Published in final edited form as:
Urban Stud. 2016 November ; 53(15): 3279–3295. doi:10.1177/0042098015608058.

Effects of greening and community reuse of vacant lots on crime

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Abstract

The Youngstown Neighborhood Development Corporation initiated a 'Lots of Green' programme to reuse vacant land in 2010. We performed a difference-in-differences analysis of the effects of this programme on crime in and around newly treated lots, in comparison to crimes in and around randomly selected and matched, untreated vacant lot controls. The effects of two types of vacant lot treatments on crime were tested: a cleaning and greening 'stabilisation' treatment and a 'community reuse' treatment mostly involving community gardens. The combined effects of both types of vacant lot treatments were also tested. After adjustment for various sociodemographic factors, linear and Poisson regression models demonstrated statistically significant reductions in all crime classes for at least one lot treatment type. Regression models adjusted for spatial autocorrelation found the most consistent significant reductions in burglaries around stabilisation lots, and in assaults around community reuse lots. Spill-over crime reduction effects were found in contiguous areas around newly treated lots. Significant increases in motor vehicle thefts around both types of lots were also found after they had been greened. Community-initiated vacant lot greening may have a greater impact on reducing more serious, violent crimes.

Keywords

community gardens; crime; difference-in-differences; greening; urban health

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A legacy of suburban out-migration, economic restructuring, and housing foreclosure crises have had a major negative impact on the physical and social structures of many urban areas (Beauregard, 2009; Mallach and Brachman, 2013; Mallach et al., 2010). However, to date, scientific analyses of dilapidated buildings and vacant land have almost exclusively focused on large US legacy cities (Branas et al., 2011; Kondo et al., 2015a), leaving in question the

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impact of these structures on mid-sized legacy cities. As a mid-sized legacy city with almost onethird of its properties listed as vacant (Mahoning Valley Organizing Collaborative, 2010), Youngstown, Ohio represented an excellent opportunity for study.

Vacant buildings and lots come with significant economic costs – remediation, demolition, reduced values to surrounding properties, and reduced tax revenues for municipalities that might otherwise apply such revenues to social and welfare programmes for their citizens (Accordino and Johnson, 2000; Han, 2014). There is growing evidence that the presence of vacant buildings and lots also have negative impacts on community health and safety (Chaix, 2009; Cohen et al., 2003; Hannon and Cuddy, 2006; Spelman, 1993; Wei et al., 2005).

In the absence of meaningful federal and state support, legacy cities have been forced to initiate new, but unproven, programmes to abate physical signs of disorder in an attempt to revitalise their neighbourhoods, reduce expenses, generate tax revenues, and potentially improve public safety (Accordino and Johnson, 2000; Cohen, 2001; Katz and Bradley, 2013; Teixeira and Wallace, 2013). These programmes are often enabled by the development of a variety of policy and administrative tools and entities, such as vacant-lot nuisance ordinances, buy-back or take-over programmes, and land banks.

Many cities are incorporating vegetation and natural features into vacant-lot remediation. Typical remediation strategies include ‘cleaning and greening’ of lots, or transformation into community gardens, stormwater management sites, or green stormwater infrastructure. Urban municipalities are hopeful that greening vacant lots will reduce crime and provide other co-benefits, including environmental, and some evidence is suggesting that this may be true (Kondo et al., 2015b, 2015c). However, there remain opportunities for further rigorous evaluation of vacant lot reuse programmes particularly on social outcomes.

This paper describes the first quasiexperimental study using a spatial panel data model that considers the impact of community involvement in vacant lot greening on crime. The City of Youngstown, in partnership with the Youngstown Neighborhood Development Corporation (YNDC) initiated a ‘Lots of Green’ (LOG) programme to repurpose and reuse vacant land in 2010. The LOG programme included a cleaning and greening ‘stabilisation’ treatment conducted by YNDC, and a ‘community reuse’ treatment that was initiated and maintained by community groups (and mostly involved community gardens). We used a difference-indifferences analytical approach to test whether the YNDC’s LOG programme had an effect on safety in Youngstown over a 25-monthperiod starting in 2010, after accounting for several key sociodemographic factors. We defined safety in terms of various crimes and tested for the effects of treated lots on crime among all vacant lots as well as separately among the stabilisation and community reuse treatment schemes. Also, given the concern that the programme could displace crime to other places, we expanded the spatial analysis to trace the geographic dynamics of the effect.

Literature review

There is evidence that vacant lots play a role in the health and safety of nearby residents. These lots are often sites of illegal dumping for materials such as construction debris, chemicals, tyres, furniture, and abandoned vehicles (Beauregard, 2013). Vacant lots are associated with fear of crime (Garvin et al., 2013; Hur and Nasar, 2014) and crime itself. For example, recent research has demonstrated a significant link between the presence of neighbourhood vacant properties and an increased risk of neighbourhood assaults (Branas et al., 2012; Garvin et al., 2012). Studies have also found associations between presence of vacant properties and physical health outcomes including rates of premature mortality (Cohen et al., 2003), drug-dependence mortality (Hannon and Cuddy, 2006), cardiovascular disease (Augustin et al., 2008; Chaix, 2009; Diez Roux et al., 2001), teen births (Wei et al., 2005), and sexually-transmitted disease (Cohen et al., 2000). Vacant properties also increase the risk of fire (Schachterle et al., 2012).

Some vacant lot remediation programmes have already shown promising results in terms of affecting crime (Kondo et al., 2015c). Greening has also been associated with an enhanced sense of safety and feelings of security (Garvin et al., 2012). Residents living near greened vacant land perceive it to be significantly safer than do people living close to untreated, often unkempt, vacant urban land (Garvin et al., 2012).

In addition, existing theory from the field of environmental criminology, known as crime opportunity theory (Wilcox et al., 2003), supports this positive association. Crime opportunity theory argues that crimes primarily occur when appropriate opportunities are present for motivated individuals. Manipulating the elements of crime opportunity in urban environments is a strategic and perhaps sustainable and cost-effective way to prevent crime (Clarke, 1980). The elements of opportunity in the occurrence of crime include a 'motivated offender' who encounters a 'suitable target' in the absence of 'capable guardians' (Cohen and Felson, 1979). Even in the presence of motivated offenders, greening an area could change routine activities of those who live in and around the area, thereby influencing the supply of suitable targets and capable guardians. For example, people may walk, run or bike in and around a vacant lot because they are experiencing less fear after it is greened, which increases the supply of potential witnesses and guardians of the spaces in question. Offenders may want to avoid a newly greened area because it is no longer a place in which they feel comfortable committing crimes without detection (Brantingham and Brantingham, 1993).

Broken windows theory provides another rationale for how greening may reduce crime. Wilson and Kelling (1982) argue that repairing broken windows and other signs of disrepair, like abandoned vacant lots, can reduce not only social disorder and public incivility but also serious crime because the former leads to the latter. Despite this, there are a limited number of field trials that support this relationship (Keizer et al., 2008). Though it is now common practice to target minor offences in order to ultimately reduce major crimes, broken windows policing draws criticism for its disproportionate harm to poor and communities of colour and its lack of sufficient empirical evidence (Harcourt and Ludwig, 2006). This suggests that there is more work to be done to better support this theory's translation into policy, and the study of actual changes to neighbourhood environments (i.e. seeing what happens after 'broken windows' are repaired), like vacant-lot greening, is a key way to accomplish this.

However, with few exceptions, most studies addressing the relationship between green space and crime have been cross-sectional, and provide limited evidence of before–after causal effects (Lee and Maheswaran, 2011). One exception, a quasi-experimental study in Philadelphia, found that greening remediation of vacant lots was associated with reduced gun assaults and vandalism, as well as improved health indicators such as less stress and more exercise (Branas et al., 2011). This study has yet to be replicated in another urban area and reflects the experience of a large US city; it is unclear whether its findings are fully applicable to medium-sized legacy cities which are much larger in number across the US and have somewhat different urban challenges.

Study context

Youngstown, Ohio like other legacy cities in the United States is dealing with effects from historical deindustrialisation, economic restructuring and suburbanisation. Around 1930 the city grew to accommodate a population of over 170,000. Since that time the city's population has been in constant decline. Youngstown's population has decreased by an average of 17% in each of the last five decades, and 65,405 residents remained in 2010 (US Census Bureau, 2010). It has been projected that without intervention, the city's population could continue to fall to 54,000 by 2030 (City of Youngstown, 2005).

A large proportion of the homes and infrastructure built to support the population of 170,000 is now vacant. A 2010 Vacant Property Survey conducted by the Mahoning Valley Organizing Collaborative found that 23,831 of 62,569 parcels were vacant. These parcels accounted for over 5600 acres or over 31% of the city's land area, which is two times the average reported for a sample of US cities with population over 100,000 (Pagano and Bowman, 2000). In addition, 3246 parcels contained vacant structures, a rate nearly 20 times the average found by Pagano and Bowman (2000). Nearly 1500 structures were in foreclosure at the time, which suggests that there was potential for an increase in the vacancy in the near future.

While early efforts to stabilise shrinking cities solely emphasised economic growth, cities such as Youngstown are now also taking 'right sizing' approaches (Rybczynski and Linneman, 1999), recognising the incongruence between existing social and market demands and city plans (Rhodes and Russo, 2013). Youngstown began a collaborative citywide effort in 2000 to develop a new comprehensive plan (called Youngstown 2010) that envisions a 'smaller, greener, cleaner' city (City of Youngstown, 2005: 8).

Part of the Youngstown 2010 strategy is adaptive mitigation or reuse of vacant land. LOG, managed by YNDC, is a vacant land reuse programme that emerged as part of this strategy. YNDC initiated LOG version 1.0 in 2010 in two target areas (Idora and East Side neighbourhoods; see Figure 1). In these areas, YNDC identifies vacant lots that are strategic for reuse, indicating for example that the lot is located in a blighted area, a prominent or visible area such as a neighbourhood entrance or an intersection, and the lot has property owners that do not object to the reuse. With funding from community block grants, YNDC applies the same basic 'stabilisation treatment' to selected lots. This treatment involves: (a) removal of debris, hazardous trees, foundations or driveways; (b) addition of topsoil and grading; (c) grass seeding and planting of two trees; (d) addition of a permeable split-rail fence around the lot perimeter to prevent future driving or dumping on the lot; and (e) lot maintenance, which includes mowing approximately every two weeks during spring and fall. At the time of this study, YNDC had applied basic treatment to 166 vacant lots.

YNDC also initiated LOG version 2.0, an application-based lot reuse programme, in 2011 (‘community reuse treatment’). Under LOG 2.0, Youngstown residents, groups or organisations apply for support and funding to reuse a vacant lot (primarily outside of Idora and East Side; see Figure 1). YNDC awards financial support with community block-grant funding to applicants that show a strong community need and benefit from reuse. Applicants determine the type of reuse. To date most are community gardens, urban farms or orchards (47), in addition to native plantings (17), athletic fields (5), or putting greens (8). This study included a total of 77 lots that received LOG 2.0 treatment. Under LOG 2.0 the applicant is responsible for maintaining the reused lot.

Methods

We conducted a difference-in-differences analysis to assess the impact of the LOG land reuse programme on crime outcomes in Youngstown, Ohio over a four-year time period. The difference-in-differences approach can model treatment effect by estimating the difference between outcome measures at two (or more) time points for both the treated and control locations (those not implementing or participating in the policy or programme) and then comparing the differences in outcomes between treated and control groups. Using this strategy helps to ensure that any unobserved variables that remain constant over time, and that are correlated with the selection decision and the outcome variable, will not bias the estimated coefficients (Branas et al., 2011; Buckley and Shang, 2003).

Study design

We considered all 244 LOG reused vacant lots as the treatment group and conducted analysis on total lots, and LOG 1.0 and LOG 2.0 lots separately. A separate set of vacant lots (with no structures) eligible to serve as controls (‘LOG-eligible’) were those that had not been greened but could have been during the same time period (N = 959). Demolitions had to have occurred prior to July 2010 for vacant lots to be considered LOG-eligible. We used 2008 and 2010 vacancy-survey data, collected by the city, to verify vacancy status for all control lots.

We then used a caliper matching method with a 4 to 1 ratio to randomly select and match untreated control lots to treated lots. We matched lots located in the same city section: North (48 treatment and 191 control sites), South (188 treatment and 736 control sites), and West (8 treatment and 32 control sites), in order to control for potential differential development patterns. We used the following criteria to match treated with control lots: (a) lot size within +/−500 square feet; and (b) surrounding median household income within +/−$5000 USD. We also manually removed and replaced any control lot within 1/4-mile of its matched treatment lot to avoid contamination of effect. The maximum distance between a matched treatment and control site was 7.6 miles. While matching using other sociodemographic indicators would improve the similarity of treatment and control groups, we found that including more indicators reduced the number of available treatment or control sample sizes in a way that would reduce model robustness. After matching, our analysis included 244 treatment lots and 959 control lots (see Figure 1).

Lot-greening completion occurred between July 2010 and August 2013. Within each group of randomly-matched lots (N = 244), we assigned the treatment date from the treatment lot to the control lots. The study period is January 2010 to February of 2014, in two-month time intervals for a total of 25 two-month time periods. The minimum pre-period and postperiod was six months, with an average pre-and post-period of 22 months.

Data

The City of Youngstown and the Center for Urban and Regional Studies at Youngstown State University provided LOG-eligible parcel data. They also provided 2008 and 2010 vacancy-survey data.

Youngstown Police Department provided crime incident data (with date, location and class) from January 2010 to February 2014. The Center for Urban and Regional Studies at Youngstown State University georeferenced these data. We aggregated the eight available crime classes into five classes: (1) felony assault (including homicides and aggravated assaults); (2) burglary; (3) robbery; (4) theft; and (5) motor vehicle theft. We used a kernel density method to estimate the density of crimes at every location. Crime locations were translated to a raster-grid format, where cells were 100 × 100 feet in size, and cell values represented density of crimes per square mile. Therefore, the dependent variable represented counts, but was continuous. The number of zero values were 1326 (felony assault), 71 (burglary), 2862 (robbery), 47 (theft), and 820 (motor vehicle theft).

We obtained demographic variables from the US Census, American Community Survey (ACS) 2006–2010 and 2009–2013 at the tract level. We gathered estimates of population density, income, residential stability, and unemployment, and interpolated values between ACS data points. Population density represented the number of persons per acre, income represented annual median household income, residential stability represented percentage of the population living in the same residence as 1-year ago, and unemployment signified percentage of the population over the age of 16 in the labour force not working.

Statistical analyses

We performed all analyses using Stata 13.1 (StataCorp LP, College Station, TX) and ArcMap 10.2 (ESRI Inc., Redlands, CA) software. We first conducted descriptive statistics using cross-tabulations and tests for normality. We tested for differences in means using a Wilcoxian rank-sum method. We then used three separate mixed models to test for the effects of vacant-land greening on crime: (1) random-effects generalised least square regression models (‘Model 1’, or ‘GLS’); (2) population-averaged Poisson regression models (‘Model 2’, or ‘Poisson’); and (3) random-effects spatial Durbin regression models (‘Model 3’, or ‘spatial model’).

First, we estimated random-effects generalised least square regression models with heteroscedacity-robust standard errors. We used a log transformation to address a severe right-skewness of the crime outcome data. Within each crime class, we assigned minimum values to any zero-crime observations to avoid missing crime counts when logged. Each regression model (see Equation 1) included a crime outcome Y_{it} (where observation (i) = 1,2,3,…,N and time (t) = 1,2,3,…,25); a pre-post construction term $\beta_1 P_{it}$; a treatment-control term $\beta_2 R_{it}$; a difference-in-differences term $\beta_3(R_{it} \times R_{it})$ which is the main variable of interest and thus β_3 is the estimate reported in the results section; a pre-period mean outcome term to adjust for regression to the mean, $\beta_4 M_i$; a series of four independent demographic covariates, $\beta_k X_{kit}$ (where k = 5,6,7,8; population density, income, residential stability, and unemployment at the tract level); and an error term u_{it} that consists of a random individual-specific effect α_i and an idiosyncratic error term ε_{it}.[1]

$$Y_{\mathrm{it}} = \beta + \beta_1 p_{\mathrm{it}} + \beta_2 R_{\mathrm{it}} + \beta_3 (\mathrm{P}_{\mathrm{it}} \times R_{\mathrm{it}}) + \beta_4 M_i + \sum_k \beta_k X_{\mathrm{kit}} + u_{\mathrm{it}} (= \alpha_i + \varepsilon_{\mathrm{it}}) \quad (1)$$

Second, because crime incidents represent count data, we ran population-averaged Poisson regression models. In these models, we assumed that crime incidents were nonlinearly and exponentially associated with covariates including the treatment. The coefficients were estimated by the maximum likelihood method. To address the risk of overdispersion in a Poisson model, it is essential to use the robust standard error (Cameron and Trivedi, 2009; Gould, 2011). Due to the lack of Stata code embracing both random effects and robust standard errors for a Poisson model, we applied a population-average estimation, which frequently performs similarly to a random-effects estimator (Cameron and Trivedi, 2009). While a negative binomial distribution is considered appropriate for the over-dispersion of crime, model results from negative binomial models were nearly identical to Poisson models with robust standard error and therefore we only include results from Poisson models in this paper. Incidence rate ratio (IRR) is reported, instead of regression coefficients, to reflect relative difference.

Our third model addressed the issue of spatial autocorrelation, or the fact that crime incidents in one area may be strongly associated with those occurring in surrounding neighbourhood areas. After testing for the presence of spatial autocorrelation of residuals in OLS models using Global Moran's I, we found that outcome incidents are not randomly distributed ($P < 0.001$), but were clustered ($I > 0$).

Therefore, our third model was a spatial regression model (called 'spatial Durbin model (SDM)') that included a spatially-lagged dependent variable and spatially-lagged all explanatory variables as covariates, having a matrix form of $Y = \rho WY + X'\beta + WX\theta + u$ (where ρ was the spatial autoregressive coefficient and θ was a $K * 1$ vector of fixed but unknown parameters). This SDM has strength as a reference spatial model (Elhorst and Zigova, 2014; LeSage and Pace, 2009). As a nesting model, SDM can be simplified to a spatial autoregressive model (SAR, that has a spatially-lagged dependent variable only) when $\theta = 0$, and to a spatial error model (SEM, that has a spatially-lagged error term as $u =$

[1]We considered time fixed effects in the model, but ultimately removed them because the results were not different without them.

$Wu + \varepsilon$) when $\theta = -\rho\beta$. We then investigated whether our SDM could be simplified to SAR or SEM by testing the null hypotheses $H_0 : \theta = 0$ and $H_0 : \theta = -\rho\beta$.

We considered seven types of spatial weight matrices (W) to describe the spatial relationship between crime incidents. The first spatial weights matrix used inverse distances between the treatment and control group units, which assumed that every unit influenced the others regardless of distance, and that closer proximity indicated greater influence. The second and third spatial weight matrices were based on inverse distances but with a cut-off of 1/8 and 1/4 miles, where two observations further apart than these distances were assumed to have no spatial relationship and thus assigned a zero value in the matrix. However, we also assigned one to the nearest neighbour of a unit if the unit did not have any neighbour under the cut-off threshold, to assure every unit had at least one spatial neighbour. We chose these distances because they are commonly used as the sphere of influence within restrictive zoning ordinances such as drug-free zones around schools (The Sentencing Project, 2015). The fourth, fifth and sixth spatial weight matrices were based on 2-, 4-and 6-mile cut-off thresholds, respectively. We chose these three cut-off thresholds based on semivariogram results that depicted the spatial autocorrelation among the lots. The semivariograms across our 25 time waves in general had three peaks at these three distances, suggesting that there might be possible spatial interactions at these distances. We also assigned one to the nearest neighbour of a unit if the unit did not have any neighbour under those three cut-offs. Finally, the seventh spatial weights matrix was based on whether units were located in the same census tract (= 1) or not (= 0). Unlike the others, this matrix was constructed as a contiguity (0/1) matrix. Finally, the seventh spatial weights matrix was based on whether units were located in the same census tract (= 1) or not (= 0). Unlike the others, this matrix was constructed as a contiguity (0/1) matrix.

In the spatial models, estimating marginal treatment effects on crime from β coefficients may be misleading because β coefficients represent only the association between the treatment (X) and the crime outcome net of spatial correlation ($(I_n - \rho W)Y$). One approach that addresses appropriate marginal effect forms in a spatial regression is to interpret partial derivatives of the impact as ‘direct’ and ‘indirect’ effects (LeSage and Pace, 2009). We applied the SDM form of $Y = \rho WY + X'\beta + WX\theta + u$. With the form re-written as $Y = (I_n - \rho W)^{-1}(X'\beta + WX\theta) + (I_n - \rho W)^{-1}u$, the partial derivatives of Y_i with respect to X_{ik} for a particular region (observation) i is denoted in the matrix shown in Equation 2 (Elhorst, 2014; LeSage and Pace, 2009).

$$\left[\frac{\delta Y}{\delta X_{1k}} \cdots \frac{\delta Y}{\delta X_{Nk}}\right] = \begin{pmatrix} \frac{\delta Y_1}{\delta X_{1k}} & \cdots & \frac{\delta Y_1}{\delta X_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\delta Y_N}{\delta X_{1k}} & \cdots & \frac{\delta Y_N}{\delta X_{Nk}} \end{pmatrix} = (I_n - \rho W)^{-1} \cdot \begin{bmatrix} \beta_k & \cdots & W_{1N}\theta_k \\ \vdots & \beta_k & \vdots \\ W_{N1}\theta_k & \cdots & \beta_k \end{bmatrix} \quad (2)$$

(2)

In this N by N matrix, the diagonal and off-diagonal components provide the bases by which direct and indirect effects are calculated. When ρ and θ_k are zeros, which means there is no spatial correlation, the right-hand side matrix has diagonal components of β_k s and off-diagonal components of zeros. The matrix corresponds to a nonspatial regression result. However, when ρ is not zero, the diagonal components are not β_k s and the off-diagonal components are no longer zeros. Also, when θ_k is not zero the off-diagonal components are no longer zeros even when ρ is not zero. For the right-hand side matrix, the *direct* effect is defined as the average of the diagonal components, and the *indirect* effect is the average of the column or row sums of the off-diagonal components. The direct effect indicates the impact that a treatment occurring in a particular region (observation) has on its own region. The direct effect is not equal to β, but instead includes a feedback effect which measures impacts that pass through neighbourhood regions and turn back to the original regions of treatment (Elhorst, 2014). The indirect effect indicates the impact that a particular region treatment has on regions except for its own. The indirect effect can also be viewed as a geographic spill-over effect, which is one of the main interests in spatial analyses.

Results

Table 1 shows the baseline characteristics of the treatment and control lots across the whole city and within each of the three designated sections. Greened vacant lots (N = 244) accounted for over 32 acres of land in the city. Control lots (N = 976) covered over 130 acres of land. The average size of treatment and control lots was 5700 square feet and 5900 square feet, respectively. Statistical comparison of demographic indicators showed that control lots in at least one geographic area had statistically lower median income, residential stability, or percentage unemployed. However, our regression models control for differences in these demographic indicators.

In addition, we calculated unadjusted estimates of differences in mean crime outcomes before and after treatment at control versus treatment lots. Difference-in-differences estimates, unadjusted for demographic confounders, lot size, or geographic relationships, are shown in bold in Table 2 for each type of crime. While regression adjusted difference-in-differences estimates may show a different magnitude and significance of effect, unadjusted estimates do suggest strong reductions in crimes.

We report results from three regression models. Model 1 (‘GLS’) represents randomeffects generalised least square regression models, and Model 2 (‘Poisson’) represents population-averaged Poisson regression models. The Wald and the likelihood ratio (LR) test results led to the conclusion that our SDM could not be simplified to a spatial autoregressive model (SAR) or an SEM, because both null hypotheses of $H_0 : \theta = 0$ and $H_0 : \theta = -\rho\beta$ were consistently rejected across all types of crime outcomes. Therefore, we use SDM as Model 3 that accounts for spatial autocorrelations of crime occurrences between lots. Also, for the spatial weights matrix selection, we report results from the models with the 1/8- and 1/4-mile cut-off inverse distance spatial weight matrices because these spatial weight matrices had the lowest AIC and BIC scores compared to other spatial weight matrices (see Table 3).

Table 4 reports difference-in-differences (DD) coefficient estimates from each model, run on all treatment lots (both LOG 1.0 stabilisation and LOG 2.0 community reuse treatment). Column 1 reports the Model 1 GLS regression DD estimates. Model results show statistically significant ($P < 0.001$) reductions in all crime outcomes at greened lots in comparison to untreated lots. With the outcome variable logged, these β estimates can be interpreted as percentage changes at greened lots after treatment: 85% reduction in felony assaults, 24% reduction in burglaries, 69% reduction in robberies, and 7% reduction in thefts, and 53% increase in motor vehicle thefts holding all other values constant.

Column 2 reports Poisson regression IRRs. Like the GLS regression results, all of the Poisson model results were statistically significant ($P < 0.01$) and negative (except for no effect on felony assaults), which suggests that greening vacant lots may be related with reductions of nearly all types of crime incidents that are considered in this study.

However, the GLS and Poisson regression models were not adjusted for spatial autocorrelation present in the data. Estimates from the spatial regression analysis using the SDM (Columns 3 to 6) contrast with the two previous models in terms of significance and magnitude of effect. Models using both the 1/8- and 1/4-mile distance thresholds show fewer and less statistically significant reductions in crimes. For each distance threshold, direct and indirect effects are presented. At the 1/8-mile distance threshold, felony assaults and burglaries have statistically significant and negative direct and indirect effects. This means that greening vacant lots is associated with reduced crime not only at the treatment locations but also in the neighbouring observation locations that were located within a 1/8-mile radius of the treatment locations. There were no statistically significant indirect effects associated with robberies. In addition, these models showed statistically significant positive association with motor vehicle theft (direct and indirect). At the 1/4-mile distance threshold, only burglaries and robberies showed statistically significant negative direct effects. Felony assaults and burglaries had significant negative indirect effects. Again, these models showed statistically significant positive association with motor vehicle thefts (direct and indirect).

Sub-population analysis results for the stabilisation treatment lots are shown in Table 5. Traditional stabilisation treatment resulted in statistically significant reductions according to GLS and Poisson models in felony assaults, burglaries, robberies, and thefts ($P < 0.01$). The GLS model again showed a significant increase in motor vehicle thefts. The SDMs, adjusted for spatial autocorrelation at the 1/8- and 1/4-mile thresholds, found the most statistically significant reductions in burglaries in nearby and neighbouring regions ($P < 0.01$). Assaults, robberies, and thefts were also significantly reduced in nearby areas ($P < 0.05$). SDM at the 1/8-mile distance threshold also found a significant indirect increase in motor vehicle thefts.

Table 6 shows that all models found more crime effects for the LOG 2.0 community reuse treatment compared to the stabilisation treatment. Community reuse treatment resulted in statistically significant reductions according to GLS models in felony assaults and burglaries ($P < 0.01$). Poisson models found statistically significant reductions in burglaries ($P < 0.001$). The largest significant magnitude of change was seen with felony assaults according to GLS models, and with burglaries according to Poisson models. SDM at the 1/8-mile threshold found felony assaults were statistically significantly reduced at both treatment locations and their neighbouring regions. Direct negative effect was seen with robberies. At the 1/4-mile threshold, felony assaults were statistically significantly reduced at treatment locations. At both distance thresholds, motor vehicle thefts had statistically significant and positive direct and indirect effects.

Discussion

Cities are embarking on innovative, and as yet unproven, programmes to stabilise neighbourhoods and reduce blight and associated crime. Youngstown, OH approached vacant lot reuse using a spatially-targeted approach; concentrating efforts in two neighbourhoods in hopes of maximising potential for stabilisation in those areas. Non-spatial regression models in our DD analyses found significant and widespread reductions in all types of crime outcomes except motor vehicle thefts. Spatial models also found similar crime reductions, except that motor vehicle thefts and theft were not significantly reduced. Overall, based on spatial and non-spatial model results, the vacant-lot greening programme resulted in statistically significant reductions in felony assaults, burglaries, and robberies. The lot stabilisation treatment was associated most consistently and significantly with reduction in burglaries, while the community reuse treatment showed more consistent and significant reduction in violent crimes.

Comparisons of results from three regression models – the GLS, Poisson and SDMs – indicate that non-spatial linear regression results may be subject to bias because coefficients are different in magnitude and significance than spatial regression results. Also, it is worth noting that the indirect effects are consistently negative (except for motor vehicle thefts), implying that neighbouring regions are not experiencing increases in crime after treatment, but rather are seeing decreases in crime. One limitation to this approach is that indirect effects do not necessarily indicate displacement of crimes to exact spatial definitions (such as 1/2- or 1-mile displacement), but instead indicate a difference between effects at the exact treatment site versus neighbouring areas. Nevertheless, these indirect effect measures find no evidence that a displacement of crimes had occurred but, rather, that there may have been a beneficial spill-over (diffusion) effect in crime reduction.

We also found a significant increase in motor vehicle thefts at treatment lots compared to at control lots. One possible explanation for this is that residents felt more comfortable parking cars near lots after the lots were greened, thus creating a larger supply of targets. Another possibility is that newly greened lots may have changed the economic structure of the surrounding neighbourhood such that more residents were suddenly able to afford personal automobiles, although this explanation is less likely given the short timeframe of the overall study.

According to multiple regression model results, vacant-lot greening was associated most significantly with reductions in burglaries. One possible explanation for this finding is that greening vacant lots may influence certain types of crime, and specifically crimes that involve advanced planning compared to other types of crimes. Greening vacant lots may lead to significant modification of crime plans by changing cognitive maps of crime environments and distorting the 'awareness space' that would-be criminals may form (Brantingham and Brantingham, 1993), leading to a reduction in crime opportunities.

Certain limitations in our study are worth mentioning. The non-random assignment of treatment and control units in a quasiexperimental study like this poses a potential limitation. However, in the absence of actual random assignment, we handled this limitation through statistical adjustment. While our models controlled for background socioeconomic conditions at each site that might relate to the treatment itself and influence crime levels, an additional limitation was that our models did not take into account other potential external influences on crime occurrences, such as geographical variation in policing practices that may have changed over time. It is possible that within each city section compliance with the ordinance may change policing patterns, so the effects we observed may be due to a shift in policing and not the change in vacant lots. Despite this, the DD approach we employed was able to adequately isolate and detect the effects of the intervention on crime at treatment sites compared to control sites (Meyer, 1995).

The findings here provide further evidence that greening of vacant lots can reduce violent crimes (Branas et al., 2011; Garvin et al., 2012), although they are novel in that what was only known to be an effect for major cities may now also potentially be applicable to medium-sized cities. The Youngstown LOG programme, and especially the community reuse programme, was associated with significant reductions in felony assaults (including aggravated assaults and homicides) in regression models that accounted for spatial clustering of the greened lots. While previous studies found this type of effect with a traditional 'clean and green' stabilisation treatment, this study found the effect to be most pronounced with community-initiated and maintained lot reuse. Perhaps it was the case that newly treated lots become a rallying point for community members' interest and energy, strengthening social ties and pride (Sampson et al., 1997), and ultimately reducing violence and crime.

Nevertheless, as a quasi-experimental study that applied a rigorous spatial analysis of panel data to detect the effect of vacant lots greening, this research contributes to the idea that the form of, and processes behind landscapes can influence the extent of health or safety effects (Cameron, 2014). Differences in the number of significant changes in crime outcomes between the stabilisation treatment and the community reuse treatment suggest that community-initiated vacant-lot greening in medium-sized cities like Youngstown can potentially have a greater impact on reducing serious violent crimes. Community reuse lots are most typically transformed in to community gardens or orchards, which are uses that invite and require residents' time and care. This type of greening perhaps provides more opportunity for developing place attachment or identity (Altman and Low, 1992; Twigger-Ross and Uzzell, 1996) and, as such, could have a more pronounced effect on violent crimes as opposed to non-violent property crimes. More studies exploring the relationship between crimes and greening form, social interactions and relationships supported by different greening forms are warranted.

Acknowledgments

Funding

This research was supported by grants from the USDA Forest Service, Northern Research Station and the National Institutes of Health (10.13039/100000002 R01 AA020331).

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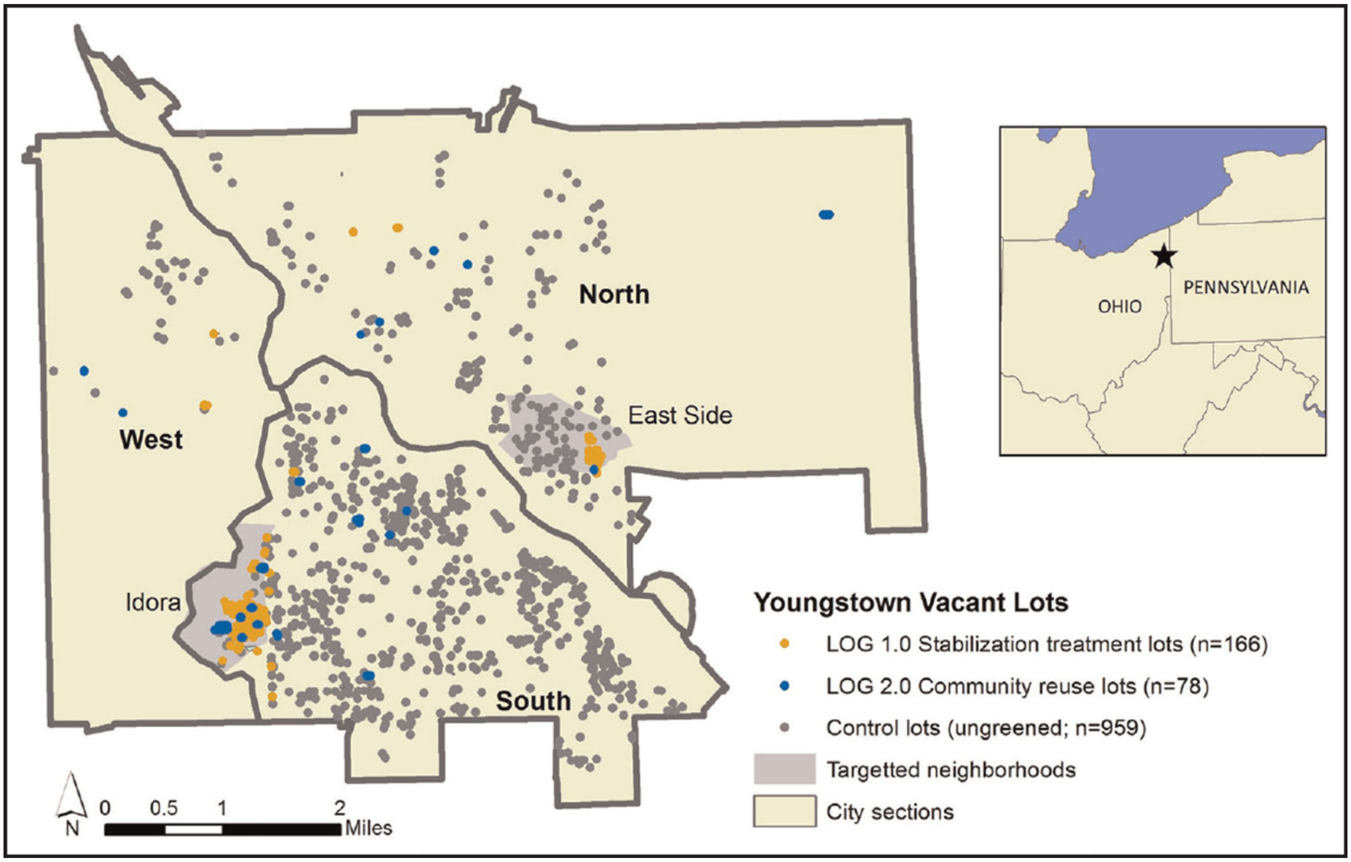

Figure 1.
Overview map of treatment and control lots in Youngstown, OH.

Table 1

Baseline summary statistics for vacant lots, by city section, Youngstown, OH, 2010–2014 (mean and median values are shown).

	No. of lots	Total area (ft^2)	Area (ft^2)	Population density[a]	Median income[b]	Residence < 1yr (%)[c]	Unemployed (%)
All sections							
Greened lots	244	1,402,710	5643	3.7	23,825	89.4	19.5
			5749	4.1	23,865	89.2	20.5
Control lots	976	5,772,842	5870	4.0	22,038**	84.7***	17.5***
			5915	3.9	22,015	84.2	17.4
North							
Greened lots	48	294,789	5250	2.2	19,978	90.8	14.0
			6141	1.8	21,144	91.1	12.7
Control lots	192	1,206,102	5550	2.5	19,592	86.7**	15.9*
			6282	2.6	19,973	84.1	17.9
South							
Greened lots	188	1,059,155	5643	4.1	24,334	89.1	20.9
			5634	4.2	24,412	89.2	21.0
Control lots	752	4,369,801	5893	4.4	22,936	84.1***	18.2***
			5811	4.2	22,465	84.2	17.7
West							
Greened lots	8	48,766	6000	4.4	27,994	86.1	16.8
			6096	4.4	27,324	86.4	17.1
Control lots	32	196,938	6040	3.9	23,767**	85.1	11.9**
			6154	4.0	23,668	85.0	11.4

* $P < 0.01$,

** $P < 0.001$, based on Wilcoxon rank-sum test.

[a] Population per square mile;

[b] median household income;

[c] residence in current household more than 1 year.

Source: Demographic data are derived and interpolated from the ACS, 2006–2010 and 2009–2013.

Table 2

Unadjusted difference-in-differences estimates for crime outcomes (units are crimes per square mile).

	Pre-period mean	Post-period mean	Mean difference
Felony assaults			
Control sites	1.86	2.63	0.77 ***
Treated sites	1.71	2.13	0.42 ***
Difference-in-differences	0.15 ***	0.50	**−0.35** ***
Burglaries			
Control sites	12.07	12.86	0.79 ***
Treated sites	15.43	13.78	−1.65 ***
Difference-in-differences	−3.36 ***	−0.92	**−2.44** ***
Robberies			
Control sites	1.18	1.68	0.50 ***
Treated sites	1.01	1.22	0.21 *
Difference-in-differences	0.17	0.46 ***	**−0.29** ***
Thefts			
Control sites	9.64	10.29	0.64 ***
Treated sites	10.49	10.65	0.16
Difference-in-differences	−0.85 ***	−0.36 ***	**−0.48** ***
Motor vehicle thefts			
Control sites	2.48	2.58	0.10 ***
Treated sites	2.25	1.97	−0.28
Difference-in-differences	0.23 ***	0.61	**−0.38** **

* $P < 0.05$,

** $P < 0.01$,

*** $P < 0.001$, based on two-sample Wilcoxon rank-sum (Mann-Whitney) test.

Sample sizes: pre-period (treatment: 12,928/control: 11,472); post-period (treatment: 3232; control: 2868).

Table 3

Comparisons of alternative spatial weight specifications with spatial lag model.

Crime	Spatial weights matrix	1	2	3	4	5	6	7
		No cut-off	1/8 mile cut-off	1/4 mile cut-off	2 mile cut-off	4 mile cut-off	6 mile cut-off	Same tracts
Felony assault	AIC	115,953	71,267	71,343	10,7735	115,302	115,949	120,376
	BIC	116,119	71,433	71,509	107,902	115,469	116,115	120,542
Burglary	AIC	65,822	16,433	17,889	53,648	62,200	65,779	66,393
	BIC	65,988	16,599	18,055	53,814	62,366	65,946	66,559
Robbery	AIC	121,202	57,970	60,336	106,464	112,023	112,054	115,988
	BIC	121,368	58,137	60,502	106,630	112,189	112,220	116,154
Theft	AIC	36,515	−20,897	−20,738	30,340	35,589	36,438	41,222
	BIC	36,681	−20,731	−20,572	30,506	35,756	36,604	41,388
Motor vehicle theft	AIC	126,086	76,849	73,657	112,654	121,692	126,054	121,013
	BIC	126,252	77,016	73,823	112,820	121,858	126,221	121,179

Table 4

Difference-in-differences estimates of the effect of vacant-lot greening (all treatments) on crime.

Outcome variable	Model 1:	Model 2:	Model 3: Spatial Durbin model			
	GLS regression	Poisson regression	1/8 mile distance threshold		1/4 mile distance threshold	
	Coefficient	IRR	Direct effect	Indirect effect	Direct effect	Indirect effect
Felony assault	−0.85*** (0.08)	1.00 (0.02)	−0.10** (0.04)	−1.04** (0.32)	−0.06 (0.04)	−2.04* (0.92)
Burglary	−0.24*** (0.03)	0.80*** (0.02)	−0.06*** (0.02)	−0.34*** (0.09)	−0.04*** (0.01)	−0.48* (0.24)
Robbery	−0.69*** (0.09)	0.93** (0.03)	−0.08* (0.04)	−0.65 (0.37)	−0.08* (0.04)	−1.31 (0.99)
Theft	−0.07*** (0.02)	0.96** (0.01)	−0.01 (0.01)	−0.08 (0.09)	−0.01 (0.01)	0.14 (0.26)
Motor vehicle theft	0.53*** (0.15)	0.90* (0.04)	0.10** (0.03)	1.40*** (0.34)	0.06* (0.03)	2.66** (0.91)

* $P < 0.05$,

** $P < 0.01$,

*** $P < 0.001$, based on z-score.

N = 30,075 (= 1203 groups * 25 times).

Robust standard errors are shown for GLS, Poisson and SDM regression.

Table 5

Difference-in-differences estimates of the effect of LOG1.0 stabilisation treatment on crime.

Outcome variable	Model 1:	Model 2:	Model 3: Spatial Durbin model			
	GLS regression	Poisson regression	1/8 mile distance threshold		1/4 mile distance threshold	
	Coefficient	IRR	Direct effect	Indirect effect	Direct effect	Indirect effect
Felony assault	−0.80*** (0.10)	1.00 (0.02)	−0.11* (0.05)	−0.64 (0.33)	−0.04 (0.05)	−0.69 (0.81)
Burglary	−0.26*** (0.03)	0.79*** (0.02)	−0.09*** (0.02)	−0.36*** (0.08)	−0.06*** (0.01)	−0.50** (0.18)
Robbery	−0.93*** (0.09)	0.89*** (0.03)	−0.09* (0.05)	−0.65 (0.36)	−0.10* (0.05)	−1.18 (0.81)
Theft	−0.11*** (0.02)	0.95** (0.02)	−0.03* (0.01)	−0.16 (0.12)	−0.02 (0.01)	−0.11 (0.28)
Motor vehicle theft	0.33 (0.17)	0.87* (0.05)	0.09 (0.05)	1.02* (0.41)	0.07 (0.05)	1.61 (0.93)

* $P < 0.05$,

** $P < 0.01$,

*** $P < 0.001$, based on z-score.

N = 20,450 (= 818 groups * 25 times).

Robust standard errors are shown for GLS, Poisson and SDM regression.

Table 6

Difference-in-differences estimates of the effect of LOG 2.0 community reuse treatment on crime.

Outcome variable	Model 1: GLS regression	Model 2: Poisson regression	Model 3: Spatial Durbin model			
			1/8 mile distance threshold		1/4 mile distance threshold	
	Coefficient	IRR	Direct effect	Indirect effect	Direct effect	Indirect effect
Felony assault	−0.93*** (0.16)	1.01 (0.03)	−0.27*** (0.07)	−0.70** (0.24)	−0.18** (0.06)	−0.88 (0.48)
Burglary	−0.19** (0.06)	0.83*** (0.04)	−0.02 (0.04)	−0.12 (0.10)	−0.01 (0.04)	−0.14 (0.19)
Robbery	−0.22 (0.19)	0.99 (0.06)	−0.18* (0.07)	−0.45 (0.26)	−0.11 (0.06)	−0.24 (0.47)
Theft	0.00 (0.04)	0.97 (0.02)	−0.00 (0.02)	−0.04 (0.06)	0.00 (0.02)	−0.03 (0.13)
Motor vehicle theft	0.79** (0.27)	0.94 (0.07)	0.32*** (0.09)	0.87** (0.27)	0.21** (0.07)	1.36** (0.42)

* $P < 0.05$,

** $P < 0.01$,

*** $P < 0.001$, based on z-score.

N = 9625 (= 385 groups * 25 times).

Robust standard errors are shown for GLS, Poisson and SDM regression.