Public Policy (2013). For the studies on BIDs in Philadelphia, see Pack (1992), Mitchell (2001), Hoyt (2004, 2005), and Morcol, Hoyt, Meek and Zimmermann (2017).

implications for the affordability of housing (Couture and Handbury, 2020; Ding and Hwang, 2016; Ellen and Ding, 2016; Freeman, 2016). While landscaping and dealing with blighted vacant land are often important components of such comprehensive programs, identifying impacts is difficult due to their multi-faceted approach to placemaking.

In contrast, the purpose of the Philadelphia LandCare program is simpler: to remove blight by cleaning and greening vacant lots through standardized initial treatment and maintenance in distressed neighborhoods. The City of Philadelphia and PHS focus this remediation on neighborhoods where abandoned lots are concentrated to counter the negative impact of land abandonment and consequent disinvestment. Neighborhood context is likely to matter to the size of the negative externality imposed by abandoned and uncared land on surrounding properties and therefore the extent of the potential benefits of remediation. In the following, we expand the literature on greening by showing how neighborhood attributes affect these benefits.

3. Institutional Background

The Philadelphia LandCare (PLC) program was designed to be a basic and low-cost treatment for vacant and abandoned plots of land. With an easily reproducible process, the typical PLC execution entails cleaning of the land, planting some greenery, and the installation of a low wooden post-and-rail-fence, as described in more detail below. Maintenance of these lots is also simple, involving regular trash cleanup and seasonal care. The initial greening costs about \$1.00 per square foot and annual clean-up costs about \$0.20 per square foot, as detailed further below.

The PLC program originated in the late 1990s, when the New Kensington Community Development Corporation proposed a partnership to the Pennsylvania Horticultural Society (PHS), later named LandCare, to clean up their neighborhood's many vacant lots and care for the abandoned land. The PHS, working with the Philadelphia Office of Housing and Community Development, expanded the initiative and established the citywide LandCare program. In 2008, the mayor of Philadelphia, Michael Nutter initiated a formal contract with the PHS to design and operate the LandCare program (Lincoln Institute, 2021; Vibrant Cities Lab, 2021).

PLC was designed to be scalable and applicable for the many vacant lots in Philadelphia's disinvested and distressed neighborhoods. The key steps of vacant lot remediation include: (1) removing trash and debris, (2) grading the land, (3) planting grass and some trees, and (4) installing low wooden post-and-rail fences with walk-in openings around each lot's perimeter. Maintenance of these lots is also simple and standardized, with contractors performing bimonthly trash clean-up and minor landscaping, from April to October, at a cost of $300 per year per property (which average 1,500 square feet in size). PHS contractors treat new vacant lots in the spring and fall. The initial cost of cleaning and landscape installation averages $1,500 per lot. The charges are recorded as a lien on the property that must be paid before a property sale (Branas et al., 2016; South et al., 2018; Shelter Force, 2018).

PHS uses Philadelphia's anti-blight ordinance to identify vacant land parcels that PHS can remediate legally. The Department of Licenses and Inspections cites owners of vacant lots with illegal dumping, untended vegetation above a certain height, excess trash, etc. as violating the anti-blight ordinance. The Department of Licenses and Inspections then grants PHS the legal right of entry to remediate vacant lots if the landowner does not respond to a violation within 10 days (Branas et al., 2016; Lincoln Institute, 2021). Importantly PLC treatment does not affect the ownership and sales rights of these plots.

Candidates of vacant lots for treatment are usually initially selected based on complaints filed by community members. PHS will talk to the local district City Council representatives who play a role in lot selections (PHS, 2021). PHS cleans and greens several vacant lots, either adjacent (in which case PHS installs one landscape with a fence) or near each other, at the same time, to economize on costs. The vacant lot greening program is designed as a temporary remedy to blight with the option of commercial development of the land going forward although the vast majority, about 80%, of PHS sites have not been redeveloped to date (Shelter Force, 2018; Lincoln Institute, 2021).

Figure 1 contrasts the difference in the visual appearance of a sample vacant lot before and after remediation and shows the substantial site improvement upon treatment. After treatment, these sites remain cleaned and greened due to the regular upkeep by the LandCare program and may also benefit from neighborhood activity to help maintain the area (MacDonald et al., 2019). Despite the potential benefits to neighbors as well as the large number of untreated vacant lots in Philadelphia, the city budgets a relatively small amount for the program and PHS treats only a few hundred additional lots each year (Lincoln Institute, 2021; Philadelphia Inquirer, 2010; City of Philadelphia, 2019, 2020). We turn to an analysis of the benefits of the program in the following sections of our paper.

4. Data

4.1 Data on Greened and Untreated Vacant Lots

The greened lot data we use come from the PHS LandCare program. For the period 2007-2017 for which we have data access, we identify 4,651 greened vacant lots with spatial coordinates or addresses. For the population of untreated vacant lots, we obtain lot-level data compiled by the Philadelphia Department of Licenses and Inspections from OpenDataPhilly (www.opendataphilly.org).[8] The data set identifies 16,799 vacant lots that remained untreated in this period with spatial coordinates or addresses.

Figure 2 shows the spatial distribution of vacant lots by treatment status (greened or untreated) in Philadelphia for the period 2007-2017. The treated vacant lots are not chosen randomly, as the untreated vacant lots are distributed more widely across the space than the greened vacant lots. The vacant lots greened in the period are concentrated in Lower North Philadelphia and West Philadelphia, neighborhoods with low household income and large shares of vacant land (see Appendix figure). Besides the PLC lots, we also collect data on

[8] From 2007, this department monitors building and lot conditions in Philadelphia and issues code violations ranging in severity for dangerous and unsafe conditions. We focus on the observations with the violation description related to vacant (non-building) violations from 2007 to 2017 and filter out duplicate violation locations to only include the first violation instance of each vacant land violation case. We use the violation description and keep all cases related to "Vacant Lot," excluding those related to vacant building or unsafe/missing structure. To avoid duplicate records, we sort the cases by address and violation date and keep the first record of each address.

city parks compiled by the Department of Philadelphia Parks & Recreation from OpenDataPhilly, as shown in Figure 3.

4.2 Housing Sales, Lot Size, and Distance to Treated and Untreated Lot Data

We obtain residential housing sales data from the Zillow Transaction and Assessment Dataset (ZTRAX) for Philadelphia (FIPS = 42101) for the period 2000-2019.[9] We include a set of housing characteristics to account for property heterogeneity, as shown in Table 1. We augment housing attribute data to include lot size and distribution data using shapefiles from OpenDataPhilly. This dataset gives the land use zoning designation for all property parcels (560,075 parcels in Philadelphia's 384 census tracts, or 1,459 parcels per tract), as compiled by the Philadelphia Department of Planning and Development.[10] We match a property sale to a land parcel and calculate the lot size using the polygon area of the parcel.[11] Both the land use designation and the size of each lot are static variables in our analysis. For all properties for which we have the sales data, we calculate the median distance to treated and untreated vacant lots up to the maximum of 4,000 feet.[12] Table 1 shows summary statistics of our housing sales and neighborhood characteristics, as further described below.

4.3 Data on Census Block Characteristics

We define our neighborhood attributes based on census block characteristics including household income, vacant land share, and crime occurrence. We obtain data on the median household income by census block

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[9] The period represents the maximum time length of the sales with a relatively stable number of sales per year and is consistent with the time availability of the lot greening activities we observe.

[10] The median size of census tracts and blocks in Philadelphia are 149 and 2.4 acres respectively, while the median population of census tracts and blocks are 3,913 and 67 from the 2010 Decennial Census, respectively. The survey is the first comprehensive rewrite of the Philadelphia Zoning Code in the past 50 years.

[11] We use the R computing environment and its spatial packages to conduct a spatial intersection of the centroid of a sale and the polygon of each land parcel. The key packages used in *R* are *sf* and *nngeo*. We use the *st_intersects* function to calculate the spatial intersection and the *st_nn* function to calculate the nearest neighbors and the pairwise distances. We also use other R packages including *doParallel* and *foreach* to accelerate the calculation through parallelization.

[12] The distance variable captures the pre-treatment spatial heterogeneity of properties. We identify up to 50 nearest greened or untreated lots for each property. In Appendix, we plot the distribution of the median distance to show the cutoff of 4,000 feet is not restrictive. We choose the cutoff for computational purposes.

groups from the 2010-2014 5-year American Community Survey (ACS).[13] We obtain data on vacant land share of a census block using shape files of lot-level land use data compiled by the Philadelphia Department of Planning and Development. We define the vacant land share of a census block as the total area of the land parcels classified as vacant in a census block divided by the total area of land parcels in a census block. We use these data to examine how neighborhood household income and the vacant land share of a census block interact with the treatment effect of greening vacant lots.

We collect data on neighborhood crimes, compiled by the Philadelphia Police Department, to examine their effect on the impact of greening. For each census block and each quarterly date, we count the neighborhood crimes within the last four quarters.[14] Instead of using the raw number of crimes in the analysis, we group 18,872 census blocks in Philadelphia into 10 groups defined by the deciles of the distribution of the census block crime counts. A larger group index indicates more neighborhood crimes in the past year. The decile group of a census block is calculated for each quarterly date. For each sale, we can find the corresponding decile group using the information on the quarter of sale and the census block of the property. Our collection of neighborhood attributes including vacant land share, median household income, and crime occurrence, capture very different aspects of neighborhoods.[15]

We also use census block data to model the selection into treatment for selection bias adjustment. For this, we collect data on census block characteristics from the summary files of the 2010 Decennial Census and calculate the housing vacancy rate, the homeownership rate, the Black householder share, and the college graduation share for the measure of education attainment. We calculate residential and commercial land

[13] We choose ACS data over the 2010 Decennial data for household income to exclude the impact of the 2008 Great Recession.
[14] Counting the crimes that happened in the last four quarters instead of only the last quarter allows us to smooth out the seasonal effect of crimes (with the number highest in July-August and lowest in January-February).
[15] For census block factors (vacant land share = V; median household income = I; crime occurrence = C), $cov(V, I) = -0.191$, $cov(V, C) = -0.029$, and $cov(I, C) = -0.176$. As the median household income comes from the 2010-2014 5-year ACS, we calculate the total number of crimes in the period from 2010 to 2014 in the calculations.

shares of a census block and use these data as well to model the selection into treatment for selection bias adjustment.

The housing attributes, the demographic variables of census blocks, the land share variables, and the household income variable are static and affect the level of the sales prices, while the sales prices, the treatment status of nearby vacant lots and neighborhood crime occurrence change over time.

4.4 Defining Treatment Group

We define a property sale as treated ($1\{treated\} = 1$) based on two conditions: (1) if a vacant lot was greened before a property sale, and (2) if the greened vacant lot lies within a certain radius from the property. The first condition assumes that the effect of green space is persistent. Once a property is identified as having received treatment in one sale, it will remain so designated in future sales. This is supported by the ongoing maintenance of each greened lot after the initial greening intervention (Branas et al., 2016; South et al., 2018; Shelter Force, 2018). The second condition assumes that the effect of green space is localized to the immediate neighborhood surrounding that lot. We check for the impact of the distance threshold and find support for a main distance threshold of 1,000 feet, in a process described in our empirical results.[16]

Compared to the size of the average neighborhood in Philadelphia, the distance threshold of 1,000 feet is 5.5 times more than the radius of a median-sized census block (182 feet).[17] The median distance to greened or untreated lots is 439 feet, suggesting that most sales in our sample have the potential to be influenced by vacant lot conversion. Using the lot-level land use data, we identify 18.2 homes on average are within 1,000 feet of a vacant lot.[18]

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[16] Similar distance thresholds have been adopted in the literature (Wachter and Wong, 2008; Voicu and Been, 2008).

[17] The radius of a census block (tract) is defined as $\sqrt{area}/\pi$. 1,000 feet is 70% of the radius of a median-sized census tract (1,435 feet).

[18] The average number of properties near greened lots is 33 (= 153,531/4,651), higher than the estimate based on the pool of greened and untreated lots. This is because more greened lots are in medium- and high-density residential areas.

4.5 Sample and Summary Statistics

The data sample for our analysis is repeated sales of residential properties in Philadelphia, which consists of about 60% of all residential sales (see Appendix table). We restrict the sample to repeated sales in our primary benchmark analysis (and then extend our results to include single sales). To match the sample period of greened vacant lots (2007-2017), we focus on the properties whose sales occurred in the period 2007-2019 and the prior sales occurring as early as 2000.

We include sales in census blocks with more than one housing unit based on statistics from the 2010 Decennial Census. This step filters out sales in the census blocks whose major types of land use are nonresidential (industrial, park or open space, cemetery) and sales that are coded as residential by error in the ZTRAX data set.[19] We exclude sales whose last sale is too close to the current sale, which are likely to be duplicated records. In each quarter of a year, if there is more than one sale of the same property, we keep the one with the highest price. More than 80% of the repeated sales that occur within the same quarter have a percentage difference in the sales prices lying within 5%, suggesting the presence of duplicated records. Properties with more than 20 records in the period 2000-2019 are more likely to face the issue of duplicated records and thus are excluded. For two consecutive sales recorded within a time interval shorter than a year, we label the later sale as the duplicate.[20] These filtering steps result in a sample where the maximum number of sales of a particular property is seven.

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[19] Most of the census blocks removed based on this restriction are in the periphery of the city (see Appendix). To reduce the impact of outliers, we restrict our sample to those with sales prices more than $10,000 in 2018 dollars. Using this price threshold helps to exclude sales that are likely to be non-arm's length (*e.g.* intra-family transfer), which is a factor that is not directly observable to us.

[20] We identify the latter sale as a duplicate and run the algorithm backward for properties with multiple sales records. For example, for a property sold in 2015M1, 2017M1, 2017M6, and 2018M2, we first check the last two records in 2017M6 and 2018M2, the time interval is shorter than one year and the record in 2018M2 is dropped. We then check the records in 2017M1 and 2017M6. We end up with the records in 2015M1 and 2017M1. Dropping the latter instead of the former record is more conservative in data filtering, because the current step of the duplicate check will not affect the next steps (if the rule is to drop the former record when the time between two records is shorter than one year, we end up keeping the records in 2015M1, 2017M1, and 2018M2 for the example).

Table 1 reports summary statistics of our housing sales and census block characteristics. For house sales, the data show that most sales are rowhouses (85%), followed by single-family homes (12%) and condos (3%). The average number of bedrooms is 3.05. The average building year is 1934. The average time gap between two consecutive sales is 6.5 years, with the average increase of real housing prices is 24% (log difference of sales prices). The mean footprint or lot size is 1,676 square feet, while the mean floor size is 1,306 square feet. 65% of the sales are in census blocks with no vacant land. About 18% of sales are identified as being treated, *i.e.,* having a vacant lot greened before the sales within 1,000 feet. We also report means of the housing and census block variables separated by proximity to greened vs. untreated vacant lots and show the covariate imbalance in almost all housing and neighborhood characteristics between these treatment and control groups through t tests of the mean difference. Graphical illustrations of the covariate imbalance in boxplots are available in Appendix.

4.6 Comparison of Green Space: Greened Lots vs Parks

While parks and greened vacant lots can provide green space to communities in Philadelphia, they differ in two fundamental aspects: the size of the green space and their spatial distribution within the city. Of the 522 parks in total in Philadelphia, 389 parks are neighborhood parks (size: 0.5-40 acres), 94 parks are identified as pocket parks (size < 0.5 acre), and the remaining 39 parks are either regional or watershed parks (size > 40 acres).[21] This smallest category, the pocket parks, have a median size of about 10,000 square feet, or approximately one-fourth of an acre. Nearly all vacant lots, whether treated or not, are much smaller with a median size of 1,043 square feet (greened lots) and 1,039 square feet (untreated lots).[22]

[21] These parks provide 12,057 acres of green space. In the period 2007-2017, we identify 4,651 greened lots that add a total of 217 acres of green space to the city, while 16,799 vacant lots that we identify as untreated occupy a total area of 2,424 acres.

[22] When treated together, on average, 3 adjacent vacant lots are combined into a fenced landscape with a median size of 2,749 square feet. This is still only 28% the median size of pocket parks (9,888 sq. ft.) or 1.8% the median size of all city parks in Philadelphia (3.6 acres).

As shown in Figure 3, the 522 parks are distributed throughout the city, whereas vacant (treated and untreated) lots are concentrated in West Philadelphia and Northwest Philadelphia, as shown in Figure 2.[23] Greened or untreated vacant lots are more concentrated in the neighborhoods with lower median household income (see Appendix). In contrast, median household income is 12% higher in census blocks with a park. In our empirical analysis, we consider how the spatial distribution of parks, along with neighborhood income and other neighborhood variables, impacts the price effects of vacant land greening on surrounding properties.

5. Model and Results

5.1 Model

5.1.1 Outcome Equation

We first generate a quality-adjusted housing price index for each repeated sale that accounts for the housing characteristics of each property sold. For the k-th sale ($k \geq 2$) of property i, we consider the following hybrid hedonic repeated-sales model.

$$\begin{aligned} \log P_{ik} &= \gamma_0 + \gamma_1 \log(P_{i,k-1}) + \gamma_2 \Delta Year_{ik} + \gamma_3 \log(P_{i,k-1}) \cdot \Delta Year_{ik} \\ &+ X_i^H \Theta^H + \sum_j \theta_j \cdot 1\{mdist_i \in dist_j\} + qdate_{ik} + tract_i + e_{ik} \end{aligned} \tag{1}$$

where the dependent variable $\log(P_{ik})$ is the log real sales price, with the current sales dates lying between 2007 and 2019 and the distance to a vacant lot smaller than 4,000 feet. We include variables about the past sale (first line) and the hedonic information (second line) in the equation. $\log(P_{i,k-1})$ is the log real sales price in the last sale which can happen before year 2007. $\Delta Year_{ik}$ is the year gap between two consecutive sales. We add the interactive term of $\log(P_{i,k-1})$ and $\Delta Year_{ik}$ to allow for the time-varying impact of the past sale on the current sale. X_i^H are a vector of the structural characteristics, including the log lot size (square

[23] 98% of the greened or untreated lots come from census blocks without a park. 2.6% of the census blocks have a park.

foot), the lot floor area (square foot), indicators of the number of bedrooms, building year, or property types.[24] We include a quarterly date fixed effect $qdate_{ik}$ to control for seasonality and macro impacts over time. The tract fixed effect $tract_i$ controls the heterogeneous impact across space, with the repeated sales coming from 376 out of 384 census tracts. e_{ik} is the error term.

Besides the structural characteristics, we include a set of distance dummies ($1\{mdist_i \in dist_j\}$ for $j \in J$) to capture the pre-treatment spatial relationship with the nearby vacant lots of a property. The median distance to the vacant lots in a radius of 4,000 feet ($mdist_i$) is coded into 10 distance groups ($dist_j$) determined by the 10th to 90th percentiles of the distribution of the median distance up to the nearest vacant lots from a sale. Vacant lots are more likely to be concentrated in distressed communities. While we consider the census tract fixed effect, the distributional pattern of vacant lots around a property can differ substantially within a tract and affect housing prices. Compared to a model assuming a constant price elasticity of the distance, the model with distance dummies can account for the non-linear impact of vacant lot distance on housing prices without assuming a specific functional form on that relationship.

We define the housing price index as the residual of equation (1), denoted as $HPI_{ik} \equiv \log(P_{ik}) - \widehat{\log(P_{ik})}$. To estimate the treatment effect of greening vacant lots, we consider the following outcome equation.

$$HPI_{ik} = \alpha_0 + \alpha \cdot 1\{treated_{ik}\} + X_i^B \Theta^B + \varepsilon_{ik} \tag{2}$$

Our main interest is the greening effect captured by the coefficient α of the binary indicator of the treatment status $1\{treated_{ik}\}$ that a property i in the k-th sale is near to a greened vacant lot. X_i^B is a vector of census block characteristics, including the vacant land share, the residential land share, the commercial land share, the housing vacancy rate, the homeownership rate, the Black householder share, and the college

[24] We test an alternative version of the housing price model with additional park-related variables (distance to nearest park, number of parks in census block, acre of parks in census block) in Appendix and it shows an insignificant effect at 10% level. We thus exclude them in the housing price model.

graduation share. As more than half of the census blocks have no vacant land, we also include an indicator of no vacant land. All non-binary variables are standardized to zero mean and unit variance before estimation.

5.1.2 Selection Equation

Estimation using ordinary least squares will lead to a biased estimate of the treatment effect due to the non-random selection into treatment. We address this selection issue in our regression-based estimate of the effect of vacant lot greening through a propensity score weighting procedure. Specifically, we create sample weights for each housing sale unit by estimating its propensity score for being in the treatment (greened) group vs. the control (untreated) group. These propensity scores are then used as sample weights in equation (2) to adjust for selection bias, with weighted least squares then used to estimate the treatment effect.

We assume that the lot selection by PHS depends on the census block characteristics X_i^B. This is supported by the evidence that PHS targets communities with large concentrations of blighted vacant lots (Heckert, 2015; Heckert and Kondo, 2018). The identification assumption is that conditioning on X_i^B, the selection into the treatment group is uncorrelated with the potential outcome of the housing price index. In other words, the correlation between the treatment status and the potential outcome should come from X_i^B. As we construct HPI_{ik} by removing the housing price variation due to the housing characteristics, the median distance to vacant lots, the past price and the year gap since the last sale, and the census tract fixed effect in equation (1), we identify the treatment effect in (2) that is not a consequence of the correlation between these variables and the treatment status.

Our estimated propensity scores for each unit are the predicted values from the following Logit model.

$$F(treated_{ik} = 1) = Logit\left(X_i^B \Gamma^B\right) \tag{3}$$

These propensity scores summarize the impact of the census block characteristics X_i^B on receiving the treatment. We include the squared terms of the z-scores of the residential land share, the homeownership rate, and the Black householder share in X_i^B to improve the goodness of fit and to account for the nonlinear effects. The higher-order terms show significant effects on the likelihood of being treated and achieve covariate balance when we compare the treatment and the control groups.[25] The assumption in equation (3) is that the likelihood of a sale being treated depends on the census block characteristics that are publicly available, but not directly on the housing characteristics (X_i^H) or the spatial attribute ($mdist_i$) of an individual property.[26]

To create the sample weight of a sale, we use a nearest neighbor matching technique to find the closest sale in the control group in terms of the propensity scores to pair with each sale in the treatment group. The sample weight on a sale in the treatment group is normalized to 1, while the sample weight on an untreated sale counts how many times it is matched (with replacement) to a treated sale. This means that an untreated sale may be matched multiple times. How untreated sales are sorted is irrelevant when they are paired with the treated sales.

In addition, we consider ties in the propensity scores in the nearest neighbor matching. As X_i^B do not depend on the sales dates, the propensity scores remain constant within a census block. Instead of randomly choosing a matched sale, considering ties will include all matched sales in the control group. A sale in the treatment group will be matched to the sales in the control group in the same census block but possibly across different years. We then assign equal weights that sum up to 1 to the matched sales in the control group in the same census block. If no sale in the control group is found in the same census block in our sample period, a sale in the treatment group will be matched to the sales in the control group that are closest in terms of propensity scores but are possibly in the nearby census block with similar characteristics. Under the matching procedure, the total sample weights of untreated sales will be equal to that of the treated sales.

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[25] To examine whether a larger vacant lot is more likely to be selected, we test with one version of the selection equation by including the median size of the 50 nearest untreated or greened lots as a control variable. The variable is insignificant in the Logit model. We also check the group balance and find that the model without the median size of nearby vacant lots can achieve the balance of this variable in the control and the treatment group (see Appendix).

[26] We test an alternative version of the selection model with additional park-related variables (distance to nearest park, number of parks in census block, acre of parks in census block) in Appendix and they show insignificant effects at 10% level. We thus exclude them in the selection model.

To estimate the treatment effect α, we jointly estimate equation (2) using the weighted least squares and equation (3) to account for the standard errors in the estimation of the propensity scores.

5.2 Main Results

5.2.1 Average Treatment Effect of Being Treated (ATET)

We report the results from our estimation of the hybrid repeated-sales model (1) in Table 2. About 70% of the housing price variation is explained by the housing characteristics, all of which have the expected signs. Evaluated at the mean characteristics, the housing price in the current sale is positively correlated with the price in the last sale but is negatively correlated with the number of years since the last sale. This is consistent with the literature that past sales farther away from the current sale have a smaller impact on the current sale (Nagaraja et al., 2011; Nagaraja et al., 2014). The coefficients on the distance indicators show an increasing relationship between the median distance to the vacant lots and the housing price level, consistent with the expected negative impact of vacant lots on the price level of the nearby properties.

We define the residual of the log sales price as the housing price index HPI_{ik}, which has a zero mean and a standard deviation of 0.58 (with the standard deviation of the log real price to be 1.01). Using the housing price index as the outcome variable, we estimate equation (2) and report the ATET in Table 3. We consider four specifications that differ in how the treatment indicator, $1\{treated_{ik}\}$, is defined. Column 1 considers the case that a property receives the treatment if a vacant lot within 250 feet was greened before a sale. For Columns 2-4, we increase the radius to 500 feet, 750 feet, and 1,000 feet, respectively.

We find a positive effect of greening vacant lots on nearby housing prices, which is reflected by the statistically significant and positive ATET for all the specifications. The treatment effects based on the distance threshold of 250, 500, 750, and 1,000 feet are 4.49%, 7.54%, 6.45%, and 4.27%, respectively.

The values in Table 3 give the estimated effects under different distance thresholds but we also explore how the greening effect changes as a function of the distance to the nearby greened vacant lots. We modify the model in Column 4 by generalizing the treatment term $\alpha \cdot 1\{treated_{ik}\}$ in (2) to the following form.

$$1\{treated_{ik}\} \cdot \sum_{j=1}^{5} \beta_j \cdot 1\{gdist_{ik} \in distbin_j\},$$
$$\text{where } distbin_j \in \{(0,250],(250,500],(500,750],(750,1000],(1000,4000]\} \tag{4}$$

This term is equal to zero if a sale is not treated. It is equal to β_j if a sale is treated ($1\{treated_{ik}\} = 1$) and the distance to the greened vacant lots in feet ($gdist_{ik}$) falls in the j-th distance group ($distbin_j$). We define $gdist_{ik}$ to be the minimum distance to the greened vacant lots before the k-th sale. The distance is divided into five levels, with the last one (1,000-4,000 feet) treated as the base level ($\beta_5 = 0$).[27]

We show the distribution of the repeated sales by distance to greened vacant lots in Figure 4. The number of sales is similar in the distance bins within 1,000 feet, so using equally spaced distance bins will not lead to limited statistical power due to small sample in some groups. Under the constraint that $\beta_j = \alpha$ for all j, the term in (4) degenerates to the treatment term in equation (2). By substituting (4) for $1\{treated_{ik}\}$ in (2), we estimate a weighted least squares model using the sample weights from Column 4 of Table 3.

In Figure 4, we also plot the estimated treatment effects β_j by the distance to greened lots. The treatment effect is a hump-shaped positive effect and reaches the peak when the distance range is 250-500 feet. We conduct a Wald test to see whether the treatment effects vary statistically by distance. We find that we cannot reject the null hypothesis ($\beta_1 = \beta_2 = \beta_3 = \beta_4$) that the treatment effect does not vary by the distance to the greened vacant lots (p-value = 0.171). However, we do reject the hypothesis that $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ (p-value < 0.001), which confirms our result in Table 3 that there is a significant effect of greening vacant lots on housing prices. Given this lack of evidence that the intensity of the treatment effect varies significantly

[27] Having a greater number of distance bins produces more intensity levels of the greening effect, and it leads to larger variances of the estimates as well. With more than four distance bins within 1,000 feet, we find the standard errors of the estimated effects increase substantially.

within a radius of 1,000 feet, we focus on the models based on the threshold of 1,000 feet, which allows us to include more sales and thus to estimate the treatment effect more precisely.[28]

5.2.2 Treatment Effect over Time

One assumption in our definition of the treatment indicator is that a sale is identified as being treated if there is a vacant lot greened before the current sale. The definition compresses the time dimension and does not consider a potentially time-varying effect of greening vacant lots. We modify the model in Column 4 of Table 3 in another direction by generalizing the treatment term $\alpha \cdot 1\{treated_{ik}\}$ in (2) to the following form.

$$1\{treated_{ik}\} \cdot \sum_{j=1} \delta_j \cdot 1\{gyear_{ik} \in timebin_j\}, \text{ where } timebin_j \in \{1,2,\ldots,9,10-12\} \tag{5}$$

This term is equal to zero if a sale is untreated. It is equal to δ_j, if a sale is treated ($1\{treated_{ik}\} = 1$) and the number of years of being treated ($gyear_{ik}$) falls in the j-th time group ($timebin_j$). In our sample, $gyear_{ik}$ can range from 1 year (a house was sold the year after a nearby vacant lot was greened) up to 12 years (a property was sold in 2019 and a nearby vacant lot was greened in 2007). There can be multiple vacant lots greened in different years before a housing sale. To define $gyear_{ik}$, we search for the greened vacant lot in the radius of 1,000 feet that is closest in time to the current sale. We put the years of being treated to one group to reduce the standard error of the estimate if few sales are observed separately in each group. This is the case for $gyear_{ik} \in \{10,11,12\}$. Under the constraint that $\delta_j = \alpha$ for all j, the generalized term degenerates to the treatment term in equation (2). We estimate a weighted regression model using the sample weights from Column 4 of Table 3.

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[28] In Appendix, we show how the data supports our choice of the distance threshold we use to define the treatment group. We plot the sales prices before housing quality adjustment at designated distances. The figure about the mean of the log real sales price and the median distance to the greened or untreated vacant lots shows that as properties get closer to vacant lots, sales prices are lower in general, as expected. We observe a sharp decrease of sales prices when the median distance to the untreated vacant lots becomes smaller than 1,000 feet. We then show in the second figure the relationship between the mean of the log real sales prices and the median distance to the greened lots only. Compared to the first figure, we see smoother price decreases in the second one when the distance is smaller than 1,000 feet, providing evidence of the improved consistency of results within 1,000 feet of treatment.

In Panel (c) of Figure 4, we plot the estimated treatment effects δ_j over time. The horizontal axis is the number of years of being treated. In Panel (d), we show the distribution of years of being treated. Our results show the amenity value of greened vacant lots takes one year to materialize and have a significantly positive amenity effect on nearby housing prices for at least 5 years. The treatment effect is insignificant in the first year and then gradually increases over time until 6 years after the greening intervention.[29] At the peak, the housing price of a treated sale is 13% higher than the price of an untreated sale. After 6 years, the amenity effect decreases. The treatment effects after 7-12 years remain positive but are no longer statistically different from zero. This may be due to a sparsity of sales in these year categories which results in larger standard errors or to attenuation bias. If a sale happens many more years after a nearby vacant lot is greened, there could be many other intervening unmeasured factors and more random noise in the housing prices unrelated to the greening intervention.

5.2.3 Selection into Treatment

In Table 4, we show the evidence that the lot selection favored vacant lots in distressed communities. We report the estimation results of the Logit selection equation (3) based on which the propensity scores are estimated. The marginal probabilities evaluated at the mean with respect to the one standard deviation (SD) increase in each variable are reported. The census block characteristics together explain 33-39% of the variations in terms of R-squared in the treatment indicators.

Take the specification with the distance threshold of 1,000 feet (Column 4) as an example. Among the census block characteristics with the largest impacts on the marginal probability of being treated, a one SD increase in the vacant land share increases the treatment probability by 0.8%. A one SD increase in residential and commercial land share decreases the treatment probability by 2.6% and 0.8% respectively. A one SD increase in the housing vacancy rate increases the treatment probability by 3%. A one SD decrease in the

[29] We only observe the timing of greening a vacant lot up to the quarter and identify the timing of a property sale by the recording date at the county office. As the decision to buy will have usually occurred several months prior to a sale, some properties whose sales precede the nearby lot conversion might be counted as treated due to the lengthy transaction process. This may explain the insignificant effect in the first year.

homeownership rate increases the treatment probability by 5%. A one SD increase in the Black householder share increases the treatment probability by 7.7%. A one SD decrease in the college graduation share increases the treatment probability by 7.3%.[30]

To support the validity of our chosen variables X_i^B in the selection equation, we perform balance checks by comparing the variable means of the treatment and the control groups in the matched sample in Appendix. We show that the means are not statistically different for two groups in the matched sample and the ratios of the variable variances in the treatment and control groups are close to 1, suggesting that the characteristics in two groups look similar.[31]

5.3 Neighborhood Attributes and their Impact on the Effect of Greening Vacant Lots

In the previous section, we estimate a city-level average treatment effect of greening vacant lands on housing prices. While we control for a set of census block characteristics that affect the price level, whether the greening effect remains constant across different neighborhood contexts is an open question. We test the hypothesis that the benefit of greening vacant lots depends on neighborhood characteristics.

We examine the impact of six neighborhood factors: vacant land share, median household income, crime occurrence, greened lot concentration, landscape size and access to city parks. We modify equation (2) by interacting the treatment indicator with a given neighborhood factor v as follows.

$$HPI_{ik} = \sum_{n=0}^{N} f(v_i, n)[(\rho_{1n} - \rho_{0n}) \cdot 1\{treated_{ik}\} + \rho_{0n}] + \bar{X}_i^B \Theta^B + \varepsilon_{ik} \tag{6}$$

For a neighborhood factor v treated as a continuous variable, $f(v_i, n) = v_i^n$ and N denotes the polynomial order. When $N = 0$, equation (6) degenerates to equation (2). We allow $N = 3$ to consider a

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[30] Because the variables in the selection equation have been normalized to zero mean and unit variance, for an SD change in a variable with a quadratic term, the marginal probability evaluated at the mean $\partial F(X_i^B \Gamma^B)/\partial x_j = (\gamma_{j1} + \gamma_{j2} x_j) F'(X_i^B \Gamma^B)$ is equal to the marginal probability of the first-order term $\gamma_{j1} F'(X_i^B \Gamma^B)$.

[31] In Appendix, we show the kernel density plots of the estimated propensity scores for the unmatched and matched sample. While the sales in the unmatched sample differ substantially in terms of propensity scores, the sales in the matched sample are similar after bias adjustment.

flexible non-linear price effect of a continuous variable within the control or the treatment groups. Choosing a larger N does not quantitatively change our findings. If a neighborhood factor v is discretized into groups, $f(v_i, n) = 1\{v_i \in Group_n\}$ indicates that the neighborhood factor belongs to the *n*-th group. The census block characteristics $\bar{X}_i^B$ excludes v under analysis to prevent a collinearity issue.[32] We estimate equation (6) by a weighted regression model using the sample weights from Column 4 of Table 3.

5.3.1 Impact of Vacant Land Share

In Figure 5, we estimate equation (6) and show how the treatment of greening vacant land interacts with the census block vacant land share. Panel (a) plots two curves showing the average response of HPI to the vacant land share. The solid blue curve is for the control group and the dashed red curve is for the treatment group. As is expected, the vacant land share is negatively correlated with the average HPI in the control group. Unlike the response of the HPI in the control group, the HPI in the treatment group is not negatively impacted by the vacant land share and remains roughly constant. Greening vacant land effectively pushes up housing prices to the same price levels as neighborhoods with less land vacancy. Panel (b) shows the treatment effect of greened vacant lots on housing prices as a function of the vacant land share, which is defined as the difference of HPI responses between the treatment and the control groups in Panel (a). Panel (c) shows the distribution of the census block vacant land share in the matched sample. The effect of greening vacant lots on housing prices is increasing as the vacant land share increases. The treatment effect is insignificant at 5% level when the vacant land share is smaller than 3%, above which the treatment effect is significantly positive. The treatment effect flattens at the right tail of the vacant land share distribution and reaches an upper bound of around 19%. Under the assumption of heterogeneous treatment effects, Panel (b) shows that the estimate of the treatment effect evaluated at the city average level of the vacant land share (5.8%) is 9%, higher than the benchmark estimate of 4.27% that assumes a constant treatment effect.

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[32] When we examine the impact of the median household income, we exclude in $\bar{X}_i^B$ the college graduation share and the Black household share that are highly correlated with the neighborhood factor.

Note that we already control for the distance to the greened or untreated lots (property-level heterogeneity) when we examine how the neighborhood land vacancy interacts with the effect of greening vacant lots. That is, we are comparing two properties with the same distance to nearby vacant lots but located in two neighborhoods with different vacant land shares. As is reported in Table 2, a property located next to a vacant lot has a price 21.9% lower than a property more than 1,000 feet away from a vacant lot. Greening vacant lots will thus only mitigate the negative pre-treatment price differential for properties close to vacant lots.[33]

Our result on the increasing relationship between the treatment effect and the vacant land share are consistent with the mapped results of Heckert and Mennis (2012; Figure 3) on the spatial variation of the price effects of greened lots. HM finds that clusters of lots with positive and significant treatment effects are located within the Southwest, West, and Eastern North regions, as well as some portions of South and Western North regions. For comparison, we aggregate the vacant land share by the city district. The top six districts with the highest vacant land share are River Wards (13.1%), Lower North (12.2%), Lower Southwest (8.4%), Upper Far Northeast (7.5%), Lower South (7.4%) and West (5.4%) and are expected to see the largest treatment effects. Five out of the six districts match the regions with positive and significant treatment effects in HM, while one district (Upper Far Northeast) lacks sufficient data for analysis.[34] Our findings on insignificant effects in areas with low vacancy (North, Lower/Upper Northwest, Upper North) are also matched to the HM's insignificant local estimate of the treatment effects in the Northwest region.

5.3.2 Impact of Median Household Income

Figure 6 shows how the treatment of greening vacant land interacts with median household income to impact housing prices. The x axis shows the census block median household income as a percent of the median

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[33] This finding that greening eliminates the heightened impact of treatment in high vacancy areas may also be due to the high concentration of PLC remediation in these neighborhoods. The quasi-experimental design imperfectly controls for all differences, as would be accomplished by a random control trial. In general, we can reasonably attribute causal impacts to PLC intervention. We note here that there may be an alternative or additional explanation for the measured effect.

[34] Five high vacant-land-share districts that match the positive and significant treatment effects in HM are Lower Southwest (Southwest in HM), River Wards (Eastern North in HM), West (West in HM), Lower South (South in HM) and Lower North (Western North in HM). There is no observation in the Upper Far Northeast in HM. See Appendix for the summary statistics by planning district and the district map.

household income in Philadelphia. This percentage measure makes it easier to see the relative rankings of neighborhood income. Panel (a) plots the average HPI against the relative neighborhood income. The average HPI in the control group is slightly decreasing but the difference is insignificant as shown by comparing the HPIs of the top and the bottom income group. The average HPI in the treatment group first increases in relative neighborhood income until 20% above the median household income in Philadelphia, and then decreases. Panel (b) shows the treatment effect of greening vacant lots on housing prices as a function of the relative neighborhood income, which is defined as the difference of HPI responses between the treatment and the control groups in Panel (a). We identify a non-linear hump-shaped relationship between neighborhood household income and the treatment effect of greening vacant lands on housing prices. The treatment effect of greened vacant lots on housing prices reaches a peak of 15% in neighborhoods whose median household income is around 20-40% above the median household income in Philadelphia.

For neighborhoods with income levels between 60% and 140% of the city's median income, the effect of greening vacant lots on housing prices is positive and increasing in neighborhood income. For high-income neighborhoods with household income 40% above the median income, we find the greening effect is decreasing in household income with the estimated greening effect insignificant at 5% level.[35] For low-income neighborhoods below 60% of the median household income in Philadelphia, the effect of greened vacant lots on housing prices is increasing in neighborhood income but is not significant at the 5% level. The decreasing greening effect shows that greening vacant lots adds a smaller amenity value in high-income and low-income neighborhoods than in mid-income neighborhoods. This latter effect is consistent with the findings in VB that show no impact of community gardens in high-income neighborhoods and may be explained by the existence of substitutes in the form of private landscaping in these neighborhoods.

[35] The widening confidence interval of the treatment effect reflects the smaller number of treated lots observed in high-income neighborhoods.

5.3.3 *Impact of Neighborhood Crime Occurrence*

We examine how the effect of greening vacant lots interacts with the occurrence of criminal activity measured as the number of neighborhood crimes with data sources as described above.[36] We calculate the number of crimes one year before each property sale in the census block where the property is located.

Figure 7 shows how the treatment of greening vacant lands depends on the neighborhood crime count to impact housing prices. Panel (a) shows the average HPI by treatment status and by decile group of the neighborhood crime count. Panel (b) shows the treatment effect by decile group, which is defined as the difference of HPIs between the treatment and control groups. We find evidence that the effect of greened vacant lots on housing prices is positive and significant in the census blocks below the 60th percentile of the crime count distribution. The treatment effect is insignificant above this threshold, suggesting that greening vacant lots is not a cure-all, with no measurable effect on housing prices in high-crime neighborhoods. The literature on crime and vacant land conversions shows that greening vacant land is associated with decreases in crime occurrence (Cui et al., 2021). Public safety improvements arising out of greening vacant lots as well as the greening of vacant lots itself may both contribute to higher valued neighborhoods.[37]

5.3.4 *Impact of Greened Lot Concentration and Size*

The effects of vacant land greening may vary by the spatial intensity of greening activities. We consider two ways to measure the intensity of greening activities: greened lot concentration and size of greened landscape. We define the greened lot concentration as the number of greened lots that were treated before the sales date within a radius of 1,000 feet. The median of the greened lot concentration in the treatment group is three

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[36] We focus on the crime count instead of the crime rate (crime count divided by population) as the measure, because major public data sets (*e.g.* American Community Survey) do not report population by census block over time. Moreover, a small change in the annual population may have a big impact on the crime rate for census blocks with very few residents. This makes the census block crime rate a less informative measure.

[37] We identify these separate effects by further exploring the panel structure of the crime data and find supporting evidence for the direct amenity effect of greening vacant lots on property values. We rule out that our effect is due to the decrease of crime occurrence. See Appendix for the details.

fenced landscapes which may consist of up to nine greened lots.[38] Adjacent vacant lots are usually greened together in the same season and are turned into a fenced landscape, either separately or together. From 4,651 greened lots, we find 1,713 landscapes with a median size of 2,749 sq. ft. 64% of the landscapes are converted from two or more adjacent lots. Similar to (4), we modify the model in Column 4 of Table 3 by generalizing the constant treatment effect $\alpha \cdot 1\{treated_{ik}\}$ in equation (2).[39]

In Panels (a) and (b) of Figure 8, we plot the treatment effects by greened lot concentration and find that concentrating greened lots increases the treatment effect of greening vacant lots on the nearby property prices, suggesting an increasing return in the number of greened lots. The treatment effects for the last three groups are all positive and significant at 5% level, while the estimate for the smallest group that indicates the number of greened lots fewer than or equal to 2 is insignificant. The group of more than 20 greened lots nearby shows a substantial impact of 12.5% on nearby housing prices, far more than the estimates of 3.4% and 5.2% for the two middle groups. The evidence shows the efficacy of concentrating neighborhood greening.

In Panels (c) and (d), we show the treatment effects of greening vacant lots by the size of the nearest landscape and find a negative relationship. The estimated effects are all positive and significant at 5% level, but they decrease with size, going down from 8.9% for the landscape size smaller than 891 sq. ft., to 4.2% for the size from 891 to 1,540 sq. ft., and to 3.0% for the size greater than 1,540 sq. ft. This unexpected effect may be due to the negative impact of the concentration of larger lots on the number of lots separately greened which we have just seen has a positive impact on the size of greening effects.[40]

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[38] To define the size of a landscape, we group lots that have the same street name (but very close building numbers) and were greened in the same season to calculate the total area of a landscape.

[39] The landscape size and the greened lot concentration in treatment group are negatively correlated (-0.31). The cutoffs of the concentration groups divide the treatment into four groups with a comparable number of treated sales. The cutoffs of the size groups are the percentiles of the size distribution of landscapes (10^{th}, 30^{th} percentiles). If multiple landscapes are identified near a treated sale, we use the size of the nearest landscape (by distance) installed before a sale.

[40] We further check the relationship between the landscape size and the neighborhood characteristics. The size of the nearest landscape is positively correlated with vacant land share (correlation = 0.26) and is negatively correlated with median household income (correlation = -0.31), which may also help explain this result.

This finding on the treatment effects suggests that in neighborhoods with comparable total areas of vacant lands, building more greening landscapes of smaller sizes has a larger impact on the nearby properties, due to the larger number of contiguous properties. We do not measure the additional indirect positive impact of greening through an externality effect, that is, the impact of higher-valued properties on neighboring property values. However, it is possible that such an effect is occurring and that it is responsible in part for our finding that the more greened lots in a neighborhood, the larger the impact.[41] As our treatment effect is the estimate of the amenity value per property, the total amenity impact from adopting the strategy of greening more lots in a neighborhood will be larger than the impact of greening a similar single larger vacant lot.[42] While the landscapes smaller than 891 sq. ft. only account for 10% of the total number of landscapes, 36% of the repeated sales are concentrated within 1,000 feet from these greened areas. The overall impact of greening space is most strongly related to the border as opposed to the size of the lot. Hence, these smaller lot conversions will have an outsized effect on nearby house values.

5.3.5 Impact of Access to City Parks

We examine the impact of access to city parks on the treatment effect of greening vacant lots. We identify 522 parks and compute the distance from a property to the nearest city park using their centroids. The median distance to the nearest park in our repeated sales sample is 1,054 feet, more than double the median distance to vacant lots (439 feet in Table 1).[43]

Figure 9 shows how the nearest park distance impacts the treatment effect on housing prices. The x axis represents the decile groups of the distance to the nearest park that measures the level of pre-treatment access

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[41] Such neighborhood effects may derive from higher neighborhood appraisals as neighboring properties sell for more or these effects may derive from a reinvestment in neighboring properties that increases the willingness to pay to locate in the neighborhood.
[42] This is despite the fact that the costs are likely to be similar or improvements and reinvestment in properties with greater value.
[43] Due to the small number of parks and the large number of census blocks, other measures of access to parks, including the number of parks or the total park areas in a census block, do not show sufficient variation in the sample.

of a property to the green space. Panel (a) plots the average HPI by treatment status and by distance group. Panel (b) shows the treatment effect on housing prices for each decile group of the nearest park distance.

If greened lots and parks are substitutes, we should expect a smaller or no price effect for properties closer to parks. On the contrary, we find that if a property is below the 60th percentile of the distance distribution to the nearest park (1,210 feet), the treatment effect of greening vacant lots is positive and marginally significant at 5% level. Beyond the 60th percentile threshold, the treatment effect is insignificant. Nearness to parks augments the positive impact of parks on vacant lot greening.

We can also test for the joint impact of the distance to the nearest park and nearest park size.[44] City parks are divided into four size groups by the quartiles of nearest park size and five distance groups by the quintiles of the nearest park distance. We interact the indicators of park size and park distance with the treatment status. In Panel (d), we show that the positive and significant treatment effect of greening vacant lots comes from smaller parks.[45] While it was anticipated that in the presence of neighborhood or regional parks, the impact of greened vacant lots on neighboring house prices might decrease, we find the reverse outcome. This suggests that greened vacant lots are not substitutes for parks but complement the pocket parks and the small-size neighborhood parks to create green space amenities.

5.4 Additional Results

5.4.1 Wachter and Wong (2008) Revisited: Impact of Bias Adjustment

Wachter and Wong (2008) estimates the impact of a tree planting program in Philadelphia but finds no impact on nearby housing prices. They estimated a housing price model using OLS so that there was no adjustment for lot selection bias. To examine how important it is to consider lot selection bias, we add equation (1) to (2) and estimate an OLS model using repeated sales, similar to Wachter and Wong (2008), so there is no

[44] We also test the impact of park size separately. 98% of the nearest parks are either pocket parks (18%) or neighborhood parks (80%). We find that the treatment effects are not statistically different across the park size by the Wald test.
[45] Within the subsample, the treatment effect is significantly positive if the nearest park distance is less than 80th percentile of the distribution.

adjustment of the lot selection bias through the sample weights. Note that the definition of the treatment status in our analysis is similar to that in Wachter and Wong (2008). In Table 5, we report the results. We consider the cases that a sale is treated, if a vacant lot greened before the sale is within certain radius (250, 500, 750, or 1,000 feet) from the property. The coefficient of the treatment indicator shows no statistical significance (p-value > 0.1) for all specifications.

There are two forces that can bias the estimate of the treatment effect. The first is that vacant lots are concentrated in distressed communities with high crime rates and low business vibrancy (Balocchi and Jensen, 2019; Humphrey et al. 2020). Controlling for neighborhood characteristics helps to address the issue of pre-treatment difference in housing sales and mitigates the omitted variable bias. The second force that biases the estimate is the non-random assignment into treatment, which leads to group imbalance. The properties in the control group are not directly comparable to those in the treatment group, because vacant lots in distressed communities are more likely to be treated (see Table 4). With equal weight on sales in OLS models, we assume that the actual sales price in the control group is the counterfactual sales price in the treatment group. The counterfactual price of those treated sales will be overstated, because the sales price in the control group reflects the sales in an average neighborhood, while the sales price in the treatment group reflects the sales in below-average neighborhoods. This may explain why Wachter and Wong (2008) find no greening effect.

To deal with the selection, our method of weighting the samples builds reasonable counterfactuals to identify the treatment effect. The weighted sample has the feature of balanced characteristics of treated and untreated sales. The technique overweighs the properties that have vacant lots nearby in the control group and can adjust for the infrequency of property sales in neighborhoods with a large share of vacant lands as well as for omitted variable bias due to differences in samples.[46] To summarize, adjusting for the selection bias is crucial to estimate the impact of green space. Our models considering lot selection bias find significant and positive price impacts, while ignoring the lot selection bias leads to an underestimated and insignificant effect.

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[46] The bias adjustment also helps to adjust for the infrequency of sales of properties with lower appreciation. See Case, Pollakowski and Wachter (1997).

5.4.2 *Treatment Effect with Single and Repeated Sales*

Our main results rely on repeated sales only but we also consider expanding our analysis to include single sales. While working with repeated sales allows us to control unobserved heterogeneity by looking at the same residence at different time points, we leave out a large share of observations. One concern is that repeated sales homes are different from the single sales homes and cannot represent the whole housing market (Clapp et al., 1991; Clapp and Giaccotto, 1992). Case and Quigley (1991) propose that a hybrid model that includes hedonic variables and information about past sales leads to more efficient estimation.

To estimate the treatment effect with single sales, we modify model (1) to derive a housing price index, using both single and repeated sales. Instead of using the year gap between two sales and the price in the last sale, we include a control function λ_{ik} to summarize the information about past sale if it is available.

$$\log P_{ik} = \gamma_0 + \gamma_1 \lambda_{ik} + X_i^H \Theta^H + \sum_j \theta_j \cdot 1\{meddist2lot_i \in dist_j\} + qdate_{ik} + tract_i + e_{ik},\ \lambda_{ik} = \begin{cases} e_{i,k-1} & k \geq 2 \\ \lambda_0 & k = 1 \end{cases} \quad (7)$$

The form of the control function is motivated by Nagaraja et al. (2011) and Nagaraja et al. (2014) that incorporate single sales in autoregressive housing price models. To estimate λ_{ik}, we first estimate equation (7) without λ_{ik} and calculate the residual e_{ik}. For the k-th sale of a property i $(k \geq 2)$, λ_{ik} is equal to the residual in the last sale $e_{i,k-1}$. A positive e_{ik} suggests that the property was sold at a premium in the last sale. We assume that the premium partially carries to the current sale ($\gamma_1 > 0$). For single sales, λ_{ik} is equal to λ_0 which will be estimated in the model. A positive λ_0 suggests that single sales homes are sold at a premium relative to the repeated sales if all else equal. We find a positive premium of single sales ($\gamma_1 \lambda_0 = 0.0695$) and a positive impact of the past sale premium on the current sale ($\gamma_1 = 0.112$). We define the residual to be the housing price index HPI'_{ik}, after estimating equation (7) with the control function.

In Table 6, we replicate the specifications in Table 3 that use repeated sales only and report the estimates of ATET using the new price index HPI'_{ik} for all sales. Consistent with the main results, we find a positive and significant treatment effect of greening vacant lots. Within a radius of 1,000 feet, the treatment effect of greening a vacant lot based on all sales and the new index HPI'_{ik} is 7.96%, larger than the benchmark estimate based on the repeated sales only and the original index HPI_{ik} (4.27%).

A higher estimate could be driven by the matching procedure that is more flexible in the model of all sales. A repeated (single) sale in the treatment group may be matched to a single (repeated) sale with a similar propensity score. This is not possible in the benchmark estimate based only on repeated sales. We thus do the matching within the subsample of single and repeated sales respectively and estimate the treatment effects. The treatment effect of greening vacant lots within 1,000 feet is 4.69% for repeated sales and 4.00% for single sales. Among the subsample of repeated sales, the estimate using the new index HPI'_{ik} (4.69% in Col. 4 of Table 6) is similar to the estimate using the original index HPI_{ik} (4.27% in Col. 4 of Table 3).[47] Under the restriction of matching within subsamples, we estimate the treatment effect using the sample of single and repeated sales and find that a positive and significant price effect of 4.38% on the nearby property values. The evidence suggests that our model and findings can be extended to the single sales and greening vacant lots have a positive impact on all types of property sales nearby.[48]

5.4.3 Impact of the Great Recession on the Effect of Vacant Lot Greening

Our main results examine the housing sales in the period 2007-2019, which includes the Great Recession between 2007 and 2009. While our definition of HPI has taken out the seasonal and macro effects, it is possible that the treatment effect α in equation (2) is time-dependent. As a further robustness test, we subset the repeated sales sample to estimate the treatment effects of greening vacant lots.

In Table 7, we report several ATETs based on different definitions of the repeated sales samples. For comparison, the first model reports the same ATET estimate of 4.27% housing price effect in Column 4 of Table 3, using the full repeated sample with the current housing sales in the period 2007-2019. The second

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[47] In Appendix, we show that the mean housing and census block characteristics of single sales and repeated sales are statistically different. This further provides supporting evidence of restricting the matching procedure within the subsample of single sales and repeated sales, respectively.

[48] For treatment effects over space and time, our findings are consistent with the main results (see Appendix).

model considers the repeated sales whose current sale dates are in the period 2010-2019. We find a larger ATET estimate of 5.93% than the benchmark estimate. The second model still includes cases in which the prior sale occurs before or during the Great Recession. The impact of the unfavorable market condition during the Great Recession on the sales prices can pass into the prices of future sales. We thus implement a third model which considers repeated sales whose prior sale dates lie in the period 2010-2019. Besides the restriction that a treated sale in 2010-2019 is matched to an untreated sale in 2010-2019 from Model 2, the third model further requires that the last sales of the matched sales happened after the Great Recession. We find an ATET estimate of 4.89% in the third model. The ATETs in Models 2 and 3 are not statistically different from the benchmark ATET in Model 1 with 95% confidence in the Welch's unequal variances t tests. Hence, using the full sample that covers the Great Recession does not affect our benchmark estimate of the treatment effect.

6. Conclusion

This paper uses a quasi-experimental design to estimate the effect of greening vacant land on the sale prices of nearby houses in the City of Philadelphia. Based on repeated sales data, we find a beneficial effect of the greening of vacant lots, with sale prices of nearby houses increasing by 4.3%. We also find that price effects are significantly impacted by the neighborhood context. We demonstrate that neighborhood attributes can explain differential neighborhood-level outcomes as observed but not explained in the literature (Heckert and Mennis, 2012, 2015).

Two of the major neighborhood attributes that impact the effect of vacant lot greening are median household income and vacant land share. We find that the price effect of vacant lot greening peaks at 15% in neighborhoods with moderately high income (whose household income is 20-40% above the median), with little to no estimated price effect in very low-income and very high-income areas. In addition to income, neighborhood vacant land share has a substantial impact on the effect of vacant lot greening. We see no price effect when neighborhood vacant land share is less than 3% but for neighborhoods with almost twice that vacant land share of 5.8% (which corresponds to the city-wide average), the greening remediation of vacant lots has an estimated 9% effect on prices, twice the magnitude of the citywide average price effect. These findings support the conclusion that cleaning and greening of vacant lots can substantially mitigate the negative effect that vacant land has on nearby housing prices, especially in moderate-income and high vacant land share neighborhoods.

The presence of nearby pocket parks enhances these effects, which are also larger in communities with lower levels of crime occurrence. This finding suggests some potential for positive interaction among public safety and greening programs and aligns with prior research showing that crime activity declines with vacant lot conversion (Cui et al., 2021). While we do not identify the mechanism behind these results, they are consistent with localized quality-of-life benefits in neighborhoods that are walkable, safe, and visually appealing.

The benefits of vacant land greening appear to far exceed the associated costs even under the lower city-wide estimate of the effect of vacant lot greening on housing prices, particularly with concentrated greening of vacant lots. The measured price effect benefits are an order of magnitude larger than the costs, calculated in a back-of-the-envelope informal estimate. Using the median priced home ($250,000) multiplied by the number of homes within 1,000 feet (about 18) and by the treatment effect (4.3%) results in a benefit of $193,500, or $9,675 annualized at a 5% discount rate, which can be compared to an annualized cost of $375 ($300 upkeep and 5% of $1,500 installation cost).[49]

We find that vacant lots in distressed and declining neighborhoods are more likely to be selected for greening, which makes adjustment for this selection bias crucial to estimating the effects of greening. We have not identified the precise mechanism by which greening vacant lots raises property prices, other than the obvious mitigation of a neighborhood disamenity. Further work on the specific geography of impact, more disaggregated than the 1000-foot area of impact identified here would be useful. Additional work to identify benefits due to environmental gains associated with greening and their potential long-term effects on

[49] We do not include quality-of-life benefits that go beyond those measured in nearby house prices. Moreover, the opportunity cost issue is moot since these lots can be developed, including for affordable housing, or maintained as permanent green space, reinforcing the utility of such programs for neighborhoods in transition.

neighborhood residents' well-being would also be useful. Finally, information on more granular neighborhood characteristics, and techniques to incorporate these into the analysis, could be helpful in further identifying how neighborhood matters to the impact of vacant lot greening.

While the program effects identified here are significant and consistent with quality-of-life improvements, they are not consistent with a neighborhood repricing beyond the beneficial effects on nearby housing prices that we have found. They do not seem to have the dramatic longer-term impact that more comprehensive neighborhood-level policies (such as re-zoning and large-scale public and private reinvestment initiatives) may have, which may provide an explanation for why greening programs have been historically underused and undervalued. Nonetheless, we document here price effects that are consistent with previously observed quality-of-life impacts (Branas et al., 2018; South et al., 2015). The change of a blighted property to a greened lot does make a difference, with this improvement appearing to matter most in neighborhoods that are currently distressed.

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7. References

Balocchi, C., & Jensen, S. T. (2019). Spatial modeling of trends in crime over time in Philadelphia. Annals of Applied Statistics, 13(4), 2235-2259.

Bolitzer, B., & Netusil, N. R. (2000). The impact of open spaces on property values in Portland, Oregon. Journal of environmental management, 59(3), 185-193.

Bowes, D. R., & Ihlanfeldt, K. R. (2001). Identifying the impacts of rail transit stations on residential property values. Journal of urban Economics, 50(1), 1-25.

Braddock, A., & Igoe, L. (2016). Introduction: Imagining Urban Ecology. In Braddock A. & Igoe L. (Eds.), A Greene Country Towne: Philadelphia's Ecology in the Cultural Imagination (pp. 1-18). University Park, Pennsylvania: Penn State University Press. Doi:10.5325/j.ctv14gp09h.5

Branas, C. C., Cheney, R. A., MacDonald, J. M., Tam, V. W., Jackson, T. D., & Ten Have, T. R. (2011). A difference-in-differences analysis of health, safety, and greening vacant urban space. American journal of epidemiology, 174(11), 1296-1306.

Branas, C. C., Kondo, M. C., Murphy, S. M., South, E. C., Polsky, D., & MacDonald, J. M. (2016). Urban blight remediation as a cost-beneficial solution to firearm violence. American journal of public health, 106(12), 2158-2164.

Branas, C. C., South, E., Kondo, M. C., Hohl, B. C., Bourgois, P., Wiebe, D. J., & MacDonald, J. M. (2018). Citywide cluster randomized trial to restore blighted vacant land and its effects on violence, crime, and fear. Proceedings of the National Academy of Sciences, 115(12), 2946-2951.

Case, B., Pollakowski, H. O., & Wachter, S. M. (1997). Frequency of transaction and house price modeling. The Journal of Real Estate Finance and Economics, 14(1), 173-187.

Case, B., & Quigley, J. M. (1991). The dynamics of real estate prices. The Review of Economics and Statistics, 50-58.

Couture, V., & Handbury, J. (2020). Urban revival in America. Journal of Urban Economics, 119, 103267.

City of Philadelphia. (2009). Greenworks Philadelphia. https://www.phila.gov/media/20160419140515/2009-greenworks-vision.pdf

City of Philadelphia Department of Commerce and Drexel University's Center for Public Policy (2013). Starting a Business Improvement District in Philadelphia. https://centercityphila.org/uploads/attachments/cit0enngu001ff6qdevaqji8v-starting-a-bid-in-philadelphia.pdf

City of Philadelphia. (2015). Greenworks Progress Report. https://www.phila.gov/media/20160419140539/2015-greenworks-progress-report.pdf

City of Philadelphia. (2019). Annual Action Plan, 2019-2020. https://www.phila.gov/media/20190928080141/Annual-Action-Plan-2019-2020.pdf

City of Philadelphia. (2020). 5-Year Financial and Strategic Plan: For Fiscal Years 2021-2025. https://www.phila.gov/media/20201013124358/FY2021-FY2025-5-year-plan-proposed.pdf

City of Philadelphia. (2022). Annual Action Plan, 2021-2022. https://www.phila.gov/media/20220119135815/Annual-Action-Plan-2021-2022.pdf

Clapp, J. M., Giaccotto, C., & Tirtiroglu, D. (1991). Housing price indices based on all transactions compared to repeat subsamples. Real Estate Economics, 19(3), 270-285.

Clapp, J. M., & Giaccotto, C. (1992). Estimating price indices for residential property: a comparison of repeat sales and assessed value methods. Journal of the American Statistical Association, 87(418), 300-306.

Conway, D., Li, C. Q., Wolch, J., Kahle, C., & Jerrett, M. (2010). A spatial autocorrelation approach for examining the effects of urban greenspace on residential property values. The Journal of Real Estate Finance and Economics, 41(2), 150-169.

Crompton, J. L. (2001). The impact of parks on property values: A review of the empirical evidence. Journal of leisure research, 33(1), 1-31.

Crompton, J. L., & Nicholls, S. (2020). Impact on property values of distance to parks and open spaces: An update of US studies in the new millennium. Journal of Leisure Research, 51(2), 127-146.

Cui, J., Jensen, S.T., and Macdonald, J. (2021). The effects of vacant lot greening and the impact of land use and business presence on crime. Forthcoming at Environment and Planning B: Urban Analytics and City Science.

Ellen, I. G., & Ding, L. (2016). Guest Editors' Introduction: Advancing Our Understanding of Gentrification. Cityscape, 18(3), 3-8.

Espey, M., & Owusu-Edusei, K. (2001). Neighborhood parks and residential property values in Greenville, South Carolina. Journal of Agricultural and Applied Economics, 33(1379-2016-113067), 487-492.

Fee, K. & Hartley, D. (2013). Th e Relationship Between City Center Density and Urban Growth or Decline. In S.W. Wachter & K. A. Zeuli (Eds.), Revitalizing American Cities (pp. 26-44). University of Pennsylvania Press.

Franco, S. F., & Macdonald, J. L. (2018). Measurement and valuation of urban greenness: Remote sensing and hedonic applications to Lisbon, Portugal. Regional Science and Urban Economics, 72, 156-180.

Freeman, L. M. (2016). Commentary: 21st century gentrification. Cityscape, 18(3), 163-168.

Garrett, A., & Leeds, M. A. (2015). The economics of community gardening. Eastern Economic Journal, 41(2), 200-213.

Garvin, E. C., Cannuscio, C. C., & Branas, C. C. (2013). Greening vacant lots to reduce violent crime: a 39andomized controlled trial. Injury prevention, 19(3), 198-203.

Guerrieri, V., Hartley, D., & Hurst, E. (2013). Endogenous gentrification and housing price dynamics. Journal of Public Economics, 100, 45-60.

Heckert, M., & Mennis, J. (2012). The economic impact of greening urban vacant land: a spatial difference-in-differences analysis. Environment and Planning A, 44(12), 3010-3027.

Heckert, M. (2015). A spatial difference-in-differences approach to studying the effect of greening vacant land on property values. Cityscape, 17(1), 51-60.

Heckert, M., & Kondo, M. (2018). Can "cleaned and greened" lots take on the role of public greenspace?. Journal of Planning Education and Research, 38(2), 211-221.

Hobden, D. W., Laughton, G. E., & Morgan, K. E. (2004). Green space borders—a tangible benefit? Evidence from four neighbourhoods in Surrey, British Columbia, 1980–2001. Land Use Policy, 21(2), 129-138.

Holme, T., A Short Advertisement upon the Scituation and Extent of the City of Philadelphia and Ensuing Platform thereof, by the Surveyor General (1683), in William Penn and the Founding of Pennsylvania: A Documentary History.

Hoyt, L. (2004). Collecting private funds for safer public spaces: an empirical examination of the business improvement district concept. Environment and Planning B: Planning and Design, 31(3), 367-380.

Hoyt, L. M. (2005). Do business improvement district organizations make a difference? Crime in and around commercial areas in Philadelphia. Journal of Planning Education and Research, 25(2), 185-199.

Humphrey, C., Jensen, S. T., Small, D. S., & Thurston, R. (2020). Urban vibrancy and safety in Philadelphia. Environment and Planning B: Urban Analytics and City Science, 47(9), 1573–1587. https://doi.org/10.1177/2399808319830403

Hwang, J., & Lin, J. (2016). What have we learned about the causes of recent gentrification?. Cityscape, 18(3), 9-26.

Kondo, M. C., Low, S. C., Henning, J., & Branas, C. C. (2015). The impact of green stormwater infrastructure installation on surrounding health and safety. American journal of public health, 105(3), e114-e121.

Kondo, M. C., Mueller, N., Locke, D. H., Roman, L. A., Rojas-Rueda, D., Schinasi, L. H., Gascon, M. & Nieuwenhuijsen, M. J. (2020). Health impact assessment of Philadelphia's 2025 tree canopy cover goals. The Lancet Planetary Health, 4(4), e149-e157.

Levy, D. K., Comey, J., & Padilla, S. (2006). Keeping the neighborhood affordable: A handbook of housing strategies for gentrifying areas. Washington, DC: Urban Institute.

Li, W., & Saphores, J. D. (2012). A spatial hedonic analysis of the value of urban land cover in the multifamily housing market in Los Angeles, CA. Urban Studies, 49(12), 2597-2615.

Lincoln Institute of Land Policies (2021). https://www.lincolninst.edu/research-data/data-toolkits/legacy-cities/initiatives/philadelphia-landcare. Accessed in September, 2021.

Lindsey, G., Man, J., Payton, S., & Dickson, K. (2004). Property Values, Recreation Values, and Urban Greenways. Journal of Park & Recreation Administration, 22(3).

Lutzenhiser, M., & Netusil, N. R. (2001). The effect of open spaces on a home's sale price. Contemporary Economic Policy, 19(3), 291-298.

Mallach, A. (2018). The empty house next door. Cambridge, MA: Lincoln Institute of Land Policy. https://nhc.org/wp-content/uploads/2018/09/empty-house-next-door-full-Allan-Mallach.pdf

Morcol, G., Hoyt, L., Meek, J. W., & Zimmermann, U. (2017). Business improvement districts: Research, theories, and controversies. Routledge.

MacDonald, J., Branas, C., & Stokes, R. (2019). Changing Places. Princeton University Press.

MacDonald, J. M., & Branas, C. (2019). Reducing Crime by Changing Places: Assessing the Benefits of Abating Vacant and Abandoned Land in Urban Spaces. Penn IUR Working Paper.

Mitchell, J. (2001). Business improvement districts and the "new" revitalization of downtown. Economic Development Quarterly, 15(2), 115-123.

Moyer, R., MacDonald, J. M., Ridgeway, G., & Branas, C. C. (2019). Effect of remediating blighted vacant land on shootings: a citywide cluster randomized trial. American journal of public health, 109(1), 140-144.

Nagaraja, C. H., Brown, L. D., & Zhao, L. H. (2011). An autoregressive approach to house price modeling. The Annals of Applied Statistics, 5(1), 124-149.

Nagaraja, C., Brown, L., & Wachter, S. (2014). Repeat sales house price index methodology. Journal of Real Estate Literature, 22(1), 23-46.

Neighborhood Scout (2021). Philadelphia, PA Crime Rates. https://www.neighborhoodscout.com/pa/philadelphia/crime#

Netusil, N. R., Chattopadhyay, S., & Kovacs, K. F. (2010). Estimating the demand for tree canopy: a second-stage hedonic price analysis in Portland, Oregon. Land Economics, 86(2), 281-293.

NKCDC (2021). New Kensington Community Development Corporation History. https://nkcdc.org/who-we-are/our-history/nkcdc-history/ Accessed in September, 2021.

Pack, J. R. (1992). BIDs, DIDs, SIDs, SADs: Private governments in urban America. The Brookings Review, 10(4), 18-21.

Pearsall, H. (2017). Staying cool in the compact city: vacant land and urban heating in Philadelphia, Pennsylvania. Applied geography, 79, 84-92.

Pennsylvania Horticultural Society (2021). https://phsonline.org/programs/transforming-vacant-land Accessed in September, 2021.

Philadelphia Inquirer (2010). New Philadelphia budget may halt funding for cleaning up vacant lots. https://www.inquirer.com/philly/news/local/20100714_New_Philadelphia_budget_may_halt_funding_for_cleaning_up_vacant_lots.html Accessed in September, 2021.

Rigolon, A. (2016). A complex landscape of inequity in access to urban parks: A literature review. Landscape and Urban Planning, 153, 160-169.

Rodin, J. (2005). The 21st century urban university: New roles for practice and research. Journal of the American Planning Association, 71(3), 237-249.

Rodin, J. (2015). The university and urban revival: Out of the ivory tower and into the streets. University of Pennsylvania Press.

Shelter Force (2018). https://shelterforce.org/2018/11/13/greening-vacant-lots-low-cost-big-effect-in-philly/ Accessed in September, 2021.

Schill, M. H., Ellen, I. G., Schwartz, A. E., & Voicu, I. (2002). Revitalizing inner-city neighborhoods: New York City's ten-year plan. Housing Policy Debate, 13(3), 529-566.

South, E. C., Kondo, M. C., Cheney, R. A., & Branas, C. C. (2015). Neighborhood blight, stress, and health: a walking trial of urban greening and ambulatory heart rate. American journal of public health, 105(5), 909-913.

South, E. C., Hohl, B. C., Kondo, M. C., MacDonald, J. M., & Branas, C. C. (2018). Effect of greening vacant land on mental health of community-dwelling adults: a cluster randomized trial. JAMA network open, 1(3), e180298-e180298.

Tranel, M., & Handlin Jr, L. B. (2006). Metromorphosis: documenting change. Journal of Urban Affairs, 28(2), 151-167.

Trust of Public Land. (2001). New York City Community Gardens Report. https://www.tpl.org/new-york-city-community-gardens-report

Vibrant Cities lab (2021). https://www.vibrantcitieslab.com/case-studies/philadelphia-landcare/. Accessed in September, 2021

Voicu, I., & Been, V. (2008). The effect of community gardens on neighboring property values. Real Estate Economics, 36(2), 241-283.

Wachter, S. M., & Wong, G. (2008). What is a tree worth? Green city strategies, signaling and housing prices. Real Estate Economics, 36(2), 213-239.

Wentland, S., Waller, B., & Brastow, R. (2014). Estimating the effect of crime risk on property values and time on market: Evidence from Megan's law in Virginia. Real Estate Economics, 42(1), 223-251.

WFMZ (2021). https://www.wfmz.com/news/area/poconos-coal/anti-blight-legislation-set-to-become-law/article_aa455bda-e237-11eb-be76-73e91debc056.html Accessed in September, 2021.

8. Tables

Table 1. Summary Statistics of Housing and Census Block Characteristics (by Property Sales)

	All Sample			Control vs Treatment			
	Mean	SD	P50	Control: Mean	Treated: Mean	Difference	t stat
Housing Characteristics							
Log sale price (2018M1 $)	11.62	1.01	11.7	11.76	10.97	0.790***	-90.53
Log price (2018M1 $), prior sale	11.38	1	11.4	11.54	10.62	0.922***	-109.31
Years since last sale	6.49	4.13	5.8	6.49	6.47	0.0223	-0.6
Lot size (sq.ft.)	1,676	2,260	1,159	1794.75	1130.74	664.0***	-32.66
Floor area (sq.ft.)	1,306	487.8	1,190	1,323.20	1,227.05	96.15***	-21.88
Number of bedrooms	3.05	0.69	3	3.04	3.1	-0.0595***	(-9.62)
Building year	1934	28	1925	1936	1927	8.421***	-34.01
Is single-family (binary)	0.12	0.32	0	0.13	0.05	0.0773***	-26.84
Is condo (binary)	0.03	0.18	0	0.04	0.01	0.0315***	-19.83
Is rowhouse (binary)	0.85	0.35	1	0.83	0.94	-0.109***	(-34.14)
Census Block Characteristics							
Has no vacant land (binary)	0.65	0.48	1	0.74	0.25	0.485***	-122.32
Residential land share (%)	85.13	20.56	94.1	86.29	79.73	6.557***	-35.57
Commercial land share (%)	5.16	10.84	1.4	5.26	4.71	0.549***	-5.61
Vacant land share (%)	3.28	7.9	0	2.16	8.51	-6.353***	(-93.50)
Vacancy rate (%)	10.32	8.53	8.3	8.79	17.44	-8.652***	(-121.74)
Homeownership rate (%)	62.98	19.3	64	65.14	52.98	12.17***	-71.88
Black householder share (%)	39.17	36.43	26.2	31.56	74.56	-43.00***	(-146.32)
College share (%)	24.01	21.84	16.5	26.71	11.46	15.25***	-80.19
Med. household income (2018M1 $)	45,278	23,083	40,482	48,964	28,135	20829***	-106.4
Med. distance to vacant lots (ft.)	504.61	313.04	439.04	571.84	191.99	379.8***	-151.55
Med. vacant lot size (sq.ft.)	4,701	24,720	1,417	5,373	1,574	3798.3***	-17.04
Crime counts in last four quarters	11.56	11.92	9	10.89	14.7	-3.806***	(-35.62)

Note: * p<0.10, ** p<0.05, *** p<0.010. A property sale is in the treatment group if there is a greened vacant lot within the radius of 1,000 feet from a property before the sale.

Table 2. Repeated-Sale Housing Price Model

	Dependent Variable: log sale price (2018M1 $)	
	Coefficient	Standard Error
Log sale price (2018M1 $), last sale	0.128***	(0.010)
Years since last sale	-0.0472***	(0.010)
Log sale price, last sale # years since last sale	0.00208**	(0.001)
Log lot size (sqft)	0.0602***	(0.011)
Log floor area (sqft)	0.537***	(0.018)
Number of Bedrooms, 1{Bedroom = 1} = 0		
Bedroom = 2	0.131***	(0.039)
Bedroom = 3	0.0945**	(0.041)
Bedroom = 4	0.0966**	(0.044)
Bedroom = 5+	0.122**	(0.048)
Building year, 1{before 1900} = 0		
Building year: 1901-1920	-0.0284	(0.020)
Building year: 1921-1940	0.00508	(0.021)
Building year: 1941-1960	0.0690***	(0.026)
Building year: 1961-1980	0.0784***	(0.028)
Building year: 1981-2000	0.0962***	(0.031)
Building year: after 2000	0.121***	(0.029)
Property Type, 1{single-family} = 0		
Is condo	-0.319***	(0.042)
Is rowhouse	-0.0723***	(0.015)
Distance to Vacant Lots, 1{(0,471] ft) = 0		
(471,707] ft	0.0653***	(0.024)
(707,937] ft	0.145***	(0.028)
(937,1.27k]ft	0.219***	(0.032)
(1.27k,1.70k] ft	0.291***	(0.038)
(1.70k,2.14k] ft	0.336***	(0.037)
(2.14k,2.54k] ft	0.353***	(0.038)
(2.54k,2.89k] ft	0.384***	(0.039)
(2.89k,3.26k] ft	0.392***	(0.040)
> 3.26k ft	0.401***	(0.041)
Constant	6.982***	(0.193)
Quarterly Date FE	Yes	
Tract FE	Yes	
Adjusted R^2	0.673	
N	84,131	

Note: * p<0.10, ** p<0.05, *** p<0.010. Cluster robust standard errors in the parentheses. Errors are clustered at the tract level. The sample is all residential sales in Philadelphia, with the current sale dates between 2007 and 2019. The base levels (Bedroom = 1; building year: before 1900; single-family; (0, 471) ft) are omitted. For each property, the median distance up to 50 nearest greened or untreated vacant lots in the period from 2007 to 2017 within a radius of 4,000 feet is defined as the distance to vacant lots.

Table 3. Average Treatment Effect of Being Treated (ATET)

Treated = 1, if	Dependent Variable: quality-adjusted housing price index HPI_{ik} (1)	(2)	(3)	(4)
Treat Before Sale	Yes	Yes	Yes	Yes
Distance to Greened Lot	<250 ft	<500 ft	<750 ft	<1k ft
ATET: α	0.0446**	0.0749***	0.0629***	0.0427***
	(0.0218)	(0.0179)	(0.0161)	(0.0147)

Note: * p<0.10, ** p<0.05, *** p<0.010. Abadie–Imbens robust standard errors in the parentheses. The sample is the repeated sales of residential properties for 2007-2019 in Philadelphia. To define the treatment indicator, two conditions are considered. Treat Before Sale: whether a vacant lot within was greened before a sale. Distance to Lot: whether the lot is within certain distance threshold (250/500/750/1,000 feet).

Table 4. Selection Equation (Logit): Marginal Probability

Treated = 1, if	Dependent Variable: Treatment Indicator (1)	(2)	(3)	(4)
Treat Before Sale	Yes	Yes	Yes	Yes
Distance to Greened Lot	<250 ft	<500 ft	<750 ft	<1k ft
Has no vacant land, z-score	-0.0229***	-0.0344***	-0.0376***	-0.0420***
	(0.001)	(0.001)	(0.001)	(0.001)
Vacant land share (%), z-score	0.00750***	0.00980***	0.00743***	0.00785***
	(0.001)	(0.001)	(0.001)	(0.001)
Residential land share (%), z-score	-0.00967***	-0.0121***	-0.0192***	-0.0255***
	(0.002)	(0.002)	(0.002)	(0.003)
Commercial land share (%), z-score	-0.00620***	-0.00352***	-0.00553***	-0.00801***
	(0.001)	(0.001)	(0.001)	(0.002)
Housing vacancy rate (%), z-score	0.00543***	0.0177***	0.0256***	0.0296***
	(0.001)	(0.001)	(0.001)	(0.001)
Homeownership rate (%), z-score	-0.0188***	-0.0336***	-0.0393***	-0.0495***
	(0.001)	(0.002)	(0.002)	(0.002)
Black householder share (%), z-score	0.0319***	0.0600***	0.0708***	0.0770***
	(0.002)	(0.002)	(0.002)	(0.002)
College share (%), z-score	-0.0422***	-0.0710***	-0.0793***	-0.0734***
	(0.002)	(0.002)	(0.002)	(0.002)
Residential land share (%),	-0.00515***	-0.00735***	-0.00751***	-0.00955***
square of z-score	(0.001)	(0.001)	(0.001)	(0.001)
Homeownership rate (%),	-0.00692***	-0.0123***	-0.0119***	-0.0152***
square of z-score	(0.001)	(0.001)	(0.001)	(0.001)
Black householder share (%),	-0.00518***	-0.00441**	0.00553***	0.0112***
square of z-score	(0.001)	(0.002)	(0.002)	(0.002)
Pseudo R^2	0.329	0.371	0.386	0.372
N	84,131	84,131	84,131	84,131

Note: * p<0.10, ** p<0.05, *** p<0.010. To define the treatment indicator, two conditions are considered. Treat Before Sale: whether a vacant lot within was greened before a sale. Distance to Lot: whether a greened vacant lot is within certain distance radius (250/500/750/1,000 feet). The variables except the squared terms are normalized to zero mean and unit variance.

Table 5. Amenity Effect of Greening Vacant Lots without Selection Adjustment

	Dependent Variable: log sale price (2018M1 $)			
Treated = 1, if	(1)	(2)	(3)	(4)
Treat Before Sale	Yes	Yes	Yes	Yes
Distance to Greened Lot	<250 ft	<500 ft	< 750 ft	< 1k ft
$1\{treated\}$	-0.00400	0.0163	0.0164	0.0215
	(0.026)	(0.028)	(0.023)	(0.023)
Log sale price (2018M1 $), last sale	0.116***	0.116***	0.116***	0.115***
	(0.010)	(0.009)	(0.009)	(0.009)
Years since last sale	-0.0421***	-0.0429***	-0.0430***	-0.0434***
	(0.010)	(0.010)	(0.010)	(0.010)
Log sale price, last sale # years since last sale	0.00157*	0.00165*	0.00166*	0.00169*
	(0.001)	(0.001)	(0.001)	(0.001)
Quarterly Date FE	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes
Housing and spatial characteristics	Yes	Yes	Yes	Yes
Block characteristics	Yes	Yes	Yes	Yes
Lot selection adjustment	No	No	No	No
Adjusted R^2	0.677	0.677	0.677	0.677
N	84,131	84,131	84,131	84,131

Note: * p<0.10, ** p<0.05, *** p<0.010. Cluster robust standard errors in the parentheses. Errors are clustered at the tract level. The table reproduces the finding on insignificant treatment effect in Wachter and Wong (2008). To define the treatment indicator of a sale, two conditions are considered. Treat Before Sale: whether a vacant lot within was greened before a sale. Distance to Lot: whether the lot is within certain distance threshold (250/500/750/1,000 feet). Housing and spatial characteristics include the variables in Table 1. Block characteristics include the variables in Table 3.

Table 6. Average Treatment Effect of Being Treated (ATET): Repeated Sales vs Single Sales

	Dependent Variable: quality-adjusted housing price index HPI'_{ik}			
Treated = 1, if	(1)	(2)	(3)	(4)
Treat Before Sale	Yes	Yes	Yes	Yes
Distance to Greened Lot	<250 ft	<500 ft	<750 ft	<1k ft
Sample: single and repeated sales (no matching restriction)				
ATET: α	0.0987***	0.0957***	0.0907***	0.0796***
	(0.0160)	(0.0131)	(0.0119)	(0.0107)
Sample: repeated sales only				
ATET: α	0.0433*	0.0794***	0.0710***	0.0469***
	(0.0225)	(0.0182)	(0.0164)	(0.0149)
Sample: single sales only				
ATET: α	0.0764***	0.0680***	0.0546***	0.0400***
	(0.0203)	(0.0161)	(0.0145)	(0.0136)
Sample: single and repeated sales (Single-Single; repeated-repeated)				
ATET: α	0.0631***	0.0732***	0.0603***	0.0438***
	(0.0214)	(0.0171)	(0.0155)	(0.0141)

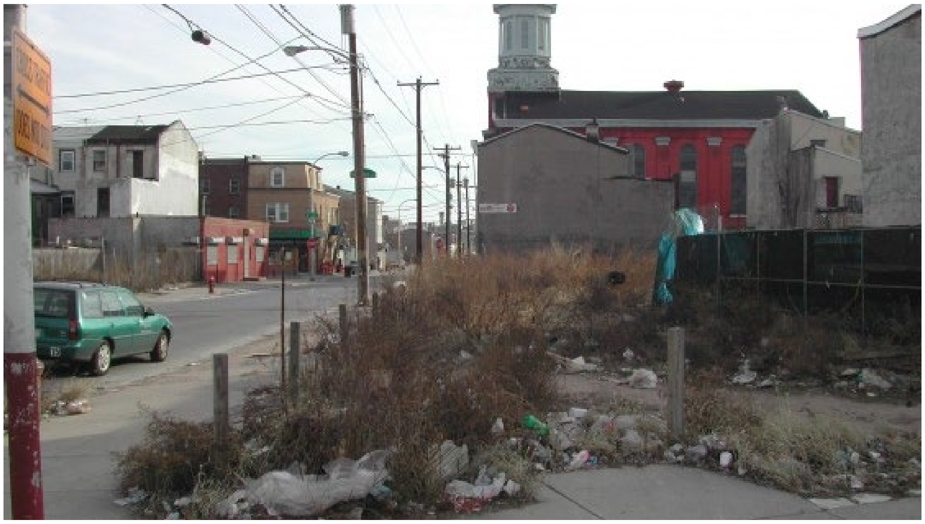
Note: * p<0.10, ** p<0.05, *** p<0.010. Abadie–Imbens robust standard errors in the parentheses. The sample is the single and repeated sales of residential properties for 2007-2019 in Philadelphia. To define the treatment indicator, two conditions are considered: (1) Treat Before Sale: whether a vacant lot within was greened before a sale; (2) Distance to Lot: whether the lot is within a certain distance threshold (250/500/750/1,000 feet).

Table 7. Average Treatment Effect of Being Treated (ATET): Years of Repeated Sales

Repeated Sales Sample	ATET	Robust SE
(1) Years of current sale 2007-2019 (benchmark)	0.0427***	(0.0147)
(2) Years of current sale 2010-2019; no restriction on last sale	0.0593***	(0.0182)
(3) Years of current sale 2010-2019; years of last sale 2010-2019	0.0489***	(0.0150)

Note: * p<0.10, ** p<0.05, *** p<0.010. Abadie–Imbens robust standard errors in the parentheses. To define the treatment indicator, two conditions are considered: (1) Treat Before Sale: whether a vacant lot within was greened before a sale; (2) Distance to Lot: whether the lot is within 1,000 feet.

9. Figures



(a) before landscape installation

(b) after landscape installation

Figure 1: Selected land lot before and after landscape installation. The vacant lot in the photos is located at N 4th St & Cecil B. Moore Ave, Philadelphia, PA 19122. Source: http://www.ocfrealty.com/naked-philly/uncategorized/philly-landcare-program-receives-recognition

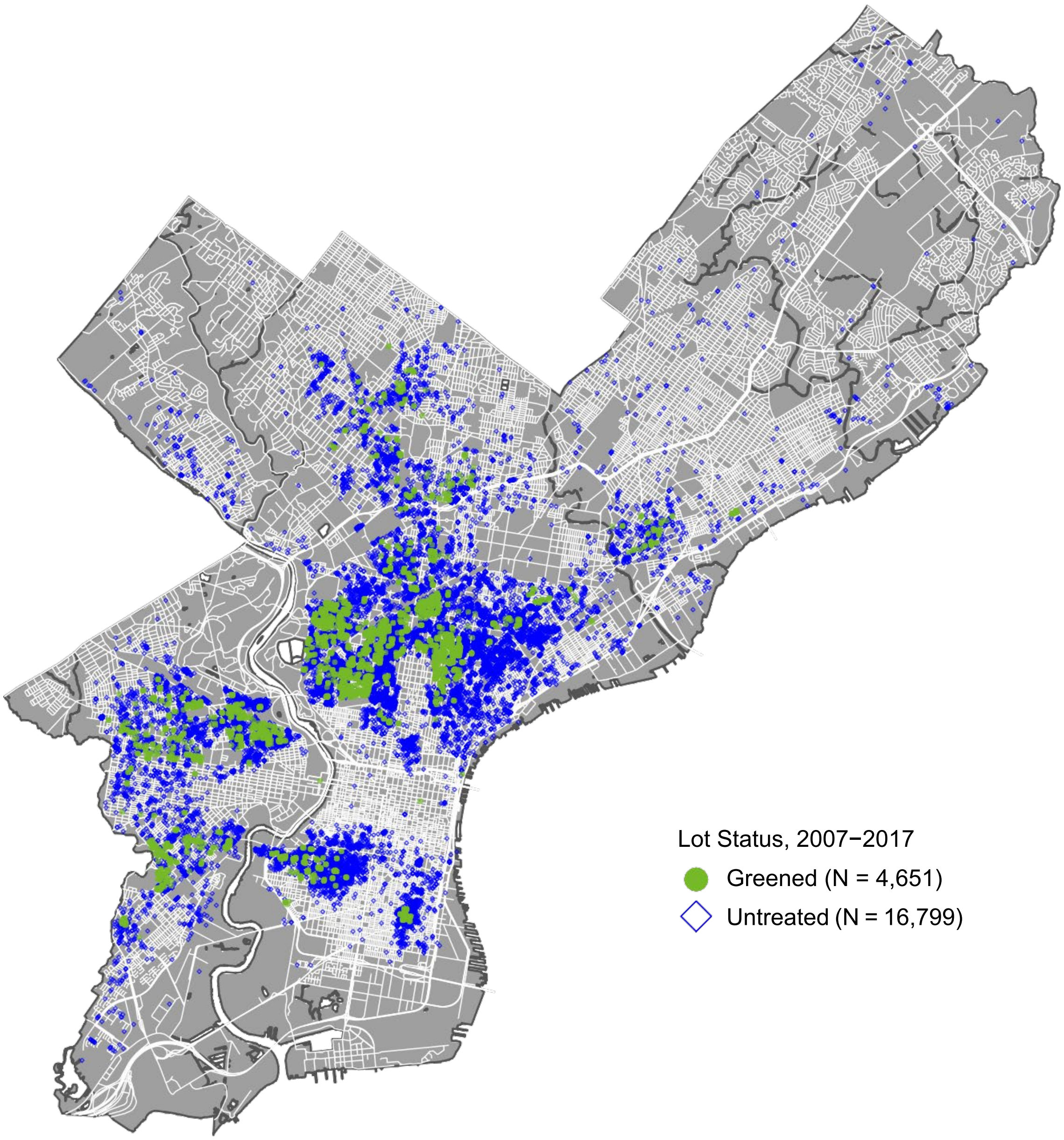


Figure 2: Spatial distribution of Greened and untreated (ungreened) vacant lots by treatment status in Philadelphia, 2007-2017. A vacant lot is defined as treated if it was greened in the period. The greened vacant lot data comes from the Philadelphia Horticultural Society and the untreated vacant lot data comes from Philadelphia Department of Licenses and Inspections. The white lines on the gray base map are the main roads in Philadelphia.

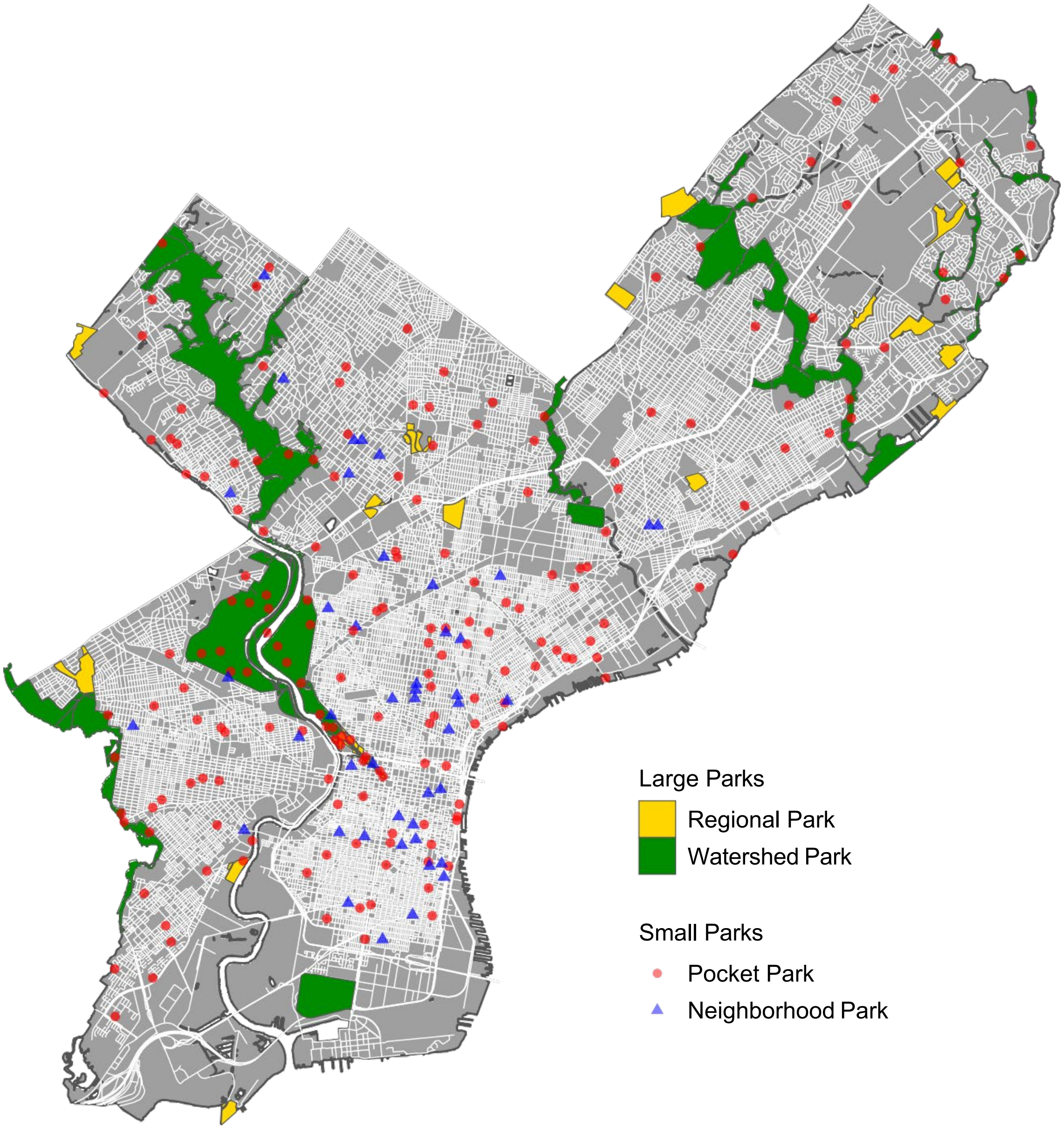
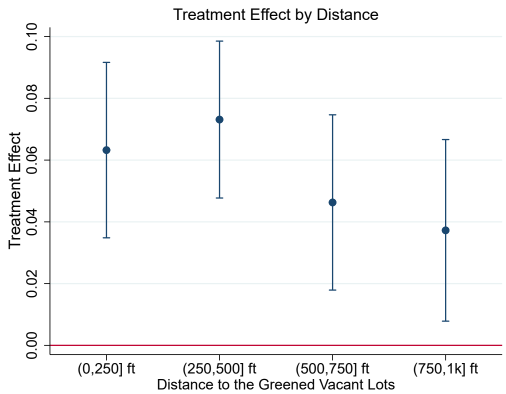
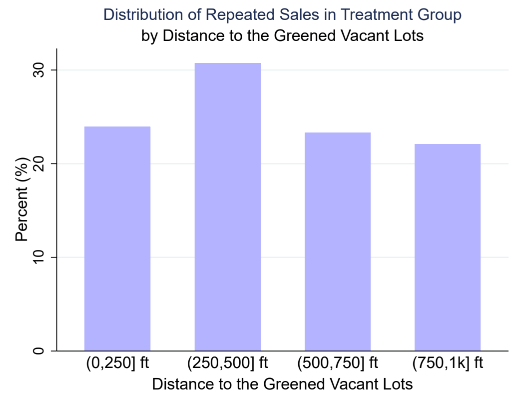


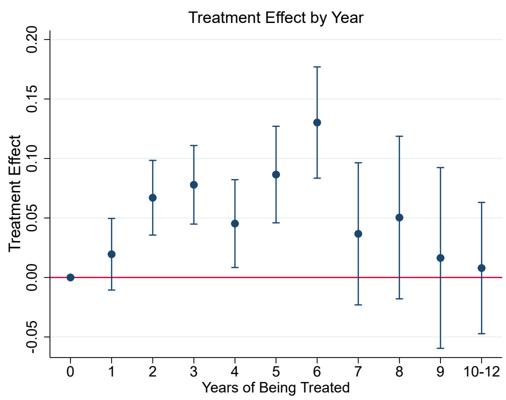
Figure 3: Spatial distribution of city parks in Philadelphia. Pocket parks: size smaller than 0.5 acre; neighborhood parks: size between 0.5 acre and 40 acres; regional parks: size between acres 40 acres and 136 acres; watershed parks: size greater than 136 acres. Large parks are shown in the exact shapes and sizes, while small parks are labeled by markers whose sizes do not represent those of the parks. The data comes from the Department of Philadelphia Parks and Recreation. The white lines on the gray base map are the main roads in Philadelphia.



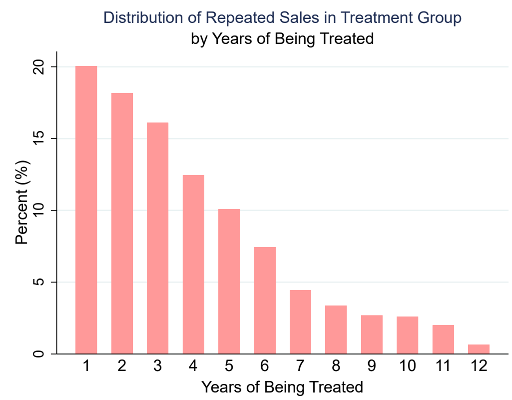
(a) Treatment Effect by Distance



(b) Distance to the Greened Vacant Lots

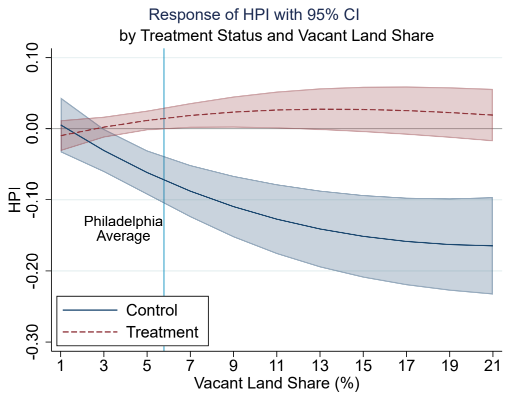


(c) Treatment effect by Year

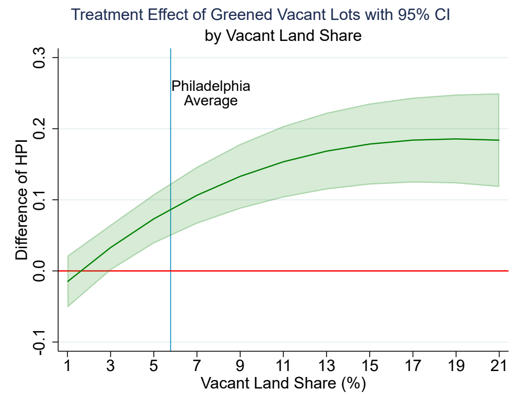


(d) Years of Being Treated

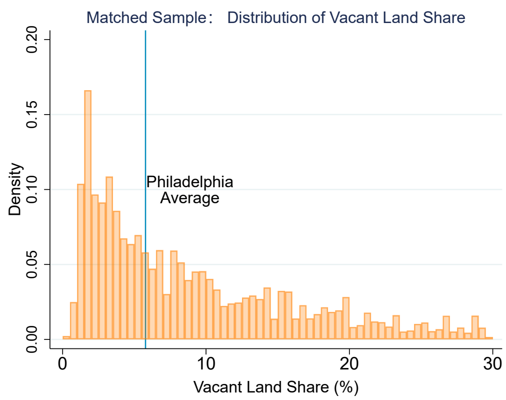
Figure 4: Treatment Effect of greened vacant lots on housing prices. Panel (a): Treatment effects and the distance to the greened vacant lots. A residential sale is defined as being treated if there is a vacant lot within 1,000 feet that was greened before the sale. The error bars represent 95% confidence intervals, using the robust standard errors. The distance to the greened vacant lots is defined as the minimum distance to the greened vacant lots before the current sale. Panel (b) shows the distribution of the distance to the greened vacant lots. Panel (c): Treatment effects and the number of years of being treated. To define the years of being treated, we search for the greened vacant lot in the radius of 1,000 feet that is closest in time to the current sale. Panel (d) shows the distribution of the years of being treated.



(a) Response of HPI to treatment status

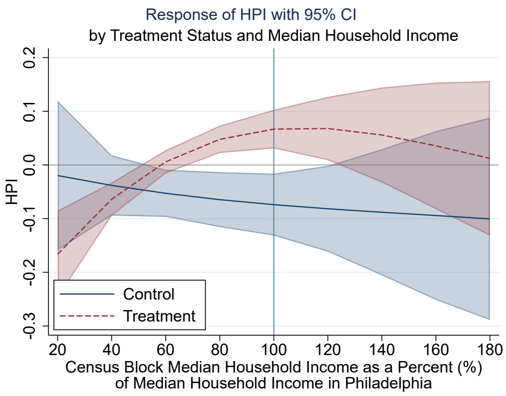


(b) Treatment effect

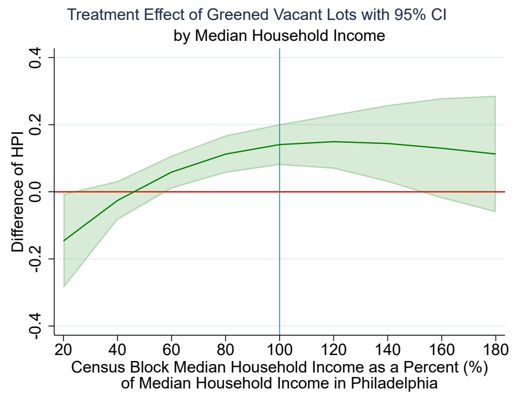


(c) Distribution of Vacant Land Share

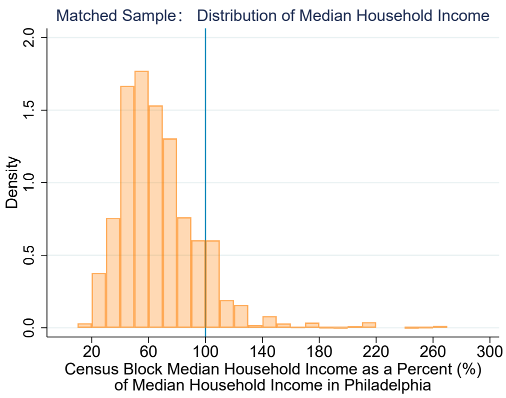
Figure 5: The impact of the vacant land share on the housing price index (HPI) and the treatment effect of greened vacant lots with 95% confidence intervals (CI). The treatment effect is the difference of the average response of HPI between the treatment and the control groups. The x axis is the vacant land share of census blocks. The vacant land share in Philadelphia (*Philadelphia Average*) is defined as the total area of the vacant land parcels in Philadelphia divided by the total area of land parcels. The y axis is HPI in panel (a) and the difference of HPI in panel (b). In Panel (c), the repeated sales are weighted, with the weights based on the propensity scores. The data on the vacant land share comes from the Philadelphia Department of Planning and Development.



(a) Response of HPI to treatment status

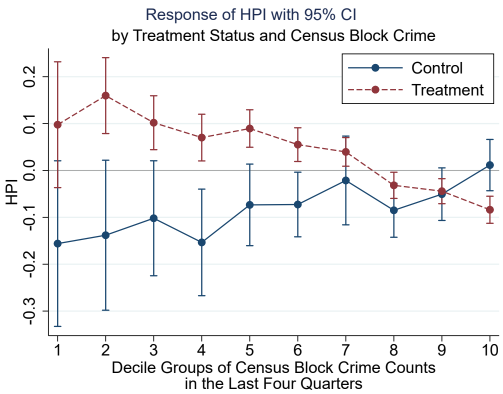


(b) Treatment effect

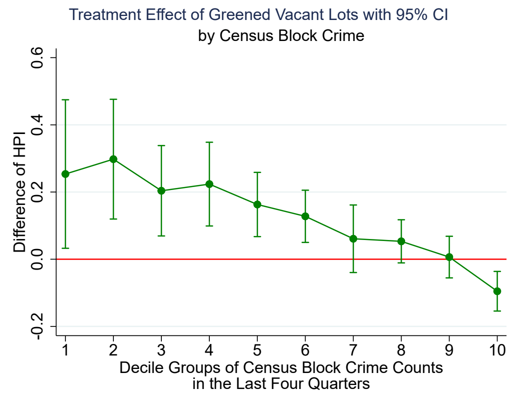


(c) Distribution of Median Household Income

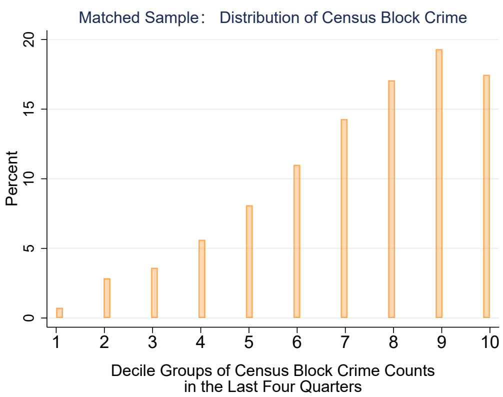
Figure 6: The impact of median household income on the housing price index (HPI) and the treatment effect of greened vacant lots with 95% confidence intervals (CI). The treatment effect is the difference of the average response of HPI between the treatment and the control groups. The x axis is the median household income of census block groups as a percent of the median household income in Philadelphia. The median household income in Philadelphia refers to the median household income in Philadelphia County in 2010. The y axis is HPI in panel (a) and the difference of HPI in panel (b). In Panel (c), the repeated sales are weighted, with the weights based on the propensity scores. The data on the median household income comes from 2010 5-year American Community Survey estimate.



(a) Response of HPI to treatment status

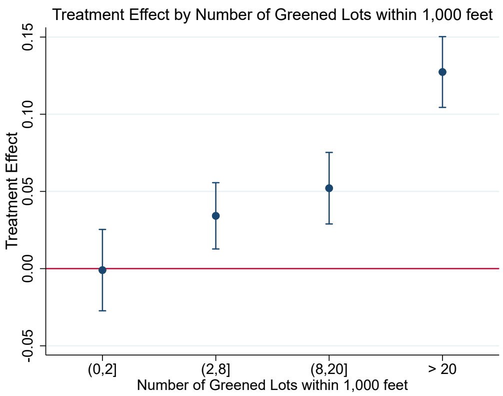


(b) Treatment effect

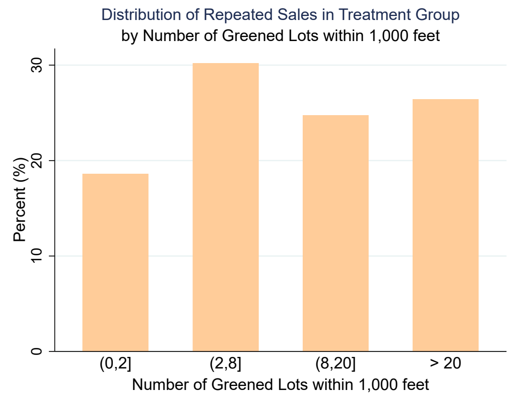


(c) Distribution of Census Block Crime Counts

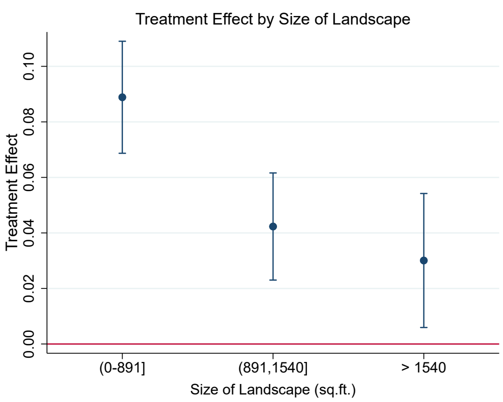
Figure 7: The impact of census block crime counts in the last four quarters on the housing price index (HPI) and the treatment effect of greened vacant lots with 95% confidence intervals (CI). The treatment effect is the difference of the average response of HPI between the treatment and the control groups. The x axis denotes the decile groups. In each year and quarter, census blocks in Philadelphia are grouped into one of the ten decile groups, based on the distribution of census block crime counts in the last four quarters. Both violent (homicides, rapes, robberies, aggravated assaults) and non-violent (burglary, thefts, vehicle thefts, other assaults, arson, vandalism, offenses against family and children, public drunkenness, disorderly conduct, and vagrancy/loitering) crimes are counted. The y axis is HPI in panel (a) and the difference of HPI in panel (b). In Panel (c), the repeated sales are weighted, with the weights based on the propensity scores. The crime data comes from the Philadelphia Police Department.



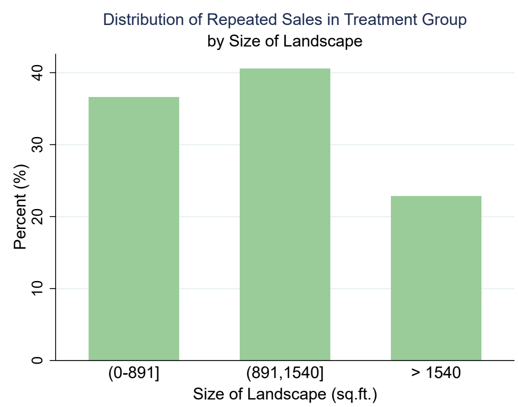
(a) Treatment Effect by Number of Greened Lots



(b) Number of Greened Lots

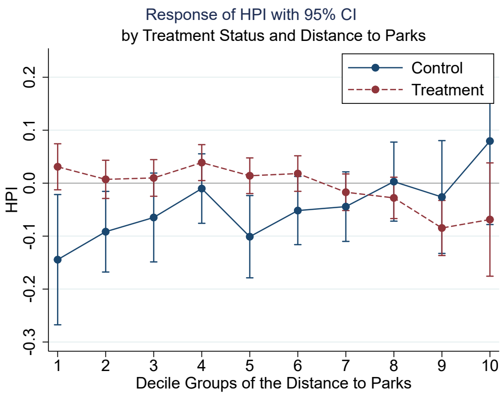


(c) Treatment effect by Size

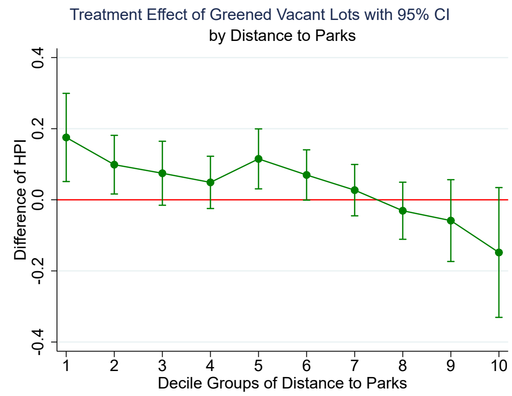


(d) Size of Landscape

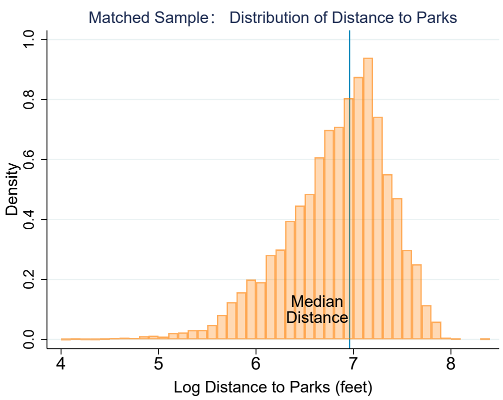
Figure 8: Treatment Effect of greened vacant lots on housing prices. Panel (a): Treatment effects and the number of greened lots within 1,000 feet. A residential sale is defined as being treated if there is a vacant lot within 1,000 feet that was greened before the sale. The error bars represent 95% confidence intervals, using the robust standard errors. The number of greened lots counts the greened lots treated before the current sale within the radius of 1,000 feet. Panel (b) shows the distribution of the number of greened lots within 1,000 feet. Panel (c): Treatment effects and the size of landscape. The size of landscape is defined as the area of the fenced green space converted from adjacent vacant lots. With multiple landscapes, the nearest landscape installed before the current sale is used. Panel (d) shows the size distribution of landscape.



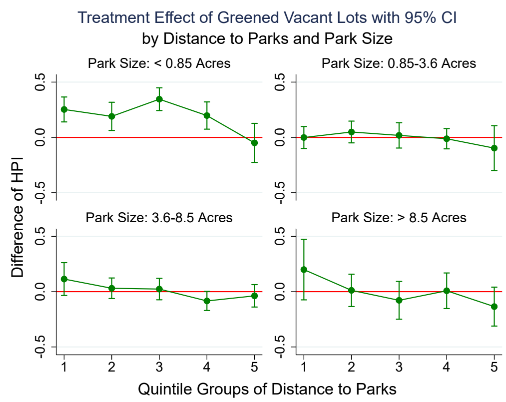
(a) Response of HPI to treatment status



(b) Treatment effect



(c) Distribution of Distance to Parks

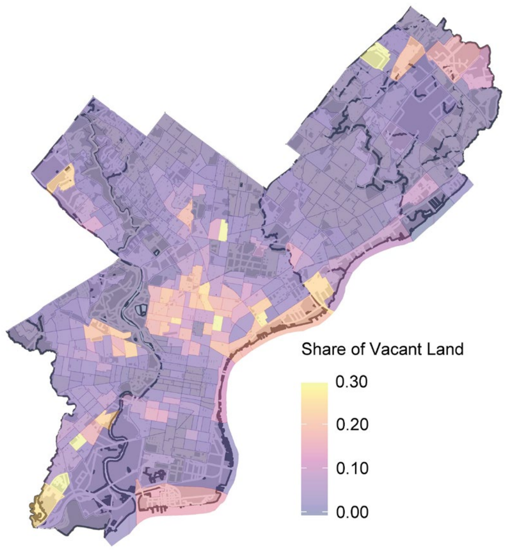


(d) Distribution of Closest Park Type

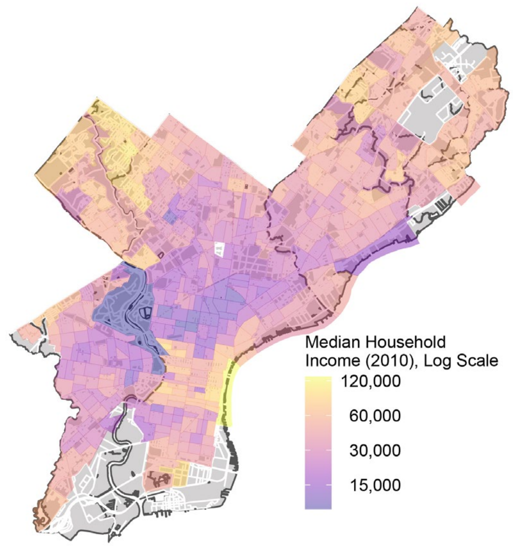
Figure 9: The impact of the access to city parks on the housing price index (HPI) and the treatment effect of greened vacant lots with 95% confidence intervals (CI). The treatment effect is the difference of the average response of HPI between the treatment and the control groups. The x axes in Panel (a) and (b) denote the decile groups. All properties in Philadelphia are grouped into one of the ten decile groups, based on the distribution of the distance from a property to the nearest city park in Philadelphia. The centroids of parks and properties are used in the calculation. The y axis is HPI in panel (a) and the difference of HPI in panel (b). In Panel (c), the log median distance to parks (*Median Distance*) is the median of the log distance distribution conditioning on the repeated sales sample. The repeated sales are weighted, with the weights based on the propensity scores. Panel (d) further divides the repeated sales by the quartiles of the nearest park size (0.85 acres, 3.6 acres, 8.5 acres), with the x axis showing the quintile groups of the distance to the nearest park. The data on the city parks comes from the Department of Philadelphia Parks & Recreation.

Online Appendix of "The Price Effects of Greening Vacant Lots: How Neighborhood Attributes Matter" by Desen Lin, Shane Jensen, and Susan Wachter

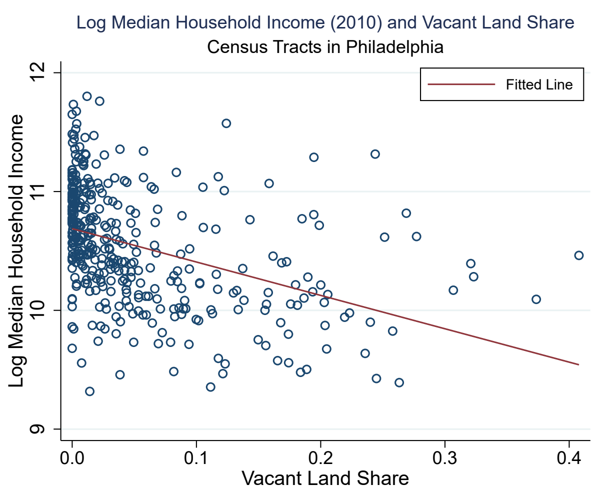
Additional Figures



(a) Vacant land share by Census Tract

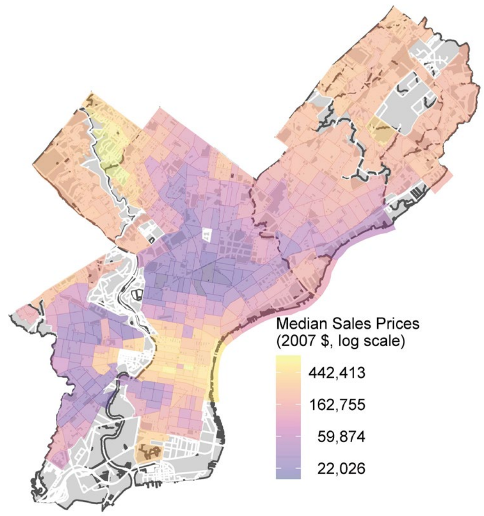


(b) Median household income by Census Tract

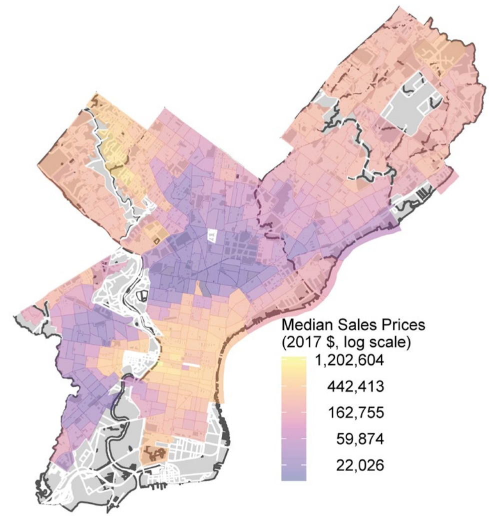


(c) Scatterplot of vacant land share and log median household income

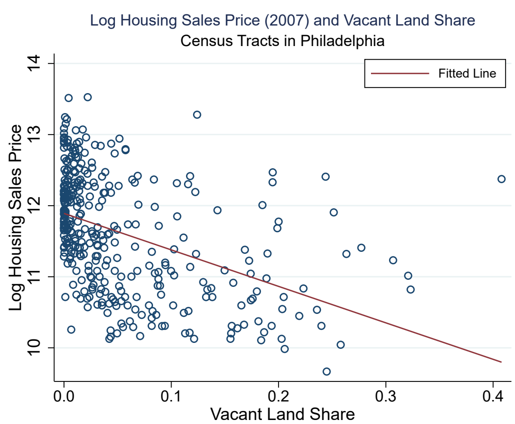
Figure A1: Vacant land share and median household income by census tract in Philadelphia. Panel (a): the heatmap of the vacant land share by census tract. The vacant land share of a census tract is defined as the total area (in acre) of the vacant land parcels divided by the total area of land parcels. The vacant land data comes from the Philadelphia Department of Planning and Development. Panel (b): The heatmap of the median household income by census tract. The color gradient reflects the intensity of the log variable. The median household income of a census tract comes from the 2010 1-year American Community Survey estimate. Panel (c): the scatterplot shows the negative relationship between the vacant land share and the log median household income, with each circle representing one census tract.



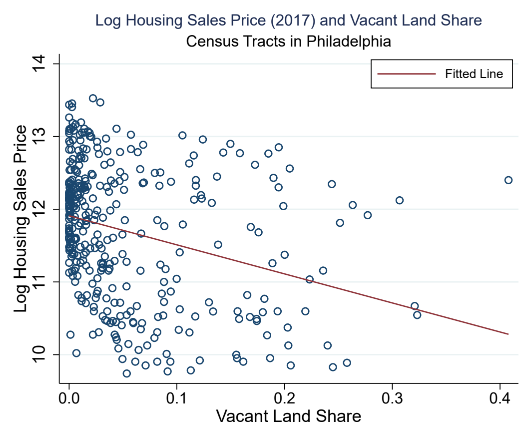
(a) Median sales price by census tract in 2007



(b) Median sales price by census tract in 2017



(c) Scatterplot of log median sales price in 2007 and vacant land share



(d) Scatterplot of log median sales price in 2017 and vacant land share

Figure A2: Median sales price (2007, 2017) by census tract and the correlation between the log median sales price (2007, 2017) and the vacant land share in Philadelphia. Panels (a) and (b): the heatmap of the median sales price by Census Tract in 2007 or 2017. Census tracts with at least 10 sales in a year are shown on the heatmaps. The color gradient reflects the intensity of the log variable. Panels (c) and (d): the scatterplots show the negative relationship between the log median sales price in 2007 or 2017 (y axis) and the vacant land share (x axis), with each circle representing one census tract. The data on the vacant land share by census tract is static and comes from a cross-sectional survey compiled by the Philadelphia Department of Planning and Development.

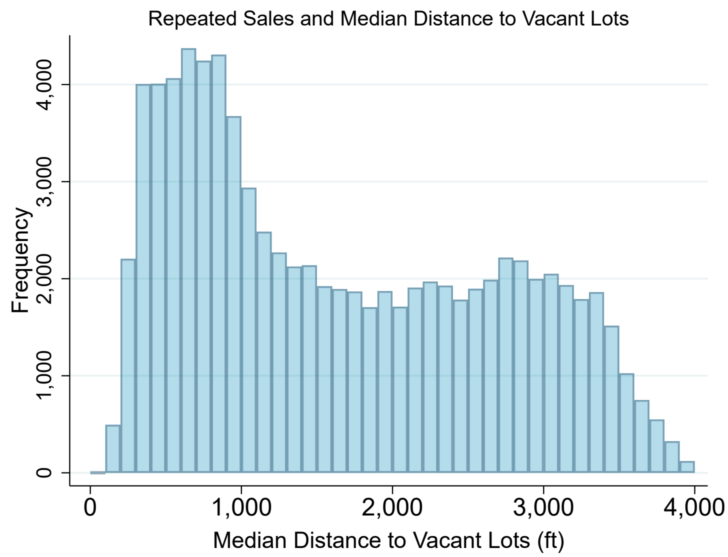


Figure A3: Frequency of housing sales by the median distance to the vacant lots. The housing sales sample considers the repeated sales in Philadelphia with the current sales date in the period from 2007 to 2019. For each property, the median distance up to 50 nearest greened or untreated vacant lots from 2007 to 2017 within a radius of 4,000 feet is defined as the median distance to the vacant lots.

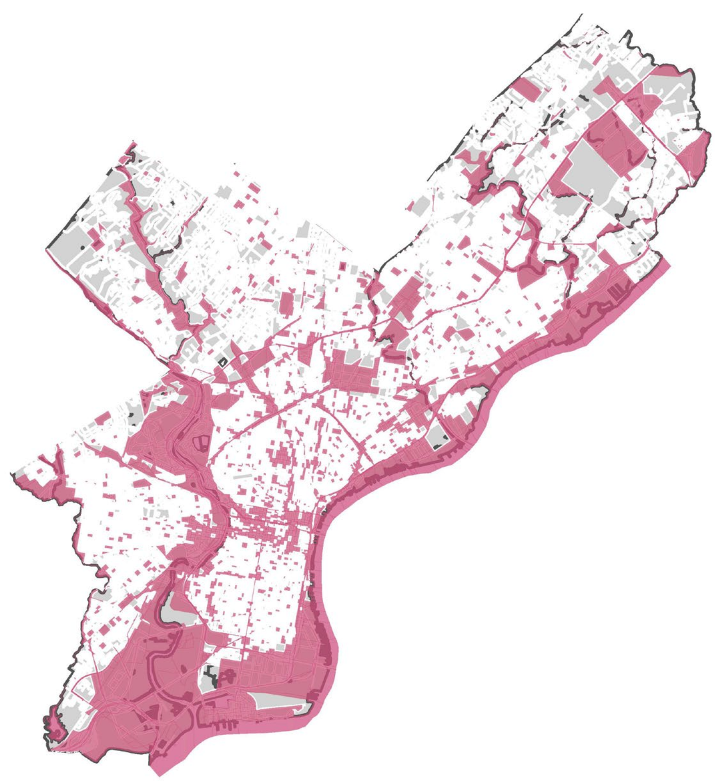


Figure A4: Map of Census Blocks with zero housing units in Philadelphia. The data on the number of housing units is from the summary files of the 2010 Decennial Census.

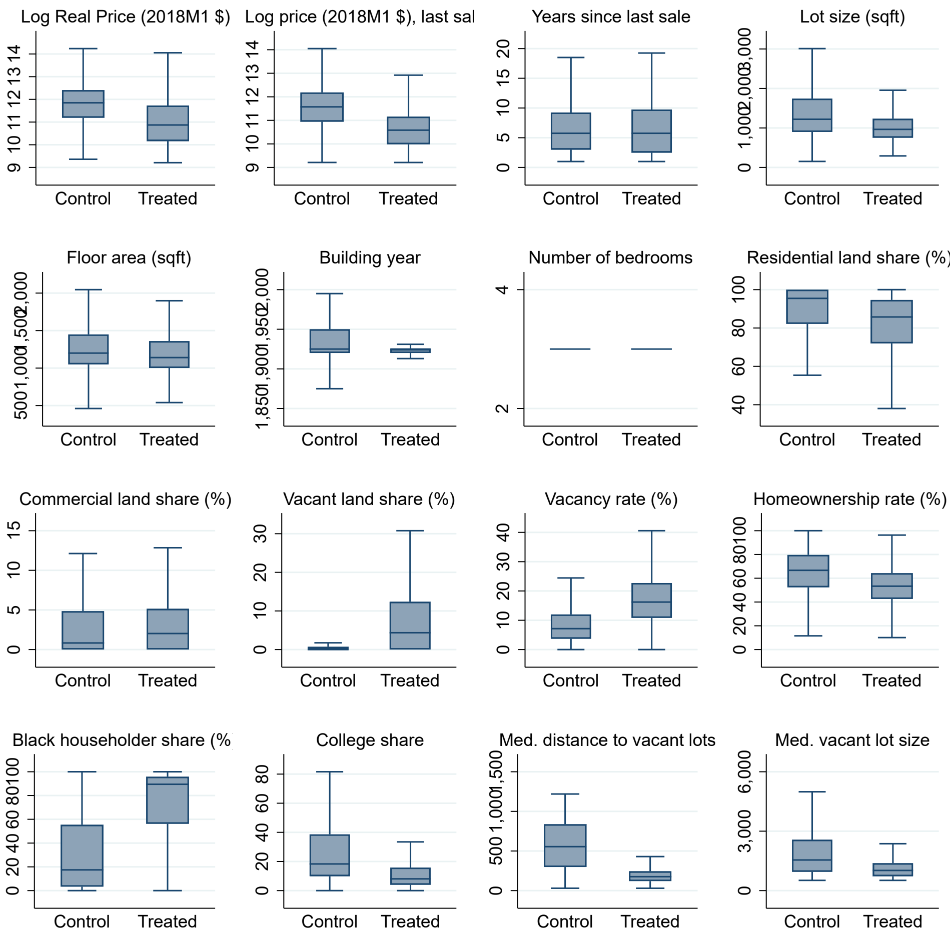
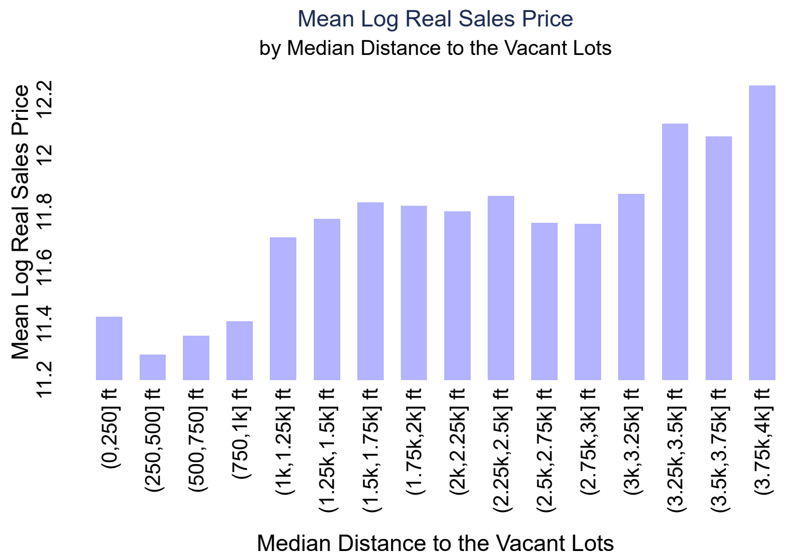
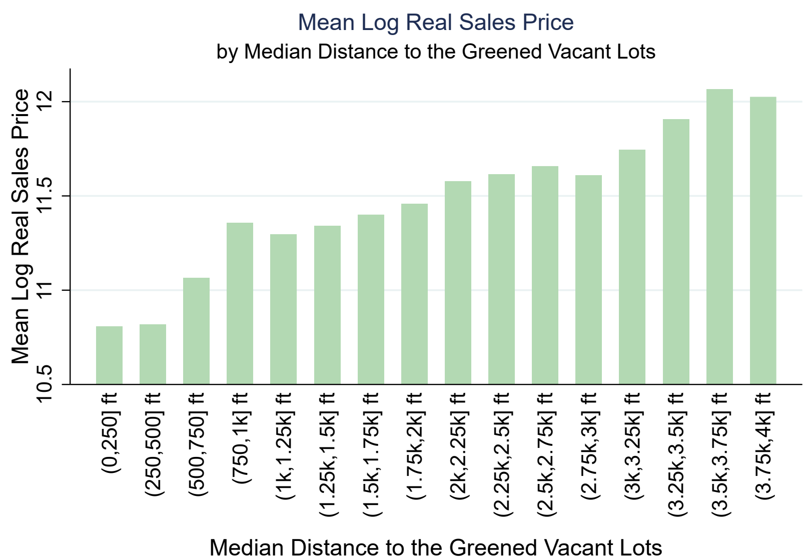


Figure A5: boxplots of the housing and census block characteristics to show the covariate imbalance in the control and the treatment groups. Non-binary variables are reported. A sale is defined as being treated if there is a vacant lot within 1,000 feet that was greened before the sale.

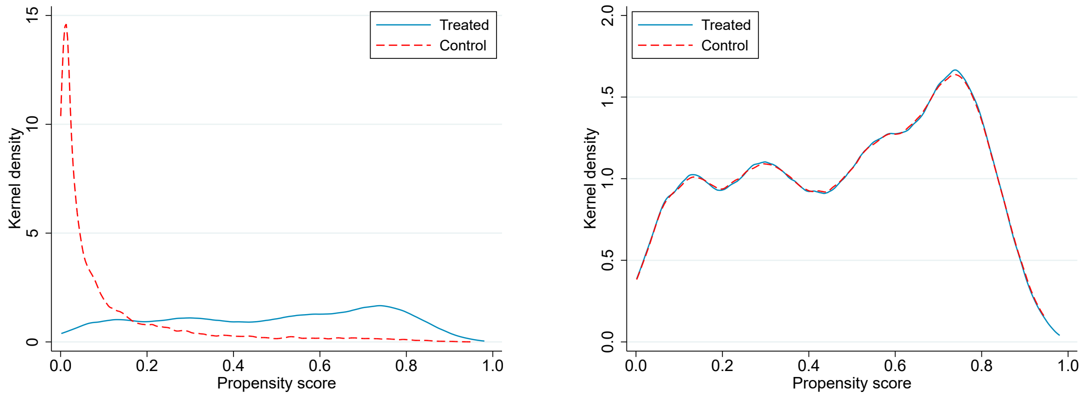


(a) By median distance to the greened or untreated vacant lots



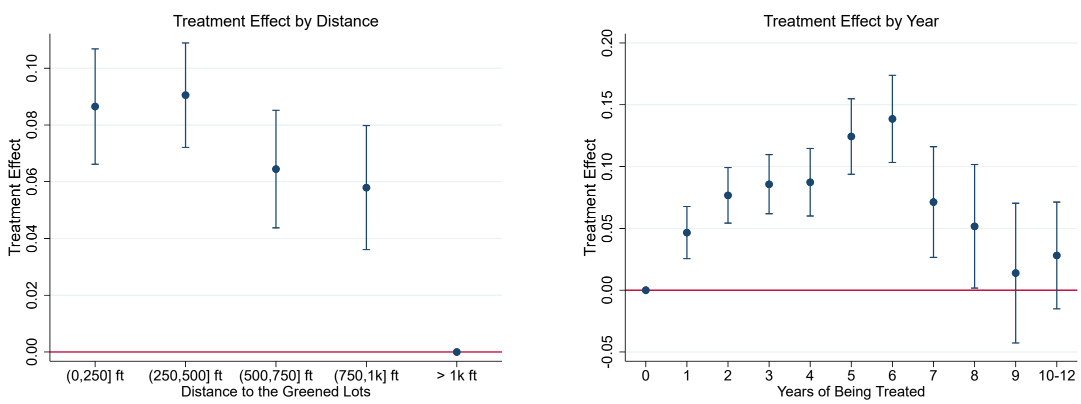
(b) By median distance to the greened vacant lots

Figure A6: Mean log real sales price and median distance to vacant lots in Philadelphia. Sales prices are inflation-adjusted to the value of 2018Q1. the housing sales sample considers the repeated sales in Philadelphia with the current sales date in the period 2007-2019. Panel (a): For each property, the median distance up to 50 nearest greened or untreated vacant lots from 2007 to 2017 within a radius of 4,000 feet is defined as the median distance to the vacant lots. Panel (b): For each property, the median distance up to 50 nearest greened vacant lots treated in the period from 2007 to 2017 within a radius of 4,000 feet is defined as the median distance to greened vacant lots.



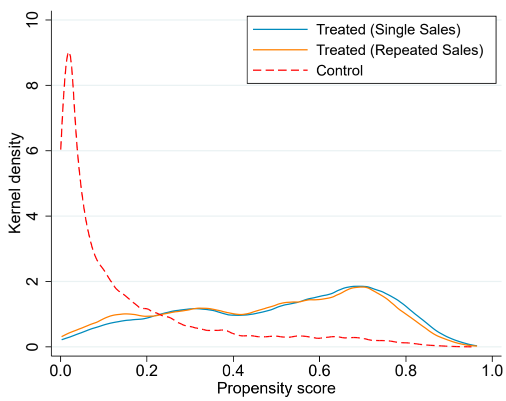
(a) Unmatched Sample (b) Matched Sample

Figure A7: Kernel density of the propensity scores in the treatment group and the control group. The treatment indicator is equal to 1 if there is a greened vacant lot within the radius of 1,000 feet from a property before a sale. The sample is the residential repeated sales for the period 2007-2019 in Philadelphia.

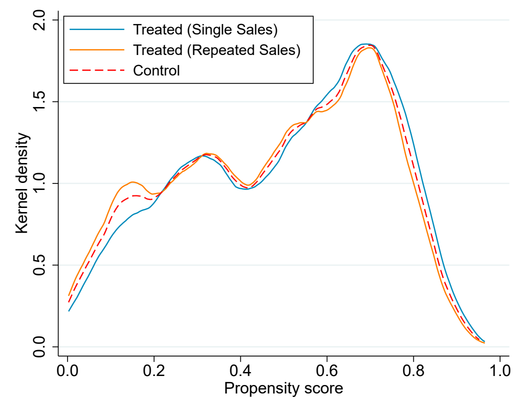


(a) Distance to Greened Lots (b) Years of Being Treated

Figure A8: Treatment effects over space and over time. The error bars represent 95% confidence intervals, using the robust standard errors. A residential sale is defined as being treated if there is a vacant lot within 1,000 feet that was greened before the sale. The sample is the residential single sales and repeated sales for the period 2007-2019 in Philadelphia.



(a) Unmatched Sample



(b) Matched Sample

Figure A9: Kernel density of the propensity scores in the treatment group and the control group. The treatment indicator is equal to 1 if there is a greened vacant lot within the radius of 1,000 feet from a property before a sale. The sample is the residential single sales and repeated sales for the period 2007-2019 in Philadelphia.

Figure A10: Outlines of the 18 Planning Districts for Philadelphia2035 District Plans. Source: OpenDataPhilly (https://www.opendataphilly.org/dataset/planning-districts)

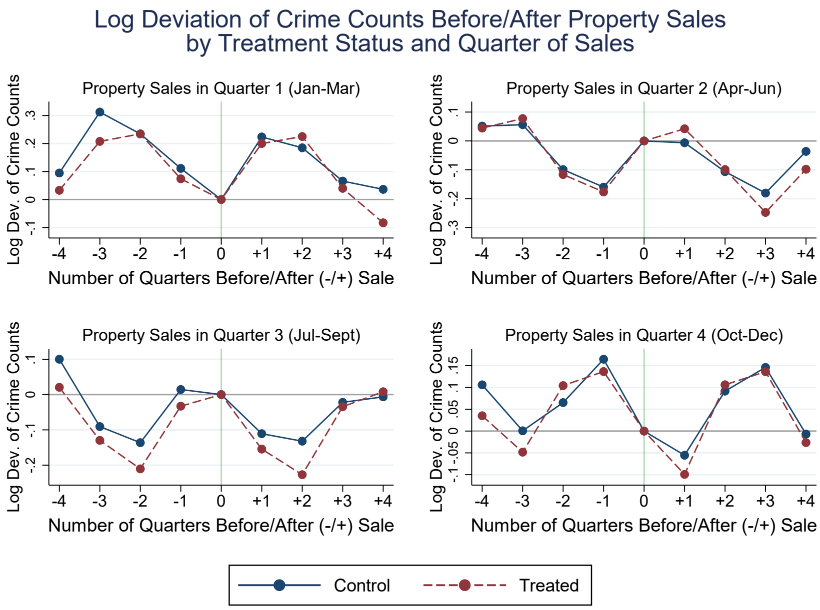


Figure A11: Log deviation of crime occurrence before or after property sales by the treatment status and the quarter of sales. Given the quarter and the treatment status, each data point in the figure sums up the quarterly neighborhood crime occurrence in the census block where a property sale is observed. To make comparisons between the treatment and control groups, we report the log deviation of the quarterly sum on the y axis to show the percentage change of crime count from the value at the quarter of sale (0 on x axis). We show that the properties in the control and the treatment groups have similar pre-sale and post-sale quarterly trends of the neighborhood crime occurrence. Hence, greening vacant lots does not increase nearby housing prices through the indirect channel of crime reduction but directly creates amenity value for the properties nearby.

Additional Tables

Table A1. Residential Property by the Number of Sales

# of Sales	# of Properties	% of Total Properties	% of Total Sales
1	173,008	61.16%	39.85%
2	77,063	27.24%	35.50%
3	25,475	9.01%	17.60%
4	6,182	2.19%	5.70%
5	1,039	0.37%	1.20%
6	105	0.04%	0.15%
7	10	0.00%	0.02%

Note: the sample is the residential properties in the City of Philadelphia. Sales in the period 2000-2019 are counted by property. The raw counts include sales that have missing information on the variables used in the analysis.

Table A2. Balance Check of Variables in the Matched Sample

	Mean			t-test		
Variable	Treated	Control	%bias	t	p > |t|	V(T)/V(C)
Has no vacant land (binary), z-score	-0.838	-0.845	0.8	0.65	0.513	1.01
Vacant land share (%), z-score	0.662	0.640	1.9	1.31	0.190	0.95
Residential land share (%), z-score	-0.263	-0.249	-1.4	-1.18	0.236	1.01
Commercial land share (%), z-score	-0.042	-0.046	0.4	0.43	0.666	1.04
Housing vacancy rate (%), z-score	0.835	0.854	-2.0	-1.50	0.133	0.88
Homeownership rate (%), z-score	-0.519	-0.525	0.7	0.63	0.530	1.01
Black share (%), z-score	0.971	0.956	1.8	1.69	0.092	0.97
College graduation share (%), z-score	-0.575	-0.581	0.8	1.04	0.297	1.07
Residential land share (%), square of z-score	1.016	1.001	0.6	0.59	0.556	1.03
Homeownership rate (%), square of z-score	0.967	0.965	0.2	0.14	0.891	1.07
Black share (%), square of z-score	1.581	1.569	1.5	1.14	0.255	0.96
Median vacant lot size (sq.ft.)	1,574	1,592	-0.1	-0.12	0.908	1.04

Note: the treatment indicator in the table is equal to 1 if there is a greened vacant lot within the radius of 1,000 feet from a property before a sale.

Table A3. Distribution of Greened Vacant Lots by Year of Treatment

year	Freq.	Percent	Cum.
2007	299	6.43	6.43
2008	672	14.45	20.88
2009	71	1.53	22.40
2010	310	6.67	29.07
2011	529	11.37	40.44
2012	393	8.45	48.89
2013	319	6.86	55.75
2014	408	8.77	64.52
2015	303	6.51	71.04
2016	1,126	24.21	95.25
2017	221	4.75	100.00
Total	4,651	100	

Table A4. Repeated-Sale Housing Price Model (with Census Block Greening Variables)

	Dependent Variable: log sale price (2018M1 $)					
	(1)		(2)		(3)	
	beta	SE	beta	SE	beta	SE
Log sale price (2018M1 $), last sale	0.128***	(0.010)	0.128***	(0.010)	0.128***	(0.010)
Years since last sale	-0.047***	(0.010)	-0.047***	(0.010)	-0.047***	(0.010)
Log sale price last sale # years since last sale	0.00208**	(0.001)	0.00202**	(0.001)	0.00202**	(0.001)
Log lot size (sqft)	0.0604***	(0.011)	0.0601***	(0.011)	0.0602***	(0.011)
Log floor area (sqft)	0.537***	(0.018)	0.536***	(0.018)	0.536***	(0.018)
Bedrooms, 1{Bedroom = 1} = 0						
Bedroom = 2	0.130***	(0.039)	0.130***	(0.039)	0.128***	(0.039)
Bedroom = 3	0.0930**	(0.041)	0.0933**	(0.041)	0.0918**	(0.041)
Bedroom = 4	0.0950**	(0.043)	0.0959**	(0.044)	0.0943**	(0.043)
Bedroom = 5+	0.121**	(0.048)	0.123**	(0.048)	0.122**	(0.048)
Building year, 1{before 1900} = 0						
Building year: 1901-1920	-0.0282	(0.020)	-0.0277	(0.020)	-0.0276	(0.020)
Building year: 1921-1940	0.00525	(0.021)	0.00499	(0.021)	0.00514	(0.021)
Building year: 1941-1960	0.0691***	(0.026)	0.0687***	(0.026)	0.0688***	(0.026)
Building year: 1961-1980	0.0786***	(0.028)	0.0784***	(0.028)	0.0786***	(0.028)
Building year: 1981-2000	0.0960***	(0.031)	0.0962***	(0.031)	0.0959***	(0.031)
Building year: after 2000	0.121***	(0.029)	0.121***	(0.030)	0.121***	(0.029)
Property Type, 1{single-family} = 0						
Is condo	-0.321***	(0.041)	-0.318***	(0.042)	-0.320***	(0.041)
Is rowhouse	-0.073***	(0.015)	-0.073***	(0.015)	-0.073***	(0.015)
Distance to Vacant Lots, 1{(0,471] ft} = 0						
(471,707] ft	0.0656***	(0.024)	0.0612***	(0.023)	0.0616***	(0.023)
(707,937] ft	0.145***	(0.028)	0.136***	(0.028)	0.137***	(0.028)
(937,1.27k]ft	0.220***	(0.032)	0.210***	(0.032)	0.211***	(0.031)
(1.27k,1.70k] ft	0.291***	(0.038)	0.280***	(0.038)	0.281***	(0.038)
(1.70k,2.14k] ft	0.336***	(0.037)	0.325***	(0.037)	0.325***	(0.037)
(2.14k,2.54k] ft	0.353***	(0.038)	0.343***	(0.038)	0.342***	(0.038)
(2.54k,2.89k] ft	0.384***	(0.039)	0.374***	(0.039)	0.374***	(0.039)
(2.89k,3.26k] ft	0.392***	(0.040)	0.382***	(0.040)	0.382***	(0.040)
> 3.26k ft	0.402***	(0.041)	0.391***	(0.041)	0.392***	(0.041)
Greening Variables						
Park Number in Census Block (CB)	0.00203	(0.041)			-0.000845	(0.041)
Log(Acres of Parks in CB + 1)	0.00502	(0.017)			0.00603	(0.018)
Log Distance to Nearest Park (ft)	-0.00667	(0.012)			-0.00672	(0.012)
Log(Sq.ft. of Greened Lots in CB + 1)			-0.012***	(0.003)	-0.012***	(0.003)
Constant	7.025***	(0.196)	6.997***	(0.193)	7.040***	(0.195)
Quarterly Date FE	Yes		Yes		Yes	
Tract FE	Yes		Yes		Yes	
Adjusted R^2	0.673		0.673		0.673	
N	84,131		84,131		84,131	

Note: * p<0.10, ** p<0.05, *** p<0.010. Cluster robust standard errors in the parentheses. Errors are clustered at the tract level. The sample is all residential sales in Philadelphia, with the current sale dates between 2007 and 2019. The base levels (Bedroom = 1; building year: before 1900; single-family; (0, 471) ft) are omitted. For each property, the median distance up to 50 nearest greened or untreated vacant lots in the period from 2007 to 2017 within a radius of 4,000 feet is defined as the distance to vacant lots.

Table A5. Selection Equation (Logit): Marginal Probability (with Park-Related Variables)

	Dependent Variable: Treatment Indicator	
Treated = 1, if	(1)	(2)
Treat Before Sale	Yes	Yes
Distance to Greened Lot	<1k ft	<1k ft
Has no vacant land, z-score	-0.0376***	-0.0420***
	(0.001)	(0.001)
Vacant land share (%), z-score	0.00743***	0.00785***
	(0.001)	(0.001)
Residential land share (%), z-score	-0.0192***	-0.0255***
	(0.002)	(0.003)
Commercial land share (%), z-score	-0.00553***	-0.00801***
	(0.001)	(0.002)
Housing vacancy rate (%), z-score	0.0256***	0.0296***
	(0.001)	(0.001)
Homeownership rate (%), z-score	-0.0393***	-0.0495***
	(0.002)	(0.002)
Black householder share (%), z-score	0.0708***	0.0770***
	(0.002)	(0.002)
College share (%), z-score	-0.0793***	-0.0734***
	(0.002)	(0.002)
Residential land share (%),	-0.00751***	-0.00955***
square of z-score	(0.001)	(0.001)
Homeownership rate (%),	-0.0119***	-0.0152***
square of z-score	(0.001)	(0.001)
Black householder share (%),	0.00553***	0.0112***
square of z-score	(0.002)	(0.002)
Park Number in Census Block (CB)		-0.0830
		(0.054)
Log(Acres of Parks in CB + 1)		-0.00491
		(0.012)
Log Distance to Nearest Park (ft)		-0.0347
		(0.022)
Pseudo R^2	0.372	0.372
N	84,131	84,131

Note: * p<0.10, ** p<0.05, *** p<0.010. To define the treatment indicator, two conditions are considered. Treat Before Sale: whether a vacant lot within was greened before a sale. Distance to Lot: whether a greened vacant lot is within 1,000 feet. The variables except the squared terms and park-related variables are normalized to zero mean and unit variance.

Table A6. Philadelphia Planning Districts and Statistics

Philadelphia Planning District (18)	Mean Sales Price (2017-2018)	Mean Price/sq.ft. (2017-2018)	No. of Sales (2017-2018)	No. of Untreated Lots	No. of Greened Lots	Black HH Share (%)	HO Rate (%)	Housing Vacancy Rate (%)	College Graduation Share (%)	Residential Land Share (%)
Central	643,413	382	5,314	776	26	14.5	38.6	10.7	67.5	33.1
Lower South	418,346	225	155	7	0	9.8	66.9	10.0	33.2	2.1
South	247,212	191	6,089	2,058	216	28.6	58.6	11.2	22.0	36.8
Lower Northwest	290,479	173	2,218	149	0	9.1	58.9	7.9	48.0	38.1
Lower Far Northeast	222,204	164	2,045	18	0	8.5	76.3	4.0	21.0	34.6
Upper Far Northeast	262,836	159	1,617	26	0	5.7	66.1	4.6	27.7	51.1
River Wards	208,001	155	3,327	1,658	7	10.4	60.8	11.1	20.8	23.2
Central Northeast	192,466	144	2,169	34	0	11.5	63.1	5.0	20.5	50.1
North Delaware	148,693	117	4,216	103	26	10.9	63.4	6.9	14.1	35.2
Upper Northwest	243,335	109	2,435	725	74	68.6	52.8	10.8	43.4	57.8
Lower North	190,585	104	3,223	4,428	2,576	69.7	37.4	18.3	13.1	33.3
University Southwest	217,357	93	1,434	674	249	51.8	30.2	12.4	33.4	35.9
West Park	155,569	90	943	463	104	73.7	52.9	12.5	31.0	25.0
Lower Northeast	101,564	81	2,791	369	40	43.4	57.2	8.4	11.0	47.0
Upper North	107,544	76	3,474	491	85	80.8	66.1	8.7	15.8	60.4
Lower Southwest	84,584	68	1,066	289	88	74.8	58.8	10.1	12.9	13.0
West	94,435	64	3,248	1,534	586	92.8	55.1	15.7	11.4	65.1
North	57,102	48	3,160	2,997	574	45.5	52.6	13.6	6.3	5.9

Philadelphia Planning District (18)	Commercial Land Share (%)	Vacant Land Share (%)	No. of Crimes (2010)	Crimes per 1,000 Population (2010)	Park Area (Acre)	Park Area (< 0.85 Acre)	No. of Park	Median Distance to nearest Park (ft.)	Median Household Income (2018)	No. of Household Units (2010)
Central	19.7	4.2	4,958	42.3	282	10.65	78	670	74,925	73,153
Lower South	2.2	7.4	229	44.3	350	0.00	2	1,775	67,319	2,631
South	13.6	3.4	3,984	30.0	117	6.07	47	831	42,722	60,156
Lower Northwest	4.2	4.0	799	15.7	528	1.04	32	1,045	66,145	25,470
Lower Far Northeast	10.3	2.1	1,214	17.3	1049	0.00	25	1,389	59,568	28,706
Upper Far Northeast	8.0	7.5	806	12.1	204	0.00	12	2,127	59,644	28,210
River Wards	8.2	13.1	2,639	38.5	64	3.97	22	913	39,894	29,005
Central Northeast	6.0	0.6	1,490	19.0	1636	0.38	15	2,137	51,117	32,012
North Delaware	4.1	4.4	2,283	22.7	573	0.25	29	1,323	46,898	38,331
Upper Northwest	4.3	2.3	2,239	26.3	2330	1.72	36	1,158	49,981	40,900
Lower North	5.6	12.2	3,793	39.8	900	10.06	58	811	23,467	40,939
University Southwest	6.6	5.1	2,363	29.0	881	2.51	19	1,266	30,082	33,461
West Park	3.8	2.5	1,072	24.6	2011	2.97	33	1,252	41,212	21,156
Lower Northeast	9.4	2.7	3,229	32.2	502	1.01	18	1,334	34,524	37,266
Upper North	6.1	2.0	3,313	23.0	203	0.23	20	1,575	39,952	59,159
Lower Southwest	6.5	8.4	1,763	41.9	134	0.81	13	1,028	33,859	16,721
West	7.3	5.4	3,776	35.7	102	2.30	26	1,145	29,332	49,299
North	1.8	1.1	5,272	38.2	190	3.83	37	1,033	24,849	53,596

Note: Philadelphia Planning Districts are proposed by the growth and development plan of *Philadelphia2035* (https://www.phila2035.org/). Mean sales price, mean price per square foot, number of sales are calculated from the Zillow transaction data in 2017-2018. The data on greened and untreated vacant lots come from the Pennsylvania Horticulture Society and the Philadelphia Department of Licenses and Inspections. The black householder share, the homeownership rate, the housing vacancy rate, college graduation share, the number of household units come from the 2010 Decennial Census. Land shares (residential, commercial, vacant) are calculated using data from the Philadelphia Department of Planning and Development. The crime data come from the Philadelphia Police Department. The park data come from the Department of Philadelphia Parks & Recreation. The median distance to nearest park is based on housing sales for 2017-2018. The median household income is the mean of the census block group median household income weighted by the census block group population; the income data comes from 2018 5-year American Community Survey. For each share or rate variable, we first aggregate the numerator and denominator to the Planning District level before calculating the share or ratio.

Table A7. Mean Characteristics in the Repeated and Single Sales Samples

	Mean Single	Repeated	Single – Repeated	t statistics
Housing Characteristics				
Log sale price (2018M1 $)	11.56	11.62	-0.0619***	(-15.81)
Lot size (sq.ft.)	2,591	1,675	915.8***	(65.83)
Floor area (sq.ft.)	1,340.8	1,306.2	34.63***	(15.94)
Number of bedrooms	3.06	3.05	0.00608**	(2.28)
Building year	1938	1934	3.730***	(33.15)
Is single-family (binary)	0.19	0.12	0.0707***	(48.85)
Is condo (binary)	0.2	0.03	0.168***	(119.02)
Is rowhouse (binary)	0.6	0.85	-0.254***	(-141.59)
Census Block Characteristics				
Has no vacant land (binary)	0.69	0.65	0.0352***	(19.70)
Residential land share (%)	82.04	85.13	-3.090***	(-33.53)
Commercial land share (%)	6.33	5.16	1.164***	(22.32)
Vacant land share (%)	3.49	3.28	0.208***	(5.78)
Housing vacancy rate (%)	9.99	10.32	-0.332***	(-9.19)
Homeownership rate (%)	62.12	62.99	-0.874***	(-10.29)
Black householder share (%)	36.88	39.17	-2.286***	(-16.31)
College share (%)	26.12	24.01	2.107***	(23.73)
Median distance to vacant lots (ft.)	554.69	504.61	50.08***	(40.86)
Median vacant lot size (sq.ft.)	7,323.7	4,700.5	2623.2***	(21.84)
Crime counts in last four quarters	5.95	11.56	-5.615***	(-130.15)

Note: * p<0.10, ** p<0.05, *** p<0.010.