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Original Contribution

A Difference-in-Differences Analysis of Health, Safety, and Greening Vacant Urban Space

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Greening of vacant urban land may affect health and safety. The authors conducted a decade-long difference-in-differences analysis of the impact of a vacant lot greening program in Philadelphia, Pennsylvania, on health and safety outcomes. "Before" and "after" outcome differences among treated vacant lots were compared with matched groups of control vacant lots that were eligible but did not receive treatment. Control lots from 2 eligibility pools were randomly selected and matched to treated lots at a 3:1 ratio by city section. Random-effects regression models were fitted, along with alternative models and robustness checks. Across 4 sections of Philadelphia, 4,436 vacant lots totaling over 7.8 million square feet (about 725,000 m^2) were greened from 1999 to 2008. Regression-adjusted estimates showed that vacant lot greening was associated with consistent reductions in gun assaults across all 4 sections of the city ($P < 0.001$) and consistent reductions in vandalism in 1 section of the city ($P < 0.001$). Regression-adjusted estimates also showed that vacant lot greening was associated with residents' reporting less stress and more exercise in select sections of the city ($P < 0.01$). Once greened, vacant lots may reduce certain crimes and promote some aspects of health. Limitations of the current study are discussed. Community-based trials are warranted to further test these findings.

city planning; crime; geography; urban health; urban renewal; wounds and injuries

Abbreviations: PHS, Pennsylvania Horticultural Society; SD, standard deviation.

Economic downturns, deindustrialization, and population outmigration have made the abandonment of land a challenge for many US cities. The Pennsylvania Horticultural Society (PHS), along with other community and municipal partners, directs a program to clean, green, and maintain abandoned vacant lots in Philadelphia, Pennsylvania. These vacant lot treatments often produce immediately noticeable, visually dramatic results; are straightforward to implement; cost little, relative to other urban health and safety programs; and are responsive to community concerns (1, 2).

The treatment of vacant lots is also in line with the 21st century "eco-epidemiology" movement, which seeks to move beyond studies of individuals and lifestyle modification to environmental modification programs that offer widespread protection and enhanced health with less reliance on personal behavior change (3). Such programs avoid working only with high-risk individuals, as it is thought that this produces, at best, only short-term improvements because the system will continue to replace persons who leave high-risk status, allowing the cycle of poor health to persist over the long term (4). Programs that focus on places or structural changes, such as vacant lot greening, may have a greater influence on more people and for longer time periods than programs that focus only on individuals (5).

With respect to health, several studies have linked urban green space to lower mortality or fewer health complaints (6–10). One suggested mechanism for this is that the availability of green space promotes physical activity, reducing obesity and improving cardiovascular and respiratory health. However, other investigators have concluded that availability, access, or proximity to green space is not related to physical activity (11–21).

Select mental health benefits of exposure to the natural environment may also operate independently of physical activity. Studies suggest that green views or access to green space may play a role in reducing cognitive fatigue, promoting emotional recovery, and reducing the influence of stressors on concentration, anxiety, or mood (22–27). This mechanism may be particularly important for buffering the impact of stress on urban residents (28). Studies have also focused on the effects of green environments for prevention and recovery from stress at a basic physiologic level (29–31).

With respect to safety, the ''broken windows'' theory suggests that vacant lots offer refuge to criminal and other illegal activity and visibly symbolize that a neighborhood has deteriorated, that no one is in control, and that unsafe or criminal behavior is welcome to proceed with little if any supervision (32–34). A related theory, the ''incivilities'' theory, suggests that physical incivilities, such as abandoned vacant lots, promote weak social ties among residents and encourage crimes, ranging from harassment to homicide (35–38).

Central to both theories is that criminals are thought to feel emboldened in areas with greater physical disorder while, at the same time, residents are driven toward greater anonymity and are less willing or able to step in and prevent crime (35, 39). Greening may thus be a partial remedy for disorder. Two studies that incorporated naturally occurring random assignment to public housing with differing levels of green vegetation showed significant reductions in intrafamily violence and possibly crime (27, 40).

The greening of vacant lots may affect health and safety, yet only limited evidence exists to support this. We conducted a decade-long difference-in-differences analysis of the PHS vacant lot program to address this gap in knowledge and determine what relation, if any, greening had with select health and safety outcomes that followed from prior theory and analyses.

MATERIALS AND METHODS

Study design

In 1999, the PHS began a program to green abandoned vacant lots in Philadelphia. This program used a consistent treatment protocol that involved removing trash and debris, grading the land, planting grass and trees to create a park-like setting, and installing low wooden post-and-rail fences around each lot's perimeter to show that the lot was cared for and deter illegal dumping. Multiple times each year, PHS returned to each treated lot to perform basic maintenance activities, such as mowing the grass, tending trees, or repairing fences. We analyzed the impact of this program for a full decade, from 1999 to 2008, using a quasi-experimental difference-in-differences study design that considered various health and safety outcomes occurring on and around vacant lots in the PHS program before and after they were treated, as compared with matched control vacant lots over the same time period (41).

Untreated control lots were randomly selected and matched to treated lots by section of the city. This was done within 4 of the 5 sections of Philadelphia. The Northeast section was excluded because a trivial number of vacant lots (<0.2%) were greened there.

Vacant lots were defined as abandoned parcels of open land with no buildings on them; they were a subset of all vacant properties, many of which contained buildings and other structures. Vacant lots eligible to serve as controls included only those that had never been greened from 1999 to 2008 but could have been chosen by the PHS for greening. As a robustness test, we compared 2 different pools of matched control vacant lots (41). The first pool limited eligible vacant lots to only those that had at least 1 open code violation. A second eligibility pool was limited to vacant lots that had at least some portion of their area within a 660-foot (202-m) buffer (1/8 mile or 1/5 km) of a recreation center, K–12 school, park, playground, or commercial corridor. Both of these pools were in line with selection criteria used by PHS (42). From each pool, a set of 3 control vacant lots was randomly selected and matched to 1 treated vacant lot within the same section of the city (Figures 1 and 2). The 3:1 ratio was chosen because at most 3 control lots per treated lot were available for random selection, without replacement, in all 4 sections of the city.

The pregreening period for each treated lot was defined as the years prior to the year that the lot was greened/treated (from 1999 to 2008). This same preperiod was assigned to the 3 randomly selected, matched control lots. The mean pretreatment period for the vacant lots in the study was 6.18 years (standard deviation (SD), 2.07; range, 1–9 years).

Data sources and preparation

A master database of 54,132 vacant lots present in Philadelphia from 1999 to 2008 was assembled from the Philadelphia Bureau of Revision of Taxes, the Philadelphia Department of Licenses and Inspections, and US Postal Service records. This database was separated into lots greened by PHS and those not greened for selection as controls (Figures 1 and 2). A total of 68 treated vacant lots became inactive before the study period ended (housing or other structures were developed on them or they became inaccessible or unmaintainable), no longer functioned in the same way as actively greened lots, and were recoded as untreated for the years they were inactive.

The Philadelphia Police Department provided the dates and longitude-latitude coordinates for several types of crimes and arrests occurring from 1999 to 2008: aggravated assaults, aggravated assaults with guns, robberies, robberies with guns, narcotics sales and possession, burglaries, thefts, vandalism and criminal mischief, disorderly conduct, public drunkenness, and illegal dumping.

The Philadelphia Health Management Corporation provided data from the Southeastern Pennsylvania Household Health Survey, which is administered via random digit dialing every 2 years to a new cohort of approximately 5,000 Philadelphians. We used responses from the survey's 1998, 2000, 2002, 2004, 2006, and 2008 waves, which had census tract-level data and an average response rate of 30.7%. Survey balancing weights and small-area estimation techniques were used to obtain adjusted estimates by census tract (43). The average of the surrounding years' estimates per tract was used to fill in years between survey waves.

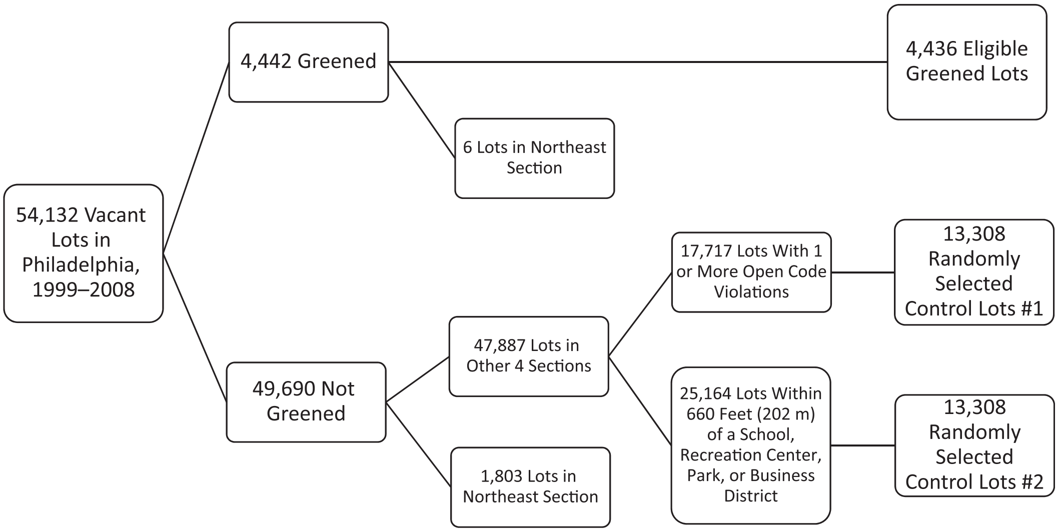

Figure 1. Strategy used to select greened and control vacant lots, Philadelphia, Pennsylvania, 1999–2008.

High stress was defined as answering ≥7 to the question, "Using a scale from 1 to 10, where 1 means 'no stress' and 10 means 'an extreme amount of stress,' how much stress would you say you have experienced during the past year?" High cholesterol was defined as answering yes to the question, "Have you ever been told by a doctor or other health professional that you have high cholesterol?" High blood pressure was defined as answering yes to the question, "Have you ever been told by a doctor or other health professional that you have high blood pressure or hypertension?" Low exercise was defined as answering <2 to the question, "Thinking about the past month, how many times per week did you participate in any physical activities for exercise that lasted for at least one half hour, such as walking, basketball, dance, rollerblading, or gardening?" Poor health status was defined as answering fair or poor to the question, "Would you say your health, in general, is excellent, good, fair, or poor?"

From Geolytics Incorporated (East Brunswick, New Jersey) and the US Census Bureau (Washington, DC), we obtained block group-level estimates of demographic variables for each year of the study. Age was defined as a median for all residents, except for the year 2000, in which it was defined as an average. Unemployment was defined in terms of the number of residents aged 16 years or older who were not working. Education was defined in terms of the number of residents aged 25 years or older who had completed at least some

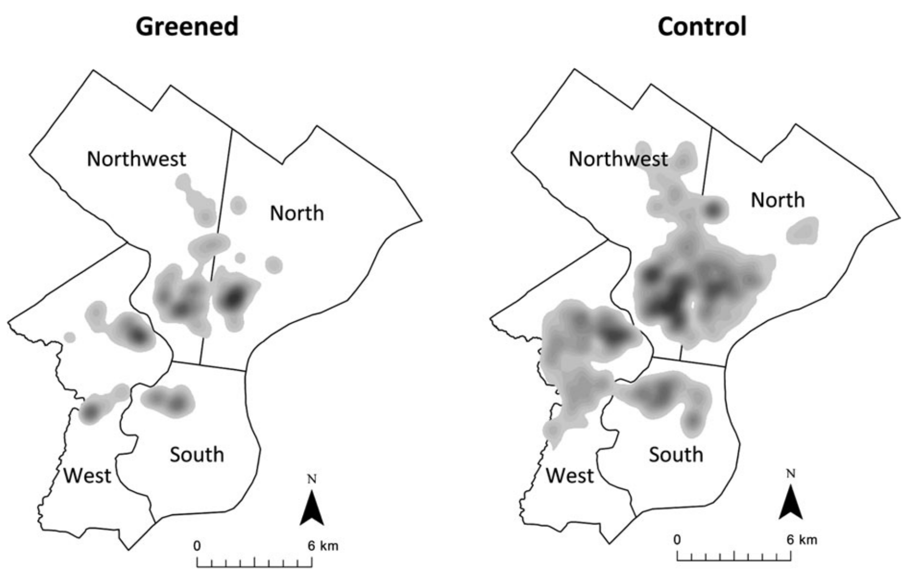

Figure 2. Kernel density map showing locations of vacant lots in 4 of the 5 sections of Philadelphia, Pennsylvania, 1999–2008. Darker colors indicate greater concentrations of lots.

college. Income was defined as median annual household income. Race was defined as the number of black residents. Ethnicity was defined as the number of Hispanic residents. Poverty was defined as the number of residents living below 150% of the federal poverty level.

We calculated crime and health outcomes, demographic measures, areas, centroid/geometric centers, contiguous lots, and kernel density estimations of vacant lot clustering in the surrounding area for all vacant lots in each year of the study. Point locations of crimes were used to calculate kernel density, census tract, and block group measures per lot. Health outcomes were tagged to tract centroids and used to calculate inverse-distance weighted, tract, and block group measures per lot. Demographic measures were tagged to block group centroids and used to calculate inverse-distance weighted, tract, and block group measures per lot. Estimates were calculated using a default bandwidth distance that was the shortest of the width or height of the extent of input features in the output spatial reference, divided by 30 (44–46).

Statistical analyses

Unadjusted analyses were conducted using summary statistics, cross-tabulations, and nonparametric Wilcoxon rank-sum tests. Regression-adjusted analyses were preceded by variance inflation factor tests to confirm that multicollinearity was minimal (all variance inflation factors < 4.0).

We specified cross-sectional time-series linear regression models in which the units of observation were number of vacant lots (i) per year of the study (t) and in which the difference-in-differences term, $P_{it} \times R_{it}$, was our focal independent variable, defined as the interaction between a pregreening-postgreening difference per vacant lot, P_{it}, where pregreening years were 0 and postgreening years were 1, and a treatment-control difference, R_{it}, where control lots were 0 and greened lots were 1. The β_3 coefficient for the difference-in-differences term is intended to estimate the true effect of the treatment on the outcome (41). Each of our regression models also included a different health or safety outcome of interest, Y_{it}; a series of p independent covariates, X_{it}; a fixed-effects city section × year interaction term to account for geographic variability and clustering over time, $S_{it} \times t$; a fixed-effects city section × preperiod mean outcome interaction term to adjust for regression to the mean, $S_{it} \times M_i$ (47, 48); a group-level random-effects parameter, ξ_i, that adjusted for the effects of individual vacant lots that were contiguous to one another using a clustered sandwich estimator; the main effects of the difference-in-differences interaction, P_{it} and R_{it}; and residual error, ε_{it}. These models are represented in the following equation.

$$\mathrm{Y}_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 R_{it} + \beta_3 (P_{it} \times R_{it}) + \beta_4 (S_{it} \times t) + \beta_5 (S_{it} \times M_i) + \sum_{k=6}^{p} \beta_k X_{it} + \xi_i + \varepsilon_{it}.$$

Adjusted analyses were performed as mixed-effects regressions, that is, one-way random-effects models with multiple fixed effects added (49–51). Previously described demographic variables, lot area, and vacant lot clustering were included as covariates in all regression models. Covariates were restricted to baseline, pregreening variation (52).

Regression models were fitted separately for point-based, tract-based, and block group-based outcomes, covariates, and other factors using one of the 2 types of vacant lot controls. Because none of the study's final conclusions markedly differed by control group type and because control lots with open violations were a better statistical match to greened lots (in terms of area, age, and unemployment), only findings obtained using this control group are reported.

Additional robustness checks were also conducted. We replaced ξ_i measuring contiguous lot groupings with treated:control matched set lot groupings. We tested the inclusion of a covariate measuring the average Euclidean distance between each treated lot and its control lots. We explored whether the decision to green a lot sooner than others was affected by pregreening outcomes using a 2-stage approach. A first-stage Cox proportional hazards regression model was fitted with a time-to-greening dependent variable and each health or crime outcome as an independent variable. We obtained an inverse predicted hazard of greening for each health or crime, which was then used as a sampling weight in a second-stage regression model with the same dependent and independent variables as in the prior mixed-effects regression models. These 3 checks made minor changes to our estimates and did not substantively change our conclusions.

In accounting for multiple comparisons in our regression analyses, we used a P value less than 0.01 (53–55). Overall model R^2 values were calculated across models (56, 57). Regression analyses and results were witnessed and confirmed by 2 statisticians, one a coauthor and one an independent statistician. We obtained approval from the University of Pennsylvania institutional review board.

RESULTS

Control vacant lots within 660-foot (202-m) buffers were statistically different from greened lots in all indicators ($P < 0.01$). Control vacant lots with open violations were not statistically different from greened vacant lots in terms of area, age, or unemployment (Table 1). Open violation control lots were separated by an average of 1.63 miles (SD, 0.80) (2.61 km) from their matched greened lots.

Unadjusted difference-in-differences estimates for several crime and health outcomes showed consistent and statistically significant ($P < 0.01$) reductions related to vacant lot greening (see the Web Appendix, which appears on the *Journal*'s Web page (http://aje.oxfordjournals.org/)). Average R^2 values were highest among the regression models incorporating point-based calculations ($R^2 = 0.70$ (SD, 0.17)), followed by tract-based ($R^2 = 0.66$ (SD, 0.17)) and block group-based ($R^2 = 0.51$ (SD, 0.17)) calculations (Tables 2–4).

Regression-adjusted difference-in-differences estimates for crime outcomes showed consistent, statistically significant reductions across point-, tract-, and block group-based calculations for gun assaults in all 4 sections of the city combined

Table 1. Baseline Summary Statistics for Vacant Lots, by City Section, Philadelphia, Pennsylvania, 1999–2008[a]

	No. of Lots	Total Area, square feet[b]	Median Area, square feet	Median Age of Residents per Square Mile[c], years	Median No. of Unemployed Residents per Square Mile	Median No. of College-Educated Residents per Square Mile	Median Annual Household Income per Square Mile, dollars	Median No. of Black Residents per Square Mile	Median No. of Hispanic Residents per Square Mile	Median No. of Residents in Poverty per Square Mile[d]
All 4 sections of Philadelphia										
Greened vacant lots	4,436	7,800,926.46	1,064.33	36.42	20.14	71.96	18,362.64	491.29	11.53	301.94
Control vacant lots (with open violations)	13,308	46,595,816.22	1,083.17	36.98	20.39	87.57**	20,223.77**	467.85**	12.74**	313.63**
North Philadelphia										
Greened vacant lots	1,195	2,395,545.47	913.28	31.76	11.11	31.58	16,362.53	174.81	220.05	227.26
Control vacant lots (with open violations)	3,585	9,832,913.43	990.14**	32.48**	13.59	54.45**	18,148.74**	202.52**	194.66**	288.60**
Northwest Philadelphia										
Greened vacant lots	1,558	2,820,673.58	1,184.42	37.73	26.36	81.13	18,358.54	629.99	8.16	334.45
Control vacant lots (with open violations)	4,674	15,652,854.65	1,105.74**	37.81**	23.82**	101.93**	18,795.24	626.79**	9.60**	329.22**
South Philadelphia										
Greened vacant lots	517	459,622.20	809.02	37.95	18.61	75.27	20,502.15	482.36	5.74	297.28
Control vacant lots (with open violations)	1,551	6,463,596.04	786.72	38.15**	17.41	122.91**	24,028.23**	428.32**	14.51**	302.92**
West Philadelphia										
Greened vacant lots	1,166	2,125,085.21	1,325.37	36.66	24.55	89.44	19,158.29	613.78	8.73	325.69
Control vacant lots (with open violations)	3,498	14,646,452.10	1,260.94	37.62**	22.99**	106.35**	2,1633.94**	601.89**	7.38**	321.42**

* $P < 0.01$; ** $P < 0.001$.

[a] All variables (except area) are point-based summary measures for lot pregreening periods.

[b] 1 square foot = 0.093 m^2.

[c] 1 square mile = 2.590 km^2.

[d] Number of residents living below 150% of the federal poverty level.

Table 2. Adjusted Difference-in-Difference Estimates of the Impact of Vacant Lot Greening on Point-based Outcomes, by City Section, Philadelphia, Pennsylvania, 1999–2008

Outcome	All 4 Sections of Philadelphia			North Philadelphia			Northwest Philadelphia			South Philadelphia			West Philadelphia		
	β	SE	R^2	β	SE	R^2	β	SE	R^2	β	SE	R^2	β	SE	R^2
Crimes and arrests, no. per square mile[a]															
Assaults	−9.78	1.69**	0.85	−24.67	3.60**	0.81	−1.83	1.98	0.89	10.49	5.20	0.88	−10.02	2.14**	0.79
Gun assaults	−7.90	0.95**	0.74	−13.66	1.93**	0.67	−4.39	1.18**	0.77	0.65	3.65	0.77	−9.02	1.37**	0.64
Robberies	−2.56	1.20	0.84	−4.81	2.63	0.82	1.75	1.47	0.85	−2.56	1.85	0.77	−3.99	2.59	0.82
Gun robberies	−3.38	0.78**	0.71	−4.68	1.56*	0.72	1.12	1.18	0.72	−4.68	1.40**	0.67	−5.44	1.36**	0.69
Narcotics sales and possession	−6.94	7.19	0.76	−26.20	21.57	0.71	9.31	6.55	0.81	20.70	8.25	0.85	−21.49	6.96*	0.74
Burglaries	0.00	1.82	0.68	−8.52	2.83*	0.77	0.37	3.05	0.63	41.62	6.88**	0.62	−9.62	3.02*	0.61
Thefts	−8.10	3.79	0.88	−3.82	9.06	0.81	−9.60	6.75	0.86	−28.63	7.48**	0.93	−1.44	3.21	0.86
Vandalism and criminal mischief	−4.92	1.71*	0.85	−3.09	3.25	0.83	1.41	3.08	0.78	22.09	3.43**	0.84	−23.11	2.99**	0.84
Disorderly conduct	20.39	1.78**	0.56	37.54	5.01**	0.48	7.68	1.54**	0.74	27.89	4.01**	0.78	14.74	1.89**	0.53
Public drunkenness	0.50	0.17*	0.34	0.99	0.29**	0.21	−0.01	0.40	0.30	0.10	0.24	0.62	0.72	0.34	0.31
Illegal dumping	−0.43	0.37	0.52	−3.12	0.66**	0.35	0.18	0.39	0.26	6.65	0.94**	0.60	−0.67	0.75	0.39
Health factors, %															
High stress	−0.02	0.12	0.68	−0.85	0.25**	0.63	0.21	0.21	0.56	0.54	0.30	0.47	0.26	0.20	0.62
High cholesterol	0.76	0.16**	0.70	1.12	0.44*	0.61	0.34	0.19	0.78	1.65	0.26**	0.70	0.57	0.23	0.59
High blood pressure	0.63	0.16**	0.57	1.32	0.44*	0.47	0.04	0.19	0.55	0.80	0.25*	0.63	0.65	0.21*	0.39
Low exercise	0.25	0.12	0.81	0.04	0.30	0.79	0.99	0.16**	0.79	−0.21	0.17	0.86	−0.57	0.14**	0.81
Poor health status	0.36	0.14	0.63	0.15	0.35	0.54	−0.02	0.17	0.68	0.66	0.38	0.69	0.91	0.24**	0.55
Property taxes, average annual dollars per household	−9.34	1.72**	0.97	−6.43	3.24	0.97	−12.76	3.74**	0.98	−24.33	3.03**	0.97	−1.88	2.16	0.97

Abbreviation: SE, standard error.

* $P < 0.01$; **$P < 0.001$.

[a] 1 square mile = 2.590 km^2.

($P < 0.001$). Vandalism and criminal mischief showed consistent, statistically significant reductions across point-based, tract-based, and block group-based calculations only for West Philadelphia ($P < 0.001$). Disorderly conduct showed consistent, statistically significant increases across point-based, tract-based, and block group-based calculations in all 4 sections of the city combined ($P < 0.001$). Illegal dumping showed consistent, statistically significant increases across point-based, tract-based, and block group-based calculations only for South Philadelphia ($P < 0.001$). Other crime outcomes also showed statistically significant changes, although not consistently across point-based, tract-based, and block group-based metrics or sections of the city (Tables 2–4).

Regression-adjusted difference-in-differences estimates for poor health outcomes showed consistent, statistically significant increases across point-based, tract-based, and block group-based calculations only for high cholesterol in all 4 sections of the city combined ($P < 0.001$). High stress showed consistent, statistically significant reductions across point-based, tract-based, and block group-based calculations only for North Philadelphia ($P < 0.01$). Exercising less than 2 days per week showed consistent, statistically significant reductions across point-based, tract-based, and block group-based calculations only for West Philadelphia ($P < 0.01$). Other poor health outcomes also showed statistically significant changes, although not consistently across point-based, tract-based, and block group-based metrics or sections of the city (Tables 2–4).

DISCUSSION

In terms of safety, our analyses showed that vacant lot greening was associated with gun assaults, which were significantly reduced citywide after the greening treatment. Vandalism and criminal mischief were also significantly reduced after the greening treatment in at least 1 section of Philadelphia. In terms of health, vacant lot greening was associated with residents' reporting significantly less stress and more exercise in select sections of Philadelphia.

Current evidence is limited in terms of connecting vacant lots directly with various health and safety outcomes. Prior studies often either have been cross-sectional and/or have bundled vacant lots into other indices of physical disorder without specifically studying them as independent factors. To our knowledge, no prior studies have directly examined the impact of greening for urban vacant lots or used a randomized trial design (58). Our study adds to this body of literature by specifically analyzing vacant lots and using detailed geographic

Table 3. Adjusted Difference-in-Difference Estimates of the Impact of Vacant Lot Greening on Census Tract-based Outcomes, by City Section, Philadelphia, Pennsylvania, 1999–2008

	All 4 Sections of Philadelphia			North Philadelphia			Northwest Philadelphia			South Philadelphia			West Philadelphia		
	β	SE	R^2	β	SE	R^2	β	SE	R^2	β	SE	R^2	β	SE	R^2
Crimes and arrests, no.															
Assaults	−0.41	0.39	0.86	−1.26	0.58	0.86	1.23	0.53	0.90	3.08	1.21	0.86	−2.89	1.01*	0.74
Gun assaults	−1.03	0.23**	0.75	−1.12	0.36*	0.86	0.06	0.27	0.80	1.07	0.82	0.74	−3.15	0.55**	0.57
Robberies	−0.13	0.37	0.83	1.39	0.88	0.84	0.32	0.46	0.84	−0.14	0.35	0.84	−2.22	0.88	0.76
Gun robberies	−0.63	0.21*	0.73	−0.14	0.49	0.73	0.11	0.28	0.75	−0.80	0.27*	0.73	−1.76	0.37**	0.65
Narcotics sales and possession	2.94	2.02	0.75	9.48	6.76	0.72	2.24	1.51	0.80	6.57	1.77**	0.81	−2.33	2.12	0.72
Burglaries	1.25	0.37**	0.75	2.55	0.72**	0.82	−0.57	0.63	0.76	7.16	0.97**	0.68	−1.14	0.62	0.64
Thefts	1.15	0.91	0.84	5.79	1.79*	0.83	1.85	1.78	0.80	−9.84	2.03**	0.91	0.63	1.49	0.84
Vandalism and criminal mischief	−0.33	0.43	0.86	2.43	0.80*	0.89	0.88	0.78	0.84	0.25	1.29	0.84	−3.93	0.73**	0.83
Disorderly conduct	4.05	0.42**	0.56	8.36	1.11**	0.52	1.86	0.39**	0.71	2.97	1.14*	0.71	3.32	0.53**	0.50
Public drunkenness	0.02	0.04	0.34	−0.05	0.06	0.31	−0.10	0.09	0.30	0.03	0.04	0.59	0.32	0.08**	0.37
Illegal dumping	−0.04	0.07	0.47	−0.46	0.15*	0.39	0.12	0.09	0.34	0.85	0.14**	0.52	0.02	0.14	0.50
Health factors, %															
High stress	−0.03	0.22	0.56	−1.20	0.45*	0.47	0.37	0.36	0.37	0.32	0.52	0.33	0.49	0.37	0.67
High cholesterol	1.01	0.16**	0.64	0.91	0.40	0.68	0.77	0.24*	0.77	0.05	0.48	0.75	1.32	0.28**	0.45
High blood pressure	0.65	0.28	0.47	1.43	0.72	0.32	0.10	0.36	0.43	1.11	0.63	0.42	0.53	0.36	0.63
Low exercise	0.23	0.21	0.73	0.49	0.49	0.60	0.80	0.32	0.63	−0.46	0.35	0.74	−0.90	0.27**	0.86
Poor health status	0.52	0.27	0.62	0.52	0.61	0.46	0.34	0.40	0.53	0.65	0.65	0.60	0.95	0.47	0.72
Property taxes, average annual dollars per household	−10.35	6.33	0.67	−19.31	15.99	0.46	−20.35	9.25	0.63	−50.95	6.42**	0.74	14.92	6.86	0.72

Abbreviation: SE, standard error.

* $P < 0.01$; ** $P < 0.001$.

and temporal data that permitted at least some level of causal inference through a quasi-experimental difference-in-differences design.

Prior theories connecting health outcomes and urban green space support some of our findings, although the complexity of the health outcomes we studied makes drawing strong conclusions difficult. The consistent increase in high cholesterol related to the greening of vacant lots in our study is surprising and runs counter to prior work. Our other finding, that greening resulted in residents' reporting significantly less stress and more exercise, is more in line with prior research and theory. Because newly greened vacant lots may serve as safe havens, residents may have felt less stress or may have seen greater outdoor opportunities for exercise in a cleaner, more attractive, and safer environment (59). This may have only occurred in select sections of the city because preexisting cultural or social norms related to residents' experience with green space differed by section. Even though these findings pertaining to stress and exercise were consistently demonstrated for only a few sections of Philadelphia, they have potentially important implications for the future study of urban vacant lot greening as a tool to enhance health.

With respect to safety, both the broken windows and incivilities theories support our findings, and we can speculate that violent crime may have simply been discouraged in the presence of greened and tended vacant lots which signaled that someone in the community cared and was potentially watching over the space in question (60–62). However, the impact of greening may have also been more tangible, especially for gun assaults, where it could be speculated that vacant lots may be a haven, storage ground, or disposal point for illegal guns. Because the penalty of being caught with an illegal gun is high, criminals may hide their guns in abandoned vacant lots (63). The greening and maintenance of vacant lots may have directly intervened in this illegal activity.

Our findings pertaining to disorderly conduct may suggest that acts of disorderly conduct, a catch-all category encompassing various violations and nuisances, increased after the greening of vacant lots. A greened lot may serve as a new opportunity for community gatherings that, in bringing large groups of people together, increase the opportunity for crowd-based nuisance crimes such as disorderly conduct. Alternatively, community interest in maintaining a newly greened lot may have increased calls to police and arrests for disorderly conduct.

Study limitations

A more rigorous matching protocol might have improved our analysis and better accounted for residual confounding. We considered synthetic control methods that search for

Table 4. Adjusted Difference-in-Difference Estimates of the Impact of Vacant Lot Greening on Block Group-based Outcomes, by City Section, Philadelphia, Pennsylvania, 1999–2008

	All 4 Sections of Philadelphia			North Philadelphia			Northwest Philadelphia			South Philadelphia			West Philadelphia		
	β	SE	R^2	β	SE	R^2	β	SE	R^2	β	SE	R^2	β	SE	R^2
Crimes and arrests, no.															
Assaults	−0.52	0.15**	0.65	−0.95	0.37*	0.60	−0.14	0.24	0.70	0.18	0.27	0.62	−0.58	0.20*	0.49
Gun assaults	−0.38	0.08**	0.49	−0.46	0.18	0.41	−0.14	0.10	0.56	−0.38	0.16	0.42	−0.49	0.15**	0.31
Robberies	0.12	0.12	0.66	−0.46	0.18	0.71	0.22	0.21	0.65	0.56	0.18*	0.64	−0.09	0.22	0.54
Gun robberies	−0.09	0.08	0.50	−0.26	0.13	0.52	0.22	0.14	0.53	0.26	0.12	0.40	−0.26	0.16	0.38
Narcotics sales and possession	−1.55	0.81	0.63	−4.49	2.49	0.61	0.94	0.40	0.63	−0.59	0.74	0.60	-0.65	0.56	0.52
Burglaries	0.24	0.12	0.51	0.40	0.22	0.57	−0.13	0.19	0.50	1.10	0.30**	0.48	0.17	0.23	0.43
Thefts	0.10	0.24	0.70	0.41	0.40	0.75	0.24	0.51	0.70	0.40	0.57	0.82	−0.17	0.47	0.55
Vandalism and criminal mischief	−0.39	0.13*	0.68	−0.28	0.24	0.66	−0.50	0.23	0.70	1.65	0.30**	0.74	−1.03	0.26**	0.58
Disorderly conduct	0.66	0.10**	0.44	1.08	0.28**	0.39	0.33	0.15	0.47	1.43	0.18**	0.64	0.50	0.14**	0.29
Public drunkenness	0.01	0.01	0.24	0.02	0.01	0.18	0.02	0.04	0.21	−0.01	0.02	0.45	0.00	0.01	0.16
Illegal dumping	0.00	0.03	0.22	−0.06	0.05	0.20	0.02	0.03	0.16	0.22	0.06**	0.21	−0.06	0.08	0.25
Health factors, %															
High stress	-0.03	0.21	0.55	−1.31	0.45*	0.46	0.39	0.37	0.36	0.21	0.54	0.31	0.65	0.38	0.65
High cholesterol	0.91	0.17**	0.62	0.79	0.42	0.64	0.75	0.23*	0.75	−0.26	0.48	0.66	1.53	0.26**	0.43
High blood pressure	0.67	0.28	0.38	1.57	0.71	0.27	0.07	0.36	0.33	1.11	0.63	0.40	0.43	0.37	0.29
Low exercise	0.24	0.21	0.73	0.45	0.49	0.60	0.90	0.32*	0.62	−0.32	0.35	0.73	−0.93	0.28*	0.85
Poor health status	0.51	0.27	0.59	0.42	0.61	0.38	0.40	0.42	0.47	0.60	0.66	0.56	0.78	0.49	0.56
Property taxes, average annual dollars per household	−6.68	7.48	0.59	−4.26	18.42	0.38	−13.76	12.06	0.47	−49.01	12.30**	0.56	22.11	10.93	0.56

Abbreviation: SE, standard error.
* $P < 0.01$; ** $P < 0.001$.

weighted combinations of control units in order to approximate treated units in terms of outcome predictors (64, 65). These methods, however, are currently designed to accommodate only a single treated unit, and our study had 4,436 treated units. As an alternative to these methods, we augmented our analyses with a 2-stage Cox regression weighted modeling approach. This approach produced no substantive changes in our conclusions. Incomplete matching remains a limitation but one that has less-than-straightforward implications for efficiency (66) and may be best handled through the random assignment of greening treatment in future studies.

Analyses in which subjects or measurements are nested within administrative geographic units (e.g., tracts or block groups) can generate challenges, including the overestimation of effects. Oftentimes, the polygons of these administrative geographic units have been determined for purposes other than the relations under study and may be awkwardly shaped, poorly correspond to lived space, have edge effects, or impose an inappropriate neighborhood scale. Point-based measures, however, are continuous and boundary-free, assign each lot to its own unique neighborhood, and avoid aggregation effects while directly accounting for spillover and the variability of neighboring areas (67–71). Moreover, the point-based measures used here produced, on average, the best model fits. We nonetheless reported findings using point and polygon geographic measures to distinguish the most important models from a large field of choices and because different metrics may be more or less valuable to different audiences.

Although aspects of the household health survey we used were advantageous (e.g., respondents were typically nontransient, long-term residents), the survey was only conducted biennially, had a low response rate, and was not originally designed for small-area analyses, and its data were based on self-report. Although we accommodated these shortcomings, our findings pertaining to health outcomes are best considered suggestive, a signpost for future studies, including randomized trials.

A spillover effect from treated lots to nearby control lots was a potential limitation but one that, if anything, tended to equalize outcomes between groups (72). On average, treated and control lots were separated by a considerable distance, and the addition of a covariate measuring this distance made only negligible changes in our findings. As a related issue, if a vacant lot was greened in one location, the crime it was thought to eliminate may have only been displaced to another, nearby location. Although this has been shown to be of limited concern (73), concentrating only on findings that were consistently significant for point-based, tract-based, and block group-based metrics reduced this limitation.

Our knowledge of how exactly the greening of vacant lots works to change health and safety remains limited. In future studies, investigators should consider mixed methods employing ethnographic techniques to observe the micro-social changes produced by vacant lot greening. Finally, some community residents object to vacant lot greening based on perceptions that it increases property taxes, although we did not find evidence of this.

Conclusion

Philadelphia, like many US cities, has an abundance of abandoned vacant lots. Our findings suggest that greening of these vacant lots may reduce certain crimes and promote some aspects of health. Although our study represents a significant step forward, we could not fully examine the causal effects of greening vacant lots on health and safety. Future studies of vacant lot greening should consider randomized experiments. In time, a sufficient mix of observational, quasi-experimental, and experimental studies will yield the best guidance for policy-makers interested in this promising strategy (74, 75).

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