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Reducing crime by remediating vacant lots: the moderating effect of nearby land uses

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Abstract

Objective Place-based blight remediation programs have gained popularity in recent years as a crime reduction approach. This study estimated the impact of a citywide vacant lot greening program in Philadelphia on changes in crime over multiple years, and whether the effects were moderated by nearby land uses.
Methods The vacant lot greening program was assessed using quasi-experimental and experimental designs. Entropy distance weighting was used in the quasi-experimental analysis to match control lots to be comparable to greened lots on pre-existing crime trends. Fixed-effects difference-in-differences models were used to estimate the impact of the vacant lot greening program in quasi-experimental and experimental analyses.
Results Vacant lot greening was estimated to reduce total crime and multiple subcategories in both the quasi-experimental and experimental evaluations. Remediating vacant lots had a smaller effect on reducing crime when they were located nearby train stations and alcohol outlets. The crime reductions from vacant lot remediations were larger when they were located near areas of active businesses. There is some suggestive evidence that the effects of vacant lot greening are larger when located in neighborhoods with higher pre-intervention levels of social cohesion.
Conclusions The findings suggest that vacant lot greening provides a sustainable approach to reducing crime in disadvantaged neighborhoods, and the effects may vary by different surrounding land uses. To better understand the mechanisms through which place-based blight remediation interventions reduce crime, future research should measure human activities and neighborly socialization in and around places before and after remediation efforts are implemented.

Keywords Quasi-experimental · Experimental · Vacant lots · Remediation · Place-based interventions

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Introduction

Crime is highly concentrated by place, with 3 to 6% of street segments accounting for 50% of crime reported to the police (Weisburd et al. 2012; Sherman et al. 1989). The concentration of crime by place also appears to be relatively stable over time (Curman et al. 2015; Sherman et al. 1989; Weisburd 2015), suggesting there are endemic features of crime "hot spots." As Sherman et al. (1989) note "the routine activities of places may be regulated far more easily than the routine activities of persons (p.49)," suggesting that place is a promising area for testing criminological theories and approaches to reducing crime. Figuring out ways to reduce the concentration of crime could also limit the need to rely on the police and criminal justice agencies to continually respond to the same problematic places (Weisburd 2016).

The extreme microspatial variation in crime suggests that there are key features of places that generate pockets of crime even among the most economically distressed neighborhoods (St. Jean 2007). Vacant lots and abandoned buildings appear to be particularly salient feature of the built environment that generates more crime (Taylor 1988). Vacant lots and abandoned buildings may be particularly endemic features of the spatial concentration of crime when they are located near crime generators, like schools, transit stations, and bars (Ratcliffe 2012; Steinberg et al. 2019; Wilcox and Cullen 2018), that bring more human activity among strangers to a place and undermine the ability of local residents to determine the ownership of the space and exert territorial control (Taylor 1988).

An emerging body of quasi-experimental and experimental studies show that the remediation of vacant lots and abandoned housing can help reduce serious crime by place (MacDonald et al. 2019). While prior studies provide support for the crime reducing benefits of blight remediation programs, they do not examine how the effects are conditioned by nearby land uses. Examining the interaction between urban blight remediation interventions and surrounding land uses could provide more insight into the understanding of potential mechanisms through which fixing the built environment could help reduce the high concentration of crime in places. After all, place-based experiments that show benefits for reducing crime are even more insightful and valid for criminology if they can test candidate mechanisms for explaining their findings (Nagin and Sampson 2019), and provide clearer implementation guidelines for replication to other areas, something clearly of use to policymakers.

The current study addresses the issue of whether the effects of vacant lot remediation on crime are conditioned by nearby land uses. We expand on earlier research that has examined the impact of remediating vacant lots on crime in Philadelphia in two important ways (Branas et al. 2011, 2018). First, we examine whether surrounding land uses moderates the impact of remediating vacant lots on crime. This extension helps elicit how the context of nearby land uses may condition the effects of vacant lot remediation, providing insight into whether potential mechanisms related to collective efficacy and environmental criminology explain the connection between greening vacant lots and crime reductions. Second, we examine whether the expansion of the vacant lot greening program across Philadelphia in more recent years continued to produce crime reduction benefits. This is an important extension as it addresses whether the effects reported in earlier research (Branas et al. 2011) endure when there are relatively lower levels of crime in Philadelphia. Thus, this study addresses a concern that estimates of treatment effects from quasi-experiments and field experiments are often not examined under "different universal treatment regimes" (Nagin and Sampson 2019, p. 124).

Theoretical framework

Theoretical explanations of how the built environment of places influences crime typically emphasize how physical disorder influences neighborly socialization (Sampson et al. 1997) or how it shapes criminal opportunities (Wilcox and Cullen 2018). Social disorganization theory (Shaw and McKay 1972) and the concept of collective efficacy, or the willingness of residents to intervene in neighborhoods for the common good and out of shared mutual trust, suggests that a disordered built environment in a neighborhood may undermine social ties that foster informal social controls that mitigate criminal and antisocial behavior. For example, neighborhood residents may feel less empowered to intervene in the common good when there is no obvious owner maintaining a space and land is left abandoned and disorderly. Vacant and abandoned lots with overgrown weeds, tall grass, and littler also signal that a site is not cared for and that there is a "hole" in the social fabric of an area (Taylor 1988, p. 186), diminishing the perception that residents will act as guardians and intervene when they witness criminal activity in an area.

A blighted built environment may further impact crime by shaping the unconscious way in which informal interactions take place on streets. Jane Jacobs famously argued that city streets with continuous use and buildings with clear sight lines down a block facilitate "more eyes upon the street" by the "natural proprietors" of a street (Jacobs 1961). Vacant lots overgrown with weeds and trash, as well as abandoned houses that are boarded up with no one living in them, reduce sight lines on a street and the number of natural proprietors of city streets. While Jacob's emphasized the design of buildings and streets to imbue natural surveillance, her work primarily focused on how crime was influenced by the "intricate, almost unconscious, network of voluntary controls by the people themselves, and enforced by the people themselves" (p. 31). By emphasizing networks of voluntary social controls, Jacobs' insights clearly link the built environment to collective efficacy.

The idea that natural surveillance can help suppress crime by fostering greater informal social controls links another theoretical tradition, that of environmental criminology and criminal opportunity, including crime prevention by environmental design (CPTED) (Jeffery 1971), situational crime prevention (Clarke 1995), routine activities theory (Cohen and Felson 1979), and crime pattern theory (Brantingham and Brantingham 1993). CPTED hypothesizes that the built environment makes places less attractive to would be offenders when there are indicators of "proprietary ownership" of places that serve as symbols of guardianship and surveillance (Cozens et al. 2005). Situational crime prevention similarly argues that the built environment can influence crime by creating real or symbolic signs of guardianship, such as fences or gates, that reduce crime by making an area appear less attractive for would be offenders (Clarke 1995). CPTED and situational crime prevention theories connects to routine activities theory, as shifts in the built environment of places can influence the number of motivated offenders in a place, the suitability of targets, and the absence of capable guardians (Cohen and Felson 1979).

Crime pattern theory predicts that people will commit more offending in activity spaces that they frequent and where there is a general awareness that criminal opportunities are more available. In particular, the edges of activity spaces where there is a physical change in the land use are particularly crime prone (Brantingham and Brantingham 1993). When spaces have no clear ownership, are abandoned, and located in areas of relatively high daily activity, they may be more likely to become a crime generator (Brantingham and Brantingham 1993) by attracting more strangers to a space to engage in illegal activities like public intoxication, prostitution, or illicit drug dealing. Vacant lots and a disorderly built environment clearly link to potential crime opportunity channels, including no clear ownership, reduced surveillance, and physical changes in land use around activity spaces that signal an area is crime prone. Qualitative observations of vacant lots in Philadelphia have found these sites are particularly attractive places for open-air drug markets and excessive public drinking (Branas et al. 2018).

Of course, broken windows theory can be linked to collective efficacy and environmental criminology, through its central idea that physical disorder engenders crime by signaling that no one is taking care of the physical space and that “untended property becomes fair game for people out for fun or plunder” (Wilson and Kelling 1982). According to broken windows theory, the erosion of the sense of control of place lowers the sense that there are active informal social controls at play, or “the sense of mutual regard and the obligations of civility,” that signal people are caring for a place (Skogan 1990, p. 29). Broken windows theory argues that physical disorder leads to increased incivilities, which increases fear of crime among local residents, public withdrawal, and fuels a cycle of decline in the sense of ownership of places (Skogan 1990). Whereas collective efficacy focuses on how the built environment of places shapes norms around civility of places and their enforcement by neighbors, broken windows theory emphasizes that the physical manifestations of disorder spread fear that undermines informal social controls.

Integrating these theoretical traditions, we argue that remediating a disorderly built environment may increase a sense of ownership of places and promote informal social controls by neighbors and deter potential offenders. Remediating vacant lots, for example, could increase natural surveillance and reduce the ease of evasion from law enforcement (Olaghere and Lum 2018; Tita et al. 2005). Thus, the remediation of vacant lots could help reduce crime by increasing offenders’ perceived risk and effort to avoid detection and arrest. Simultaneously, setting up fences around vacant lots that act as symbolic barriers may send a signal to would be offenders that someone is maintaining control of the space. Cleaning a vacant lot and installing fencing may also allow nearby residents to quickly identify someone who should not be in the area and is engaging in activities that violate community norms. The remediation of vacant lots also reduces the level of physical disorder in a place and may help reduce fear of crime (Branas et al. 2018), increasing the active use of places by local residents (Branas et al. 2011), and mitigating would be offenders’ sense that an area is uncared for (Wilson and Kelling 1982).

Prior literature

A growing body of research has examined the relationship between various vacant lot and abandoned housing remediation programs and changes in crime nearby. These studies differ from a past generation of research linking physical disorder to crime by examining what happens to crime *after* places have been remediated (MacDonald 2015). Branas et al. (2011) examined the impact of a vacant lot greening remediation program in Philadelphia on changes in crime at the lot, block group, and census tract level between 1999 and 2008. They found consistent reductions in assaults, gun assaults, gun robberies, and disorderly conduct associated with remediating vacant lots. Kondo et al. (2016) examined vacant lot remediation programs in Youngstown, Ohio, and found significantly greater reductions in felony assault, robbery, and theft around lots that were remediated compared to those that remained vacant and disorderly (Kondo et al. 2016). Heinze et al. (2018) examined a vacant-lot cleaning and greening program in Flint, Michigan, where community members received funding for mowing, weeding, and trash removal of vacant lots. The program was associated with significantly fewer assaults and violent crimes when compared to streets with lots that were not enrolled in the program (Heinze et al. 2018). Kondo et al. (2018) analyzed the effect of New Orleans' Fight the Blight program, which removed debris and vegetation from vacant lots, and found no differences between remediated and control lots in levels of violent, property, and domestic crimes. However, the number of drug crimes per square mile decreased significantly, and the study notes that the limited reductions in crime may be due to New Orleans' climate and vulnerability to natural events which likely help regenerate physical disorder at the lot location (Kondo et al. 2018).

Several studies also examine what happens when abandoned housing is remediated. Kondo and colleagues examined the impact of compliance with a Philadelphia ordinance that required property owners to install working windows and doors abandoned houses. They found small but statistically significant reductions in crime around the properties that complied with the ordinance compared to properties that did not comply but were nearby (Kondo et al. 2015). Spader et al. examined the demolition and rehabilitation of vacant housing spurred federal financing to localities as part of the Housing and Economic Recovery Act of 2008. In Cleveland, the demolition of vacant housing was associated with a small reduction in property nearby, but no reduction in violent crime (Spader et al. 2006). Wheeler et al. examined the impact of the demolition of abandoned houses on crime in Buffalo, NY, and found significant reductions in crime after properties were demolished compared to properties that remained abandoned and had similar preexisting levels of crime (Wheeler et al. 2018). Jay et al. found that the demolition of vacant buildings in Detroit, MI, was associated with significant reductions in firearms assaults (Jay et al. 2019). The effects were larger for locations receiving a moderate number of demolitions rather than a high number, suggesting that the demolitions may have helped stabilize neighborhoods where residents still lived and had existing levels of collective efficacy.

These studies provide useful evidence that remediating vacant lots and abandoned houses may help reduce crime in neighborhoods. At the same time, the research has largely neglected examining how the effects of urban blight remediation efforts may be conditioned by their surrounding context. Vacant lot remediation, for example, may produce more crime reduction benefits when a lot is situated on a block with fewer situational opportunities for crime. For example, vacant lot remediation efforts may have less effect on reducing crime in neighborhoods when they are located nearby train stations, alcohol outlets, or schools that generate high daily anonymous social interactions and serve as crime generators (Brantingham and Brantingham 1993; Bernasco and Block 2009; Ratcliffe 2012; Steinberg et al. 2019). Research suggests that people are more likely to commit crime in areas with active retail markets close to where they live (Bernasco and Block 2009), and in settings (e.g., the corners of buildings or darkened alleyways with less lighting) where the built environment provides an offender an "ecological advantage" (St. Jean 2007). Remediating vacant lots in areas of active retail markets with vibrant businesses may provide greater crime reduction benefits because merchants can more easily act as proprietors of the vacant space and offenders are less able to use these spaces at the edges of activity nodes to their ecological advantage.

Research also suggests that non-residential land uses bring "busier nodes" that may provide a "target rich" environment for criminals (Wilcox and Cullen 2018). Blight remediation efforts may then be less effective when they are nearby crime attractors that draw a sufficiently large number of people who are predisposed to illicit activities, as residents or nearby merchants will potentially recede and not take ownership of these remediated spaces.

Current study

The current study extends earlier quasi-experimental and experimental research on the impact of the Philadelphia LandCare (PLC) vacant lot greening program on crime (Branas et al. 2011, 2018; Moyer et al. 2019). The PLC program emerged from the legacy of deindustrialization in Philadelphia. Between 1976 and 1987, the deindustrialization of Philadelphia led to a loss of nearly 160,000 manufacturing jobs, a substantial decline in the city's population, and the growth in abandoned buildings (Wilson 1996). A 2001 survey of Philadelphia noted the presence of over 25,000 abandoned buildings and 30,000 vacant lots (City of Philadelphia 2002). To address the issue, Philadelphia implemented the Neighborhood Transformation Initiative that dedicated three-fifths of its budget to the demolition of abandoned buildings and homes (McGovern 2006), further increasing the number of vacant lots in Philadelphia (Pearsall et al. 2014; Econsult Corporations and Penn Institute for Urban Research 2000). In 1996, residents living in the Kensington area, one of the neighborhoods hardest hit by deindustrialization and abandonment, decided to address the disorder accompanying the vacant lots in their neighborhood and partnered with Pennsylvania Horticultural Society (PHS) to start a pilot program that remediated vacant lots. The pilot program, initially called "land and care" emerged into the Philadelphia LandCare (PLC) program. The PLC program launched citywide in 1999 and has expanded over time through partnerships with local contractors to the entire city, transforming more than 12,000 vacant lots and more than 18 million square feet of land. The selection of lots to be remediated typically involves local residents and community groups identifying problematic vacant lots in violation of Philadelphia's disorder ordinance, contacting PHS to ask to have the vacant lots added to the list for PLC program, and contacting the local city council representative to obtain legal permissions to access lot and conduct the remediation. Today, roughly one-third of vacant lots in Philadelphia have been remediated through the PLC program (see Branas et al. 2011 for additional details on the criteria for selection of lots).

The PLC program intervention is simple to implement and scalable to an entire city. Vacant lots have trash and debris removed. The land is then graded and grass, small bushes, or a few trees are planted. A small wooden post fence is installed around each of these parcels to prevent illegal dumping of garbage and to signal that someone is caring for the property and the community is caring for its use. The rehabilitation of lots is fast, taking only a day to clean and green a vacant lot (MacDonald et al. 2019). Lots are then maintained through a twice a month cleaning, weeding, and mowing from April through October. The actual costs of this intervention are also relatively low, only \$1000–\$1300 to "clean and green" a lot and \$150 per year for biweekly cleaning and mowing.[1] These newly greened trash free lots create the appearance of small pocket parks in Philadelphia's highest crime blocks.

The PLC program signals an investment on a segment of the street block that may ultimately strengthen social ties and collective efficacy among residents and send a signal that crime will not be tolerated on these newly care for lots. The improved natural surveillance from cleaning debris and mowing down overgrown weeds may also increase perceived risk that criminal offending will be detected.

Methodology

Data

We construct a database of 12,788 vacant lots that were cleaned and greened (treatment) by the PLC program ($n = 4046$) between 2008 and 2016 or those that remained vacant (control) in violation of city ordinance[2] ($n = 8742$) during the same year and were located in the same census tracts.[3] We used the latitude-longitude coordinates for each crime to calculate a kernel density estimate of the monthly rate of crimes per square feet at the centroid of each lot for years 2006 to 2018.[4] The kernel density provides a smoothed estimate of the monthly crime per square feet around each vacant lot, such that closer distances are given more weight in the summed count of crime (Rosenblatt 1956).[5] This approach provides a lot-specific estimate of crime. We select a bandwidth of 500 ft., as that reflects the average size of a Philadelphia block. We chose the period 2006 to 2018 so there would be a balanced panel of months for

[1] https://phsonline.org/programs/transforming-vacant-land (Accessed September 4, 2020).

[2] The location and violation data were provided by Philadelphia Office of License and Inspection (L&I) and retrieved from: https://www.opendataphilly.org/dataset/licenses-and-inspections-violations

[3] The original study by Branas et al. (2011) examined yearly crime data from 1999 to 2008 around 4436 vacant lots remediated by PLC compared to a matched sample of 13,308 lots that remained vacant in the same sections of the city.

[4] The crime incident data includes the type of offense, the date, time and location (geocoded to the nearest latitude-longitude coordinate, GCS WGS 1984). Monthly crime incident data retrieved from: https://www.opendataphilly.org/dataset/crime-incidents.

[5] According to this bandwidth of 500 ft., crimes occurring at the 500, 10, and 1 ft. boundary are given weights of 0, 0.616, and 1 respectively. When the buffers around lots overlap and crime incidents fall within the range of multiple lots, kernel density estimates are advantageous to a simple count as it will give the approximate weight to each discrete distance from a given crime to a given lot. Kernel density estimates were calculated for each crime to each lot per month using the *dnorm* function in R.

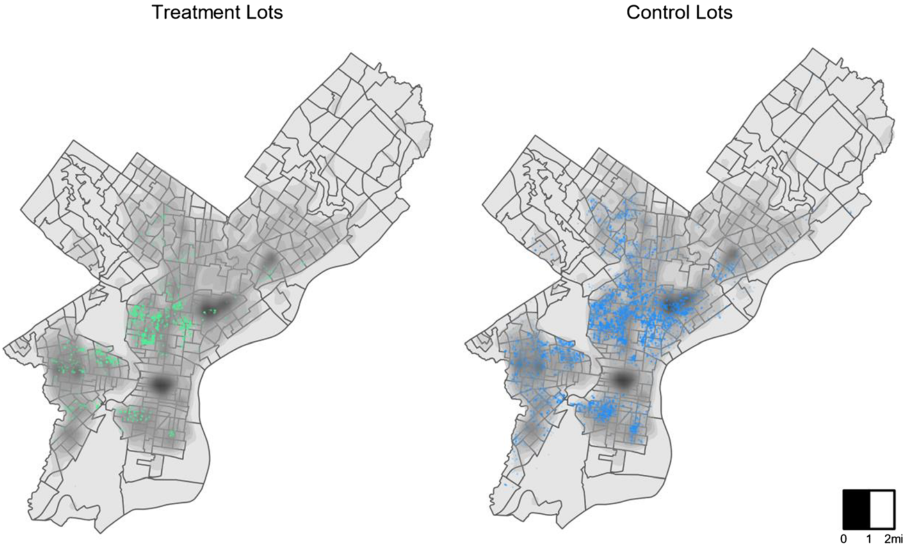

Fig. 1 Kernel density crime map with lot locations in Philadelphia. Darker shape reflects higher density of crime (per square feet). Green dots reflect locations of the PLC greened vacant lots. Blue dots reflect locations of lots that remain vacant in violation of city ordinance

lots that were greened and those that were selected as controls. Specifically, each lot contains a total of 48 monthly crimes per square feet for the 24 months before and after a lot was greened or was cited for a violation of city's vacant lot ordinance. Figure 1 shows the overall kernel density estimates of crime in Philadelphia around the location of vacant lots that were greened and the control comparisons.

We supplement monthly weighted crime counts with demographic and economic data from the American Community Survey (ACS). We merge the 5-year ACS estimates from 2009 to 2018 at the census tract level to describe the demographic and economic characteristics of locations where lots were remediated by PLC or remained vacant and in violation of city ordinance. We include measures of race, ethnicity, age, sex, household income, and housing vacancy to show that the lots remediated by PLC were comparable on structural covariates of crime as the comparison lots that remain vacant and in violation of city ordinance.

We relied on several sources of data to generate measures of land uses that may generate human activity nearby vacant lots. We construct school location data from the U.S. Department of Education, Common Core of Data (CCD) and the Pennsylvania Department of Education (PDE). The CCD includes school addresses, allowing us to link the vacant lot master database to the location of all traditional and charter public schools in Philadelphia that were open between 2006 and 2016. We construct measures of transit stop locations from the South Eastern Pennsylvania Transit Authority (SEPTA) shapefiles for trolley, subway, and regional rail line stations (SEPTA 2019). These data provide the name of station, the type of transportation, and the station coordinates. We construct alcohol outlet locations (bars, clubs, and restaurants) from the Pennsylvania Liquor Control Board within the city of Philadelphia each year that have an active liquor license.[6] We rely on data from Philadelphia's Office of Property Assessment for years 2006 through 2018 to measure the zoning of land use types near vacant lots.[7] We rely on business license data from Philadelphia's Office of Licenses and Inspections to measure business activity nearby vacant lots.

We also used data from an earlier randomized control trial by Branas et al. (2018) of the PLC program. During the spring of 2013, a total of 541 vacant lots in 110 contiguous geographic clusters were randomly assigned to the full PLC greening intervention (37 clusters, 206 lots), a mowing and maintenance intervention (36 clusters, 174 lots), or a no-intervention control condition (37 clusters, 161 lots). We set up this randomized control trial data with the same balanced monthly panel data, and append the corresponding land use variables and survey responses from 445 randomly sampled residents living nearby vacant lots that were collected before the intervention period (see Branas et al. 2018 for details).

Measures

We measure vacant lot greening by a dichotomous variable that captures whether (= 1) or not (= 0) the vacant lot was remediated by PLC. For the RCT remediation treatment also included the mowing and maintenance intervention. We then interact that variable with the timing of the remediation to capture the period before (= 0) or after (= 1) the PLC remediation occurred. Census population information on each tract is measured from the ACS by percent share of the total population of a given race (percent Black), ethnicity (percent Asian or Hispanic), age (percent 18–24; percent 25–29), income (percent household incomes below $20,000), and the housing vacancy rate. Socioeconomic characteristics (race, ethnicity, age) are measured as proportions of population, and housing vacancy is measured a proportion of the total number of housing units.

We measure nearby land uses through six measures. We create dichotomous variables capturing if the lot is located near a school, transit station, or alcohol outlet (bars, clubs, and restaurants) (1 = yes, 0 = no).[8] School locations and alcohol outlets can change when they close or open in Philadelphia (Steinberg et al. 2019), so this measure varies by year in its distance to a vacant lot. Proximity to transit stations does not change over time. We also produce measures of the prevalence of nearby assessed commercial and mixed-use properties that fall within 500 ft. of vacant lots (equivalent of a city block) in the 2 years before the PLC intervention or code violation date.[9] We created dichotomous indicators of the presence (1 = yes) or absence (0 = no) of commercial or mixed use property zoned nearby.[10] We also produce weighted counts of

[6] https://metadata.phila.gov/#home/datasetdetails/55e9a66a18af3c363f8733df/representationdetails/563cc91d7b4dd09a0fb886da/ (accessed September 1, 2020)

[7] The assessment data contains the description of the zoning code for each property (e.g., multi-family, single family, commercial, industrial, and mixed-use). We focus on commercial and mixed-use as areas of commerce have been shown be associated criminal activity (Bernasco and Block 2009).

[8] We define nearby as distances of 750 ft., or roughly 1.5 city blocks, for schools and transit stations and 500 ft. for alcohol outlets.

[9] We use Euclidean distance for these land use measures. Euclidean and street network (Manhattan) distance measures were highly correlated (.95–.99).

[10] The distributions of the count of nearby commercial (kurtosis = 27.21; skewness = 3.84) and mixed used (kurtosis = 11.75; skewness = 2.45) properties were skewed to the right. By creating dichotomous variables measuring prevalence, we mitigate against extreme outliers of counts of commercial or mixed-use properties.

active businesses that fall within 500 ft. of vacant lots for each month of data. The weighted count is equal to the total number of days that businesses are open within a given month divided by the number of days within the same month. For example, if two businesses are open for the entire month and another business is open for half of the month, the weighted count will equal 2.5. We calculate weighted counts for eight business types.[11] We then created a measure of the sum of the eight weighted counts. For ease of interpretation and to assess higher levels of potential human activity generated by nearby businesses, we created a dichotomous variable measuring the presence of high (= 1) or low (= 0) business activity nearby vacant lots. Lots were assigned high business activity if they were in the upper 75th percentile of distribution, reflecting 8 or more active businesses in a month within 500 ft. of the lot.[12] To check the robustness of this measure, we also examine variation across quartiles.

From the randomized controlled trial (RCT) (Branas et al. 2018), we created the same land use measures for the 24 months before and after the RCT. For the analysis of the RCT, we also add baseline survey measures of social cohesion. Social cohesion was measured by combining eight Likert scale survey items from respondents' living nearby vacant lots before the PLC intervention (average of two survey waves). Respondents were asked to indicate their level of agreement on a four-point scale ranging from "agree disagree" to "strongly agree" to the following six statements: "If there is a problem around here, the neighbors get together to deal with it," "this is a close-knit neighborhood," "When you get right down to it, no one in this neighborhood cares much about what happens to me (reverse coded)," "There are adults in this neighborhood that children can look up to," "People are willing to help their neighbors", and "People in this neighborhood generally don't get along with each other (reverse coded)." Respondents were also asked for their responses on a five-point scale ranging from "never" to "always" in the past 30 days to the following two statements: "People worked together to improve my neighborhood," and "People were willing to help their neighbors." These eight measures were combined into a summed, normalized scale. The alpha reliability for this scale was 0.85.[13] Social cohesion at baseline was then averaged over the two baseline survey waves for the clusters that were part of the RCT. We then created a dichotomous variable measuring the presence of above (= 1) or below (= 0) average social cohesion.

For our outcome measures, we rely on crime incident data provided by the Philadelphia Police Department that includes all thirty-six reported index (Part 1) and non-index offenses (Part 2) categories for years 2006 to 2018. We focus on five major aggregations created from these data: (i) total crimes, (ii) aggravated assault, (iii) robberies, (iv) drug offenses, and (v) public order offenses. Aggravated assault and robberies consist of both armed and unarmed incidents. Public order offenses are derived from offenses of disorderly conduct, public order violations, vandalism and mischief, and prostitution.

[11] The eight common types of business identified are as follows: food establishments and restaurants, food manufacturers and wholesalers, motor vehicle repair and sale shops, vendors, childcare facilities, amusement-related businesses, public garages and parking lots, and pawn shops.

[12] Lots with high business activity had an average of 12 active businesses within 500 ft. compared to 3 for lots that were assigned low business activity.

[13] Principal components analysis showed that one component explained 51% of the variance across the eight items.

Model for quasi-experimental study

To estimate the effect of PLC remediation of vacant lots on crime, our approach is to compare vacant lots that are greened to those in the same census tract that remain vacant and in violation of city ordinance. We restrict our comparisons to the 24 months before and after greening to have a balanced panel for estimating the effects of the greening over a 2-year cycle. We align the data according to the time since the lot was greened for the PLC remediated lots or was first in violation of vacancy ordinance for the comparison lots. This design ensures that each greened lot is being compared to a set of vacant lots with similar surrounding context and a shared history. Specifically, we estimate a regression model in which we interact the greening treatment variable with the period after the PLC remediation. We include lot-level fixed effects in this model. The lot-level fixed effects control for time stable unmeasured differences between all vacant lots and allow us to identify on the change attributed to the interaction between greening treatment and the period after remediation. Our fixed-effects regression estimates the average change in crime per square feet in the 24 months before and after a lot is greened relative to lots that remain in violation of city ordinance, thus taking the form of a difference-in-differences design (Bertrand et al. 2004).[14]

To guard against the possibility that spatial autocorrelation impacts the standard errors of our estimates, we also estimated additional regression models that allowed the covariance matrix to vary at smaller to larger levels of geography around each lot. Specifically, we estimated models in which the standard errors are clustered at the block, block group, and census tract level (Bester et al. 2011; Ridgeway et al. 2019). The results are displayed in the Appendix 1 Table 4.[15]

One of the identifying assumptions of a difference-in-differences estimate is that the trends in the greened lots prior to the PLC remediation are parallel to the comparison vacant lots that remain disordered and are in the same census tracts (Angrist and Pischke 2008). This ensures that the estimated change after greening is the result of the timing of remediation and not preexisting trends (e.g., a temporary spike in crime and then regression to the mean). To ensure that estimates from our fixed-effects regressions satisfy the parallel trends assumption, we rely on entropy balancing that reweights the comparison vacant lots to have identical mean counts of crime as the greened lots in the 24 months preceding the PLC remediation (the month before (− 1) serves as the reference period). In this process, each greened vacant lot is given a weight of 1, and the comparison lots that remain vacant are assigned more weight if their crime averages in the months before (− 24 to − 1) the PLC treatment are more

[14] Bertrand et al. (2004) show that this version of a fixed-effects estimator is a difference-in-differences model. For example, the standard difference-in-differences model of vacant lot (i) greening treatment (T) by post (P) intervention time period (t) could be estimated by the following form:

$Yit = \beta 0 + \beta 1Ti + \beta 2Pt + \beta 3(Ti \times Pt) + \varepsilon it$ (1). In contrast, a fixed-effects estimator could be estimated by the following form: (2) $Yit = \alpha i + \theta t + \delta Dit + \varepsilon it$, where D is time varying dummy of the interaction of greening and post treatment period (Ti*Pt). By integrating equations 1 and 2, one can see that the matrix of fixed-effects for lots α (i) and time θ (t) cancels out $\beta 1$ and $\beta 2$ in equation 1, thus leaving one with only the difference-in-differences coefficient that is identified by $\beta 3$ or δ.

[15] This approach to assessing spatial autocorrelation is more flexible than imposing a given spatial distance structure on the data, like a distance weight or nearest neighbor matrix.

similar.[16] Weights were chosen using an algorithm that minimizes an entropy distance metric between an estimated weight (w_i) and a base weight (q_i).[17] Weights are normalized to have a sum of 1, thus preventing the algorithm from over fitting the comparison.

To examine whether greening is moderated by nearby land uses, we included interaction terms for each individual measure of nearby land uses and the timing of the vacant lot greening intervention and estimate the joint contribution of all interaction terms.[18] This allows us to observe whether the effect of the greening intervention on crime is moderated by nearby land uses, reflected by a significant interaction between a single feature of land use (e.g., greening*train station) or the collection of interaction terms (e.g., greening*train station + greening*commercial, etc.).

Model for randomized controlled trial

The same difference-in-difference fixed-effect model with group interactions is estimated for data from the Branas et al. (2018) RCT, but standard errors are clustered on the lot's assigned cluster rather than the block. Given that vacant lots were randomized to receive the PLC intervention, the fixed-effects model for the RCT analysis does not require entropy balancing.[19]

Results

Descriptive statistics

Table 1 shows descriptive statistics for socioeconomic, housing, and crime measures for vacant lots greened by PLC and those that remained vacant in violation of city ordinance. Across both greened and vacant lots, lots tended to fall into census tracts with adverse economic conditions and higher concentrations of minorities. On average, nearly half (45.9%) of household incomes in the corresponding census tracts were \$20,000 or below. In addition, a little under a quarter of housing units (23%) were vacant. Black residents are the predominant racial category of the population of residents in census tracts that received PLC greening or had a vacant lot violation. The differences between socioeconomic and housing vacancy are comparable between vacant lots that were greened and those that remained vacant by construction, as the lots were matched based on census tract locations.

Table 1 also shows the average weighted count of crime around vacant lots that were greened and those that serve as controls in the 24 months before and after the PLC remediations or vacant violation date. Column 3 in the bottom panel (B) shows kernel density estimates of crime for vacant lots after balancing on entropy distance. The

[16] The method also guards against the influence of unusually large weights from driving results, as large weights reduce the effective sample size, thereby increasing variance and reducing the precision of estimates.

[17] Weights are chosen by the following reweighting scheme subject to balance and normalization constraints: $\min_{w_i} H(w) = \sum_{\{i|t=0\}} w_i \log w_i/q_i$ (Hainmueller 2012).

[18] A separate analysis examining single models for each interaction term shows substantively similar results.

[19] Crime trends are parallel between the treatment and control arms when we adjust standard errors for the clusters.

Table 1 Summary comparisons

Panel A	Greening		Vacant			
	(Mean)	(SD)	(Mean)	(SD)		
Percent male	45.91	4.56	45.86	5.17		
Percent 18–24	12.65	9.14	13.18	7.77		
Percent 25–29	8.06	3.00	7.21	2.85		
Percent White	11.10	13.12	12.23	14.18		
Percent Black	80.23	22.58	76.25	27.03		
Percent Asian	1.29	3.79	1.85	4.88		
Percent Other	7.38	11.38	9.68	14.66		
Percent Hispanic	10.30	19.36	14.72	24.86		
Percent income < \$20,000	49.38	10.16	49.35	10.60		
Percent vacant housing	23.08	6.56	23.74	7.18		
Panel B	Greening before	Vacant before	Vacant before (W)	Greening after	Vacant after	DD
	(Mean)	(Mean)	(Mean)	(Mean)	(Mean)	
Robbery	0.05	0.05	0.05	0.04	0.05	−0.01
Assault	0.08	0.08	0.08	0.08	0.08	0.00
Drug offenses	0.15	0.18	0.16	0.13	0.16	−0.02
Public order	0.14	0.15	0.14	0.13	0.14	−0.01
Total	1.36	1.46	1.39	1.28	1.37	−0.06
N =	97,104	209,808	74,860	97,104	74,860	

N = number of lots * 24 months; Weighting (W) on entropy distance. *SD*, standard deviation; *DD*, difference-in-differences

offense weighted counts in the period before the PLC remediation are on average identical between the two groups across the five offense categories. In the period after the PLC intervention, they appear to diverge and the difference-in-difference calculation (column 6) shows a relative reduction in robbery, drug offenses, public offenses, and total crime around greened lots.

Quasi-experimental results

Table 2 shows the results for the estimates of vacant lot greening on distance weighted total crime, public order offenses, drug offenses, aggravated assault, and robbery and how these estimates vary by nearby land uses. The *p* values for test of parallel trends confirms that all crimes aside from aggravated assault are trending similar in the months preceding vacant lot greening for the treatment and weighted control comparison of lots. Estimates are also converted into percentage reductions to facilitate interpretation.

Table 2 shows that all but one of the crime outcomes decrease significantly after the greening of vacant lots. Specifically, total monthly crimes per square feet decreases by

Table 2 Effect of vacant lot greening on crime by nearby land use

Variables	(1) Robbery	(2) Robbery	(3) Assault	(4) Assault	(5) Drugs	(6) Drugs	(7) Public Order	(8) Public Order	(9) Total	(10) Total
Greening	−0.011**	−0.011**	−0.001	−0.001	−0.016**	−0.005	−0.013**	−0.010	−0.076**	−0.107**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.008)	(0.004)	(0.005)	(0.015)	(0.021)
Greening*Train		0.002		−0.002		−0.018		−0.022		0.157**
		(0.005)		(0.005)		(0.015)		(0.016)		(0.043)
Greening*Alcohol Out.		−0.001		−0.001		0.001		0.008		0.077**
		(0.004)		(0.004)		(0.009)		(0.007)		(0.029)
Greening*School		0.008**		−0.005		−0.007		−0.002		−0.020
		(0.003)		(0.004)		(0.010)		(0.008)		(0.032)
Greening*Commercial		−0.003		0.001		0.014		−0.007		−0.018
		(0.003)		(0.005)		(0.014)		(0.007)		(0.039)
Greening*Mixed Use		−0.001		0.001		−0.018		0.008		0.005
		(0.003)		(0.004)		(0.009)		(0.006)		(0.030)
Greening*Business		−0.004		0.005		−0.013		−0.020		−0.042
		(0.004)		(0.005)		(0.015)		(0.012)		(0.040)
Percent Change	−20.75%		−1.28%		−10.88%		−9.28%		−5.59%	
Observations	613,824	613,824	613,824	613,824	613,824	613,824	613,824	613,824	613,824	613,824
Number of lots	12,788	12,788	12,788	12,788	12,788	12,788	12,788	12,788	12,788	12,788
Lot fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p value for parallel trends	1.00		.004		1.0		0.914		0.885	
F=	46.11	7.429	0.448	1.045	11.26	3.762	14.34	4.948	26.20	6.743

Robust standard errors (block level) in parentheses. F = test. $^{**}p < 0.01$, $^{*}p < 0.05$

5.59% per month after vacant lots are greened. Public order offenses decrease by 9.28%, drug offenses decrease by 10.88%, and robbery decreases by 20.75%.[20]

Figure 2 shows the monthly averages in the 24 months before and after lots are greened compared to those that remain vacant and disorderly. Figure 2 demonstrates that after weighting on entropy distance, the treatment and control lots have parallel trends preceding the PLC remediation, but that robberies drop to a significantly lower level for treatment lots after they are greened.

Table 2 shows that the greening of vacant lots has a larger impact on total crime when it is *not* nearby a train station or an alcohol outlet (bar, club, or restaurant), suggesting that these land uses may attenuate the crime reduction benefits of vacant lot greening. The marginal effects from these estimates imply that the total monthly crime per square feet is approximately 12.2% to 15.7% higher when a lot is greened near a train station or bar than when it is not. The results are also suggestive that greening vacant lots near areas with more active businesses may have greater crime reduction benefits, but the interaction is not significant at the $p < .05$ level. When we examine how the results vary when interactions are modeled across quartiles of business activity, we see larger effects in the upper quartile, and that the variation in business activity does significantly moderate the effect of greening vacant lots.[21] No other single set of land use interactions are statistically significant. An F-test of the joint significance of land uses interactions indicates that they explain a significant share of the variation in the change in total weighted crime ($F(dfn = 6, dfd = 2653) = 3.73$; $p = .001$).

The interaction effects for robbery, assault, drug, and public order offenses are not significantly different from zero, suggesting that the moderating effect by nearby train stations and alcohol outlets on total crime is not driven by any of these subcategories. While the effect of the greening intervention on vacant lots with nearby mixed land-uses appears to have significantly larger impacts on drug offenses, this estimate is significant at only the $p < .05$ level and after multiple tests should be viewed as a potential false discovery.

Experimental results

Table 3 shows the results for the estimates from the RCT of vacant lot greening on total crime, public order offenses, drug offenses, aggravated assault, and robbery and how these estimates vary by nearby land uses. The results show that the greening intervention reduces total crime, public order offenses, drug offense, and aggravated assault,[22] but there is only partial evidence of a moderating effect of nearby land uses and social cohesion. The direction of the estimates of nearby land use and vacant lot greening

[20] Percentage reductions were calculated from difference-in-difference estimates by the following formula: (estimate/(absolute value of estimate + post mean of greened lots))*100. For example, the estimates from robbery are − .011 and the post-mean for greened vacant lots is .042, using this formula then yields (− 0.011/(0.011 + .042))*100 = − 20.75.

[21] An F-test of the joint significance of the interaction of the greening intervention with quartiles of business activity indicates that they explain a significant share of the variation in change in total crime ($F(dfn = 3, dfd = 2653) = 2.84$; $p = 0.036$).

[22] These results are slightly different from those published by Branas et al. (2018) because our replication includes a different follow-up period and set of crime categories.

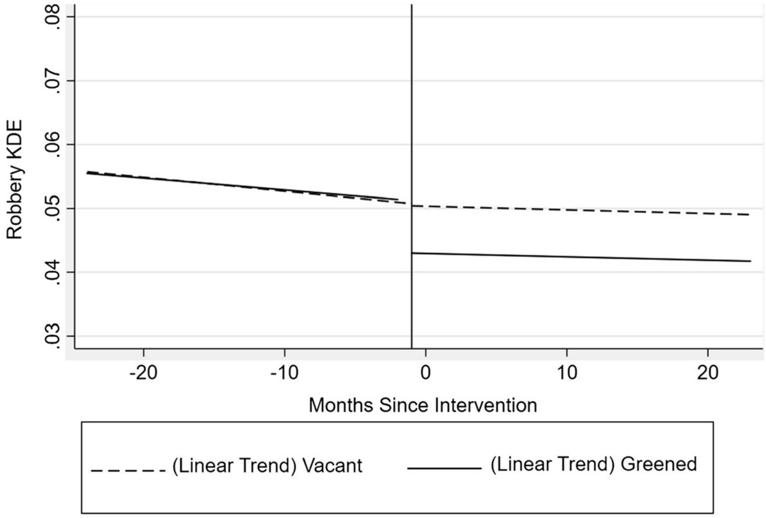

Fig. 2 Trends in robbery between greened and vacant lots

interactions are similar to the quasi-experimental results, suggesting that lots greened near train stations and alcohol outlets have smaller reductions in crime relative to those not greened near these locations. In contrast to the quasi-experimental estimates, however, the moderating effects of nearby train stations and alcohol outlets are not statistically different from zero difference, which is attributable to the fact that the RCT has a substantially smaller sample size than the quasi-experimental study and less statistical power to detect subgroup differences.

The results, however, show that lots that were randomly assigned to be greened nearby areas of active businesses have larger crime reductions than those that were near areas with less active business presence. The moderating effects of greening vacant lots nearby areas of active business are statistically significant for total crime and robbery offenses. For total crime, the marginal effect implies a 20% relative reduction when vacant lots are greened near areas of high business activity relative to lower business activity. While not statistically significant, the moderating effects are also in the same negative direction for aggravated assault, drug offenses, and public order offenses. Across most crime outcomes, the direction of the estimates of vacant lot greening is also suggestive of greater reductions in crime in areas with above average social cohesion, though the estimates are generally not significant and vary from 1 to 2 standard deviations.[23]

Figure 3 shows that the upper 75th percentile is driving the moderating effect of active businesses, as this is this the only quantile in which there is a significant interaction, and demonstrates that the effects of vacant lot greening on crime are larger near areas with high business activity.

[23] The results are substantively similar if we model the interaction of social cohesion quartiles and greening, or only the upper 75th percentile of social cohesion.

Table 3 RCT effect of vacant lot greening on crime by nearby land use and social cohesion

Variables	(1) Robbery	(2) Robbery	(3) Assault	(4) Assault	(5) Drugs	(6) Drugs	(7) Public Order	(8) Public Order	(9) Total	(10) Total
Greening	−0.004	0.005	−0.014*	−0.009	−0.037**	−0.005	−0.026**	−0.019	−0.163**	−0.058
	(0.005)	(0.007)	(0.006)	(0.012)	(0.010)	(0.018)	(0.008)	(0.012)	(0.035)	(0.059)
Greening*Train		0.018		−0.005		−0.018		0.027		0.128
		(0.014)		(0.014)		(0.031)		(0.020)		(0.109)
Greening*Alcohol Out.		0.006		−0.019		−0.010		−0.006		0.022
		(0.009)		(0.012)		(0.032)		(0.015)		(0.062)
Greening*School		−0.001		−0.004		0.019		0.045*		0.013
		(0.010)		(0.012)		(0.023)		(0.017)		(0.086)
Greening*Commercial		−0.008		0.001		0.017		0.003		−0.074
		(0.007)		(0.011)		(0.023)		(0.017)		(0.068)
Greening*Mixed Use		−0.018*		0.003		−0.003		−0.000		−0.038
		(0.007)		(0.011)		(0.014)		(0.013)		(0.060)
Greening*Business		−0.020*		−0.008		−0.019		−0.050		−0.308**
		(0.009)		(0.017)		(0.059)		(0.027)		(0.105)
Greening*Cohesion		−0.005		0.006		−0.054*		−0.007		−0.106
		(0.008)		(0.011)		(0.021)		(0.014)		(0.065)
Percent Change	−8.91%		−16.18%		−20.79%		−17.33%		−11.93%	
Observations	25,968	25,968	25,968	25,968	25,968	25,968	25,968	25,968	25,968	25,968
Number of lots	541	541	541	541	541	541	541	541	541	541
Lot fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors (cluster level) in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$

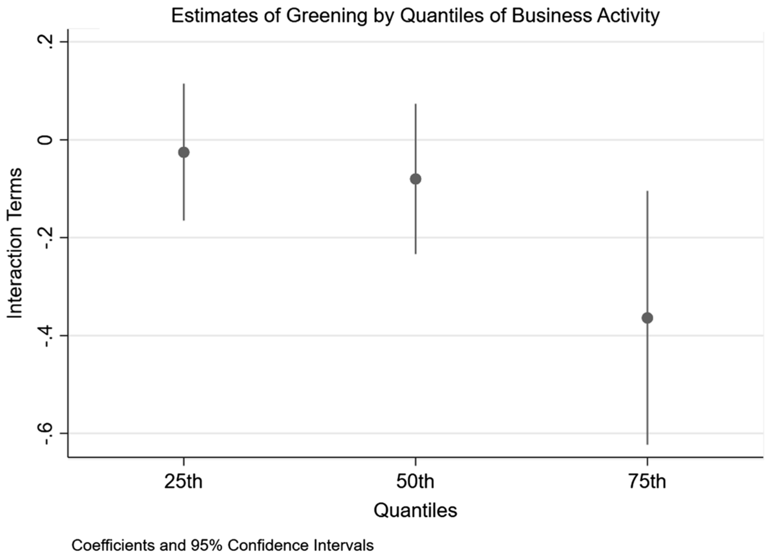

Fig. 3 Effect of vacant lot greening on crime by business activity

Robustness tests

One concern with the primary analysis in the quasi-experimental study is the potential for spatial autocorrelation to impact standard errors. Appendix 1 Table 4 shows that across all crime outcomes adjusting for spatial autocorrelation at higher geographic levels of analysis (block group and tract) has minimal impact on standard errors of the estimates. The lack of evidence for spatial autocorrelation impacting estimates is not surprising given that crime measures are calculated based on kernel density estimates of distance from lots.

An additional concern for both the quasi-experimental and experimental analyses is that the treatment effect of vacant lot greening may be confounded with displacement. We assessed displacement by creating three buffers corresponding to 500, 1000, and 1500 ft. around each lot. We then calculated the number of crimes occurring within the rings of these three buffers (0–500 ft., 501–1000 ft., and 1001–1500 ft.). If greening vacant lots leads to crime being displaced nearby, the estimates would be biased and we would observe crime falling in the first buffer of 500 ft. (consistent with our kernel density bandwidth) and rising in subsequent buffers. We re-estimated the same difference-in-difference models and clustered standard errors at the census tract level, to adjust for spatial autocorrelation within buffers that exist within the same census tracts.[24] Separate displacement tests in both quasi-experimental and experimental analyses are displayed in Appendix 2 Table 5 and show there was a significant reduction in total crime around 500 ft. of greened vacant lots that was not coupled with significant increases in the outer rings. In fact, total crime was significantly lower in the outer rings after the greening intervention, suggesting there may be minor spillover benefits of the remediation rather than displacement.

[24] The quasi-experimental analysis also included a weight for the entropy distance between greened and control lots on the average count of crime in the months preceding remediation.

Discussion

We presented evidence that greening vacant lots continues to reduce crime in Philadelphia during the period of 2008 to 2018. These findings suggest that the benefits of the PLC vacant lot greening intervention were sustained as the program expanded across Philadelphia and was subjected to a significantly lower level regime of crime than in the earlier study by Branas et al. (2011). Importantly, the sustainable benefits of vacant lot greening are corroborated in our replication of outcomes from the citywide RCT of the PLC program. Collective efficacy (Sampson et al. 1997) and situational opportunity theories in environmental criminology (Wilcox and Cullen 2018) led us to hypothesize that the effects of vacant lot greening on crime would be moderated by nearby land uses. In particular, these theories would predict that the benefits of vacant lot greening may be less pronounced when located nearby land uses that generate additional foot traffic among strangers, making it more difficult for residents take collective action to enforce norms of civility and to act as capable guardians of these newly remediated spaces. Greening vacant lots nearby train stations and alcohol outlets has less of a total crime reduction benefit than when lots are remediated on blocks further away from these locations. These findings suggest that the extra foot traffic generated by transit and alcohol outlets may attenuate the crime reduction benefits of vacant lot greening. Similar results also appear from the RCT, but the effects are only suggestive. By contrast, nearby business activity appears to help amplify the crime reducing benefits of vacant lot greening. These findings suggest that business owners may become more effective place guardians or take “proprietary ownership” (Cozens et al. 2005) of these spaces when they are remediated compared to when they are overgrown, full of trash and debris, and disorderly. The lack of any significant differences between vacant lots that were greened near commercial properties, mixed-use properties, or schools may mean these land uses are not moderators of remediation, or they generally do not capture significant variation in daily human activity around the vacant lots before and after the greening intervention. These findings suggest that the changing places benefits of the PLC program on crime are only partially impacted by nearby land uses.

Earlier works on the PLC program suggest that norms around use of vacant spaces changes after lots receive the greening intervention. For example, a study conducted on a random sample of PLC remediated lots in the summer 2013 found that nearly 10% of PLC remediated lots had signs of new physical uses including the presence of tables and chairs, gardens, barbeques or grills, inflatable swimming pools, and swings (Heckert and Kondo 2018). The results from the RCT that show suggestive evidence that areas with higher levels of social cohesion among residents may help amplify the benefits of vacant lot greening are consistent with observations that nearby residents take ownership of these remediated spaces for socialization, a mechanism that would be consistent with collective efficacy (Sampson et al. 1997).

By contrast, the greening of vacant lots may be less effective at reducing criminal activity when they are located adjacent to a crime generator like a train station or a bar. Ethnographic work by Branas et al. (2018) of the PLC program found that drug dealers were more likely to rely on overgrown vacant lots because they provided easier “concealment” for drug users and escape routes from the police. It is conceivable that the crime reduction benefits of vacant lot greening may be less pronounced in transient areas around train stations where concealment from witnesses to crimes is not as important as it is in a neighborhood where residents have organized to use remediated vacant lots for prosocial activities and will call the police.

However, this study does have several limitations. First, while the location of lots that were cleaned and greened by PLC had few restrictions beyond the violation of city ordinance, the choice of which lots receive remediation is not random in the quasi-experimental study, so these results do not provide inference for what would have happened to crime in neighborhoods where vacant lots were never remediated. The scale of the PLC program suggests this is a negligible fraction of Philadelphia neighborhoods. Similarly, while lots for the RCT were randomly selected from an available inventory of vacant lots in violation of city ordinance, chance differences in which areas were selected for the experiment means we cannot reliably apply the estimates of the RCT to other areas of the city. Second, we cannot say much about how the effects of vacant lot greening would be impacted by human activity if the PLC program were more strategically placing its intervention around businesses, schools, and transit stations. The PLC program was specifically designed to remediate vacant lots and stabilize neighborhoods so future housing could be built, so the intention of the program operates as it was planned. Third, the study relies on nearby land uses and residents' perceptions of social cohesion with their neighbors to serve as proxies for human activity and socialization. We did not actually measure human activity and socialization nearby these vacant lots. Finally, the estimates from this study provide only inference for the effect of vacant lot greening on crime in the months immediately after the intervention. Other larger changes in neighborhoods can emerge over a longer time horizon, including redevelopment and gentrification (MacDonald and Stokes 2020), racial segregation, or further abandonment, which may produce more systemic changes in patterns of crime (Taylor 2012).

The moderation analyses suggest that greening vacant lots may have larger effects on crime when they are situated in neighborhoods away from transit stations and alcohol outlets, and in areas that draw pedestrians because of the presence of more business activity. Train stations bring an influx of strangers to an area, which may weaken residents' capacity to establish norms and territorial markers of control that deters crime. By contrast, when vacant lots are greened near vibrant businesses, they may benefit from increased surveillance that comes with close proprietors of the space, such as local merchants acting as place guardians (Jacobs 1961).

Future research should examine how foot traffic and other measures of actual human activity vary around vacant lots before and after they are remediated in Philadelphia and other cities with similar programs. For example, studies could use time lapse photography, systematic social observation, or mobile phone location data to capture how many people are actively using the space around vacant lots before and after they are greened. Such research could also chart how the uses of vacant lots changes once they are greened. Research could also measure whether users of remediated vacant lots are local residents, and elucidate the extent to which the greening of vacant lots increases collective efficacy (Sampson 2012), increases markers of territorial control by local residents (Taylor 1988), and makes these spaces less inviting of criminal activity.

The field of criminology would benefit from expanding efforts to study place-based changes to address blight and abandonment in urban spaces. In particular, examining programs that are scalable to entire cities, reproducible from one city to another, and sustainable over a long-period of time would help produce evidence that could more directly engage city planners and local policy makers interested in both reducing crime and improving economic development (MacDonald et al. 2019). At the same time, studying place-based efforts to remediate blighted land with methods to capture the movement of people and the uses of the space could help clarify the mechanisms through which changing places helps reduce crime.

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Appendix 1

Table 4 Sensitivity estimates for spatial autocorrelation

Variables	(1) Robbery	(2) Assault	(3) Drugs	(4) Public Order	(5) Total	(6) Robbery	(7) Assault	(8) Drugs	(9) Public Order	(10) Total
Greening	−0.011**	−0.001	−0.005	−0.010	−0.107**	−0.011**	−0.001	−0.005	−0.010	−0.107**
	(0.003)	(0.004)	(0.010)	(0.006)	(0.026)	(0.003)	(0.003)	(0.015)	(0.006)	(0.030)
Greening*Train	0.002	−0.002	−0.018	−0.022	0.157**	0.002	−0.002	−0.018	−0.022	0.157**
	(0.005)	(0.006)	(0.022)	(0.019)	(0.047)	(0.005)	(0.005)	(0.025)	(0.019)	(0.051)
Greening*Alcohol Out.	−0.001	−0.001	0.001	0.008	0.077*	−0.001	−0.001	0.001	0.008	0.077*
	(0.005)	(0.006)	(0.010)	(0.008)	(0.032)	(0.005)	(0.004)	(0.013)	(0.008)	(0.034)
Greening*School	0.008*	−0.005	−0.007	−0.002	−0.020	0.008*	−0.005	−0.007	−0.002	−0.020
	(0.004)	(0.005)	(0.013)	(0.009)	(0.040)	(0.003)	(0.005)	(0.014)	(0.010)	(0.045)
Greening*Commercial	−0.003	0.001	0.014	−0.007	−0.018	−0.003	0.001	0.014	−0.007	−0.018
	(0.004)	(0.005)	(0.016)	(0.008)	(0.052)	(0.004)	(0.005)	(0.020)	(0.009)	(0.052)
Greening*Mixed Use	−0.001	0.001	−0.018	0.008	0.005	−0.001	0.001	−0.018	0.008	0.005
	(0.003)	(0.006)	(0.011)	(0.008)	(0.035)	(0.003)	(0.006)	(0.015)	(0.008)	(0.039)
Greening*Business	−0.004	0.005	−0.013	−0.020	−0.042	−0.004	0.005	−0.013	−0.020	−0.042
	(0.005)	(0.006)	(0.016)	(0.015)	(0.044)	(0.006)	(0.007)	(0.017)	(0.015)	(0.041)
Cluster block group	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Cluster tract	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	613,824	613,824	613,824	613,824	613,824	613,824	613,824	613,824	613,824	613,824
Number of lots	12,788	12,788	12,788	12,788	12,788	12,788	12,788	12,788	12,788	12,788
Lot fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F=	4.349	0.773	3.002	3.221	4.073	4.070	0.930	4.023	3.810	5.407

Robust standard errors (block group or tract level) in parentheses. F = test. $^{**}p < 0.01$, $^{*}p < 0.05$

Appendix 2

Table 5 Displacement test for total crime

Variables	(1) 0–500 ft.	(2) 501–1000 ft.	(3) 1001–1500 ft.	(1) 0–500 ft.	(2) 501–1000 ft.	(3) 1001–1500 ft.
Quasi-experiment			RCT			
Greening	− 0.564**	− 1.73**	− 2.55**	− 1.03**	− 2.10**	− 3.02
	(0.187)	(0.547)	(0.719)	(0.204)	(0.480)	(0.832)
Percent change	− 6.23%	− 6.40%	− 5.82%	− 10.62%	− 7.57%	− 6.80%
Observations	613,824	613,824	613,824	25,968	25,968	25,968
Number of lots	12,788	12,788	12,788	541	541	541
Lot fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster tract	Yes	Yes	Yes	Yes	Yes	Yes
F=	9.05	10.10	12.59	25.71	19.14	13.23

Robust standard errors (tract level) in parentheses. F = test. $^{**}p < 0.01$, $^{*}p < 0.05$

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