Center for
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Vacant Spaces into Vibrant Places

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THE REIMAGINING CLEVELAND VACANT LOT GREENING PROGRAM:

Evaluating Economic Development and Public Safety Outcomes

Center for Community Progress Report to Cleveland, Ohio,
2016 Technical Assistance Scholarship Program Recipient

A Center for Community Progress Technical Assistance Report

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ABOUT THE CENTER FOR COMMUNITY PROGRESS

Founded in 2010, the Center for Community Progress is the only national 501(c)(3) nonprofit organization solely dedicated to building a future in which entrenched, systemic blight no longer exists in American communities. The mission of Community Progress is to ensure that communities have the vision, knowledge, and systems to transform blighted, vacant, and other problem properties into assets supporting neighborhood vitality. As a national leader on solutions for blight and vacancy, Community Progress serves as the leading resource for local, state, and federal policies and best practices that address the full cycle of property revitalization.

RESEARCH BRIEF

In September 2015, the Center for Community Progress (Community Progress) announced that the Reimagining Cleveland Workgroup, in partnership with the City of Cleveland, was one of three applicants competitively selected to be a recipient of our Technical Assistance Scholarship Program (TASP). The Workgroup's successful application sought assistance with two key items: (1) Conducting a comparative analysis of the economic impacts of different greening interventions carried out under Reimagining Cleveland, and (2) Exploring opportunities to better align and coordinate local funding streams for a more impactful approach to greening vacant land in the City. This research brief presents the key findings and conclusions of the economic impact analysis conducted as a part of the Cleveland engagement.

The Reimagining Cleveland greening program is a vacant land reuse initiative (Initiative), launched in 2008, rooted in a strong network of partners across the public, nonprofit, and civic sectors, and supported by a broad base of residents and community stakeholders. The nationally recognized initiative, which was originally convened and is still led by Cleveland Neighborhood Progress, seeks to "create sustainable solutions to vacancy while building a movement of solidarity and stewardship."[1]

The Initiative has generated a number of valuable and informative written resources pertaining to vacant land reuse—from the original Reimagining a more Sustainable Cleveland Plan (December 2008) that was endorsed by the City to the most recent Field Manual For Vacant Land Reuse Projects (June 2015). Since 2009, the Initiative has also issued 127 grants over three rounds of funding to support neighborhood-driven greening interventions on vacant lots. Nearly $2 million in grants has been awarded to implement a variety of reuses, such as community gardens, orchards and vineyards, pocket parks, green infrastructure, street edge improvements, neighborhood pathways, and side yard expansions.

Two of the stated goals of the Initiative are 1) to reuse vacant land in a way that "creates sustainable solutions to vacancy while building a movement of solidarity and stewardship", and 2) to "empower residents to reclaim their neighborhoods, become ambassadors for their communities, and start regaining a sense of pride and value."[2] The Project Manager for the Initiative stated in 2010 that the benefits of the program include the provision of local food,

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[1] More information is available at http://www.clevelandnp.org/reimagining-cleveland/.

[2] Cleveland Neighborhood Progress (2016).

sustainable land development, and to "relieve some of the stress on the city of Cleveland.[3]" These goals were not the subject of this analysis, but, as we discuss later, are critically important and should be pursued by Cleveland stakeholders, whatever an economic impact study may or may not show.

The question of social and economic impacts operates at a number of different levels. At one level are the measurable, or quantifiable, impacts of an intervention on such social and economic conditions as real estate markets measured by house prices, tax delinquency and crime. At another are larger and less readily quantifiable matters, including the relationship of greening interventions to the ongoing demolition activity taking place in Cleveland, and the overall role of greening interventions in a city's vacant property strategy.

Cleveland is still losing population and households, albeit at a slower rate than before 2010. Programs to green vacant lots in that setting reflect a fundamental recognition that the presence of large numbers of vacant lots, particularly in the city's distressed neighborhoods, is a long-term reality, and that the ongoing demolition program being pursued in the city means that the number of vacant lots will increase steadily for a number of years to come. Figuring out how to deal with these lots is a critical issue. Although there is growing demand for new homes and commercial buildings in Cleveland, it tends to be concentrated in a relatively few areas, and, even under the most optimistic assumptions, unlikely to be able to absorb the nearly 28,000 vacant lots identified in the 2015 Parcel Survey conducted by the Western Reserve Land Conservancy.

In that context, greening interventions have significant value independent of their measurable impact on real estate markets. They utilize lots in ways that are likely to be beneficial to the community, and at a minimum reduce the negative effect associated with an untreated vacant lot. They reduce the inventory of lots that must be maintained by public entities at substantial public cost in staff and equipment. They may increase the level of engagement and cohesion, as well as the quality of life, of the people involved in the green space, or those living in its immediate vicinity.

In this particular case, we sought to determine whether the Reimagining Cleveland greening interventions have had significant quantitative effects in three specific areas: house prices, tax

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[3] Brasche, Arionna. "Greening vacant land," Shelterforce. December 24, 2010, http://www.shelterforce.org/article/2085/greening_vacant_land/.

delinquency and crime. Community Progress worked with Ken Steif, PhD, of Philadelphia-based Urban Spatial and the University of Pennsylvania as principal investigator, with Alan Mallach providing oversight and direction on behalf of Community Progress. Ken is a highly-respected researcher with expertise in both econometrics and spatial analysis. While he was directly responsible for the analysis and findings described in detail below, they represent a work product of both Urban Spatial and the Center for Community Progress.

This research brief summarizes but does not provide detailed information about the sophisticated methodology that was used by Prof. Steif for the analysis. Further detail is available in his separate research report, which appears as Appendix A to this brief.

We matched each block on which greening interventions took place (the treatment blocks) with a block of similar character in the same neighborhood (the control blocks), in order to compare the effects in each of those three areas of having a community garden or other green space created on the treatment blocks. The matching process was extremely rigorous; indeed, substantially more so than in most studies looking at similar questions. Specifically, we matched for the following variables:

- Distance to green space;
- Number of green infrastructure projects in the area;
- Percent commercial land use in the immediate area;
- Single-family vacancy;
- Demolitions;
- Number of foreclosures;
- Number of sheriff sales;
- Number of land bank dispositions;
- Total usable area on the block;
- Number of rehabs;
- Total amount of loan dollars toward rehabs.

We extended that comparison in both time and space. Specifically, we looked at data for four time periods – the quarter before the greening intervention took place, and for one, two and four quarters afterward. With respect to space, we looked at data for the block on which the intervention was situated itself, and for a larger area defined as a circle with a 1/8 mile (660 feet) radius from the center of each block.

A number of previous studies of greening interventions such as community gardens, most of which were conducted in Philadelphia, have shown positive effects, in some cases with respect to property values[4] and in others with respect to crime incidence[5] or perception of safety[6]. We had hoped to replicate some of the more positive findings from this research in our work in Cleveland, but for the most part the analysis found no significant impact associated with the greening interventions.

The one area where we found a statistically significant difference between the treatment blocks and the control blocks was with respect to the incidence of aggravated assault. Specifically, there was a significant drop in aggravated assaults in treatment blocks one quarter after the green space was put in place relative to the control blocks. That drop appears, however, to be temporary; the difference between treatment and controls becomes less significant after two quarters, and insignificant after four quarters. We found no significant differences in house prices or tax delinquency associated with the greening intervention.

These findings raise two questions: why do they appear to be at odds with research conducted elsewhere; and what implications do they have for the value of the Reimagining Cleveland greening interventions?

The question of consistency between this study and research conducted elsewhere has a corollary; namely, is that research generalizable in other settings, such as Cleveland? It is worth noting that with one exception (Kondo et al., 2015) all of the research that has found significant impacts from greening interventions has been conducted in Philadelphia and in New York City, two cities with substantially stronger overall market conditions than Cleveland. One aspect of stronger markets is that areas in those cities with relatively weak submarkets tend to be more sensitive to upward pressure and interventions than similar areas in weak market cities. It is for this reason that a house in need of major repair in the most distressed parts of Washington, D.C., for example, will still command a price of $200,000 or more, while a similar house in a neighborhood with similar social and economic conditions in Cleveland will have little or no value.

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4 Heckert, Megan and Jeremy Mennis. ''The economic impact of greening urban vacant land: a spatial difference-in-differences analysis'' Environment and Planning A 44 (2012); Voicu, Ioan, and Vicki Been. ''The Effect of Community Gardens on Neighboring Property Values,'' Real Estate Economics, 36:2 (2008).

5 Branas, Charles C., Rose A. Cheney, John M. MacDonald, Vicky W. Tam, Tara D. Jackson, and Thomas R. Ten Have. ''A Difference-in-Differences Analysis of Health, Safety, and Greening Vacant Urban Space'' American Journal of Epidemiology 174:11 (2011); Kondo, Michelle, Bernadette Hohl, SeungHoon Han, and Charles Branas. "Effects of greening and community reuse of vacant lots on crime." Urban Studies (2015): 0042098015608058.

6 Garvin, Eugenia C., Carolyn C. Cannuscio, and Charles C. Branas. "Greening vacant lots to reduce violent crime: a randomized controlled trial." Injury Prevention 19.3 (.2013): 198-203.

While Cleveland has some strong market areas, they are relatively few, and their impact does not spill over to the high-vacancy low-price areas where the greening interventions tend to be concentrated. Indeed, one reason why the study may not have found significant impact on sales prices was that there were too few non-zero sales transactions in many of the areas around the greening interventions to be meaningful. It is worth noting that one of the studies (Heckert and Mennis 2012) found that the impact of the LandCare interventions in Philadelphia was significantly less in deeply depressed areas, which correspond most closely to most of the areas in Cleveland that received greening interventions. It is also worth noting that two recent studies in Cleveland, one looking at the effects of demolition and other at the effects of rehabilitation, also found no impact on property values (and, indeed, a negative cost-benefit relationship between the intervention and the neighborhood outcomes) in distressed neighborhoods.[7]

A second issue is the nature of the research design. As Prof. Steif points out below, only one of the reported studies (Garvin et al., 2013) was experimental in nature, meaning that greening was allocated at random and outcomes for greened 'treated' parcels were systematically compared to non-greened "control" lots. The Garvin study found no statistically significant change in crime associated with the greening interventions. The Garvin study included interviews with residents. In an important finding, the interviews found that that people living close to treated parcels reported feeling significantly safer after greening compared to those living around control parcels, despite the absence of direct measurable effect of the greening interventions on crime.

We do not know whether a similar series of interviews in Cleveland would have found outcomes similar to those found by Garvin, but it is certainly possible. If resources are available, such a study would be well worth pursuing. In addition, it is equally possible that more rigorous research designs in the case of some of the other studies would have eliminated some of the significant findings that appear in the literature. Finally, it must be recognized that just as selection bias exists with respect to interventions, selection bias is also found in scholarly publication. Few if any studies that fail to show significant findings in the desired direction ever see the light of day. Thus, we know of six studies on record that show positive outcomes associated with greening interventions, but we have no idea how many, if any, other studies have been conducted up to this point that did not find significant impacts and have not been published.

[7] Griswold, Nigel G., Benjamin Calnin, Michael Schramm, Luc Anselin & Paul Boehnlein .Estimating the Effect of Demolishing Distressed Structures in Cleveland, OH, 2009–2013: Impacts on Real Estate Equity and Mortgage-Foreclosure. Detroit: Griswold Consulting Group (2014); Dynamo Metrics. Decision Support for Property Intervention: Rehab Impacts in Greater Cleveland 2009-2015. Detroit: Dynamo Metrics (2016).

With respect to the second issue, we feel very strongly that the inconclusive nature of this research study does not mean that greening is not a valuable activity in Cleveland or other similar post-industrial cities. As reflected in the goals of the Initiative briefly noted at the beginning of this brief, the benefits of Reimagining Cleveland in terms of social cohesion, building neighborhood solidarity, and through those effects stabilizing neighborhoods, are both the central purpose of the program and critical to the future of the community. Prof. Steif's suggestion that a survey be conducted among residents and business owners to gauge their feelings about the greening interventions and their effects on their quality of life is well worth pursuing if resources permit.

The larger conclusion that we reach, however, while not bearing directly on the greening program as such, has significant implications for community development strategy in distressed areas as a whole. Prof. Steif's rigorous work on this analysis, taken in conjunction with much of the research cited above, including the work by Griswold and his colleagues on demolition and rehabilitating, and the work by Heckert and Mennis on the Philadelphia LandCare Program, makes clear that the challenges in distressed urban neighborhoods in legacy cities, which are suffering from high levels of vacancy, extremely low property values, and concentrated poverty and unemployment, are unlikely to be significantly mitigated by what must be recognized as small-scale, limited property interventions. That does not mean those interventions are not valuable and important. On the contrary, it is in part because of the intense distress of these neighborhoods that interventions that can improve, even modestly, the quality of life of their residents and provide hope for the future, are particularly valuable and desperately needed.

APPENDIX A: ECONOMIC IMPACT STUDY

“Evaluating the ‘Reimagining Cleveland’ Vacant Land Greening Program on Economic Development and Public Safety Outcomes”

Ken Steif, PhD
Lauren Parker, MCP

Evaluating the 'Reimagining Cleveland' vacant land greening program on economic development and public safety outcomes

Ken Steif, PhD
Lauren Parker, MCP

Abstract:

Using a rich set of place-based administrative data from Cleveland, Ohio, the authors evaluate the effect of a non-profit led, vacant land greening intervention on outcomes including home prices, tax delinquency, building permits, burglaries, aggravated assaults and simple assaults. We match treated areas to control areas using a set of baseline neighborhood characteristics and estimate various space/time difference-in-difference regressions.

The only evidence of greening-driven improvement is for aggravated assaults in the short term. These findings are comparable to other vacant land greening studies. The authors conclude that non-profits willing to make these investments should focus on outcomes related to community building and social cohesion. In this case, the goals of Cleveland Neighborhood Partners, the non-profit responsible for planning and implementation, were sustainability, solidarity and stewardship.

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1. Introduction

This analysis asks whether the Reimagining Cleveland urban greening intervention in Cleveland, Ohio was associated with significant improvements across a host of outcomes relative to comparable, non-greened areas.

Reimagining Cleveland is a vacant land reuse initiative launched in 2008 and led by Cleveland Neighborhood Progress (CNP). Through Reimagining Cleveland, CNP engaged in a city-wide strategy with public partners to put vacant land to more productive and sustainable uses. CNP worked with local CDCs on projects ranging from smaller pocket parks, pathways and community gardens to more intensive uses, such as urban orchards and vineyards. Figure 1.1 and 1.2 provide some visual examples.

Two of the stated goals of the Reimagining Cleveland program are 1) to reuse vacant land in a way that "creates sustainable solutions to vacancy while building a movement of solidarity and stewardship", and 2) to "empower residents to reclaim their neighborhoods, become ambassadors for their communities, and start regaining a sense of pride and value"[1]. The Project Manager for the Reimagining Cleveland project stated in 2010 that the benefits of the program include the provision of local food, sustainable land development, and to "relieve some of the stress on the city of Cleveland[2]."

The goal of this research is not to study the intended direct benefits of CNP's vacant land greening. Instead, our purpose is to investigate whether greening lead to indirect benefits in the form of economic development and public safety improvements. Specifically, this analysis hypothesizes that the Reimagining Cleveland vacant land greening program generated positive spatial spillover effects that improved local housing submarkets and reduced crime.

Greening is one step along a trajectory that ends with land being put back into a productive use. This trajectory often begins with housing vacancy which can result from deindustrialization; the filtering of households to successively newer housing either in city or suburb; a change in demand for public services and amenities; shifts in employment markets and other factors. In Cleveland however, the foreclosure crisis and Great Recession left a lasting impression on the built environment. According to the Western Reserve Land Conservancy, Cleveland experienced 84,513 foreclosures between 2007 and 2012[3].

As a result of these forces, approximately 3,300 acres, or 20,000 parcels in Cleveland are vacant land, and 7,000 of these lots contain vacant and deteriorating homes[4]. These vacant properties represent under-utilized community and economic assets

[1] Cleveland Neighborhood Progress (2016)
[2] Brasche (2010)
[3] Ford (2016)
[4] City of Cleveland Planning Commission (2013)

which may present a safety hazard and degrade the overall condition and perception of neighborhood blocks.

Local governments often pick up the tab for maintenance costs associated with vacancy. A 2008 study found that vacant properties in 8 Ohio cities including Cleveland cost those cities $15 million in code enforcement, the boarding of buildings, demolitions, maintenance and police and fire response[5]. In addition, researchers in several cities including Cleveland[6], Chicago[7] and St. Louis[8] have found that foreclosed vacant homes in a state of disrepair can drag down local property values.

In some cases, cities choose to demolish vacant buildings leaving behind land which may in itself, have negative consequences for communities. The motivation behind vacant land greening programs is to reutilize this land in a way that can generate significant social benefits at little cost. These programs have sprouted up in several post-industrial cities including Baltimore, Buffalo, Cleveland, Milwaukee, Philadelphia and others.

Researchers have tested the effect of vacant land greening on a host of outcomes including health[9], public safety[10], economic development[11] and stormwater management[12]. The findings suggest that greening programs are associated with significant improvements in these outcomes. However, all but one of these studies (Kimbauer et al., 2013) was conducted in Philadelphia, Pennsylvania.

It is equally important to note that only one of these studies (Garvin et al., 2013) was experimental in nature, meaning that greening was allocated at random and outcomes for greened 'treated' land was compared to non-greened 'control' lots. This landmark study found no statistically significant decrease in crime around treated land compared to control land but did find that people around treated lots reported feeling significantly safer after greening compared to those living around greened land in the control group.

There are two important questions for city managers and city planners: Are these predominately Philadelphia-based findings generalizable to all post-industrial American cities? If so, should other cities consider these budget allocations for similar interventions as a means to combat the negative consequences of blight?

It is the first question that situates this study. We evaluate the effect of the Reimagining Cleveland vacant land greening intervention on several outcomes including crime, home prices, tax delinquency and building permits. The goal is to derive apples to apples comparisons between blocks with greening interventions and similar control blocks

[5] Rebuild Ohio (2008)
[6] Whitaker & Fitzpatrick (2011)
[7] Immergluck & Smith (2006)
[8] Rogers & Winter (2010)
[9] Garvin et al. (2013)
[10] Branas et al (2011); Garvin et al (2013)
[11] Heckert & Mennis (2012)
[12] Kimbauer et al. (2013)

without and then compare outcomes both before and after the greening and between control and treatment groups.

We match treatment blocks to control blocks using eleven land use variables while ensuring that matches occur in the same neighborhood. Of the eight outcomes analyzed, we find statistically significant improvements for just one - aggravated assaults. This may offer further evidence that vacant land greening initiatives help generate positive public safety spillovers.

The next section describes our research design. Section 3 describes the research design. Section 4 presents our results and the final section concludes.

Figure 1.1: E 139th St. Pocket Park

Figure 1.2: Brooklyn Centre Community Orchard

2. Data sources used for this study

We used three types of proprietary and publicly-available datasets to evaluate the social and economic impacts of greening interventions that were a part of the Reimagining Cleveland program:

- Intervention data on Reimagining Cleveland greening projects,
- Neighborhood context data to develop profiles of blocks and facilitate the treatment and control group matching process, and
- Outcomes data to model the social and economic impact of the presence (treatment) or absence (control) of greening interventions.

Table 2.1 displays the characteristics of each dataset used in the study. Column 2 of Table 2.1 specifies whether each data source was used for matching or as an outcome. These various datasets were cleaned and aggregated into quarterly time-series using the statistical programming language, R. Relationships between files were managed using the database system, PostgreSQL which allowed for quick queries and joins of large datasets.

The universe of interventions includes those parcels that received Re-Imagining greening interventions from 2011 through 2014. Grants for these projects ranged from around $1,500 to $70,000 and on average, were $20,700. A total of 239 parcels received greening interventions as part of the Re-Imagining Cleveland program during the study period. Figure 2.3 shows the spatial extent of all geocodable Reimagining Cleveland projects from 2011 through 2014.

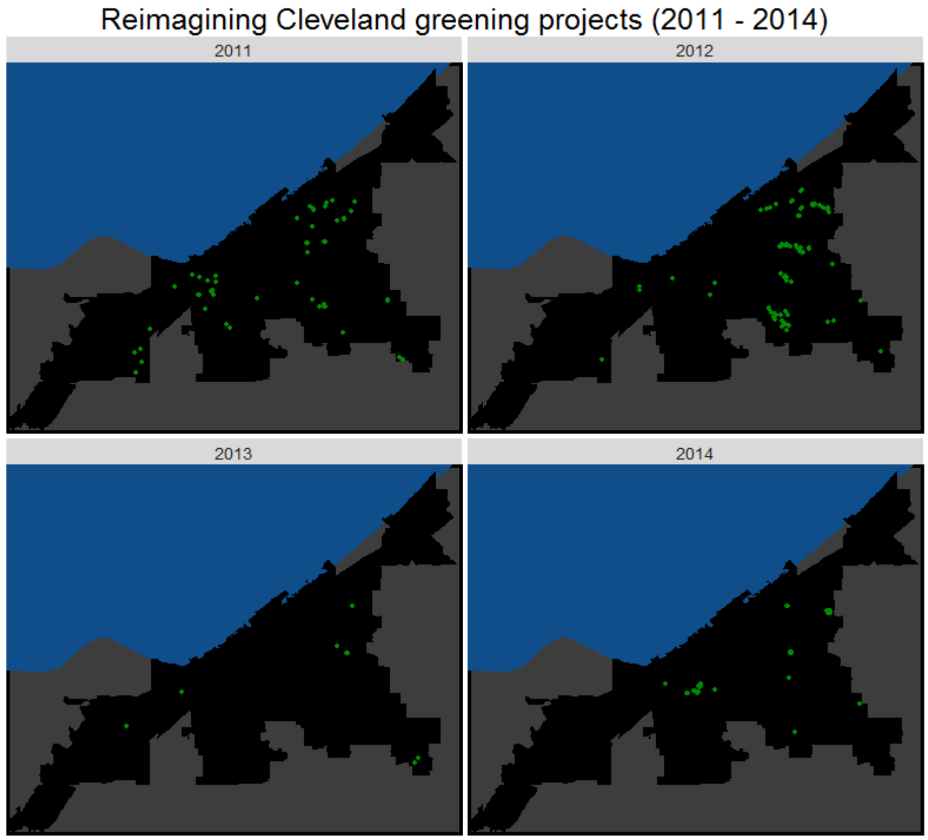

Figure 2.3: Reimagining Cleveland greening interventions 2011 - 2014

We created a baseline dataset representing the quarters and blocks in which greening interventions occurred. These blocks were joined to data on vacant land derived from tax bill records to exclude any blocks that did not contain at least one residential vacant lot. In total, 112 blocks received some greening intervention in 9 quarters between 2011 and 2014 as part of the Re-Imagining Cleveland program.

We obtained property-level data on demolitions, 90-day postal vacancy, foreclosure filings, Sheriff sale auctions, Cuyahoga Land Bank dispositions, total usable square feet of property space, rehabilitation and renovation activity, green infrastructure projects, and land use. Local partners at NEO-CANDO, Case Western Reserve University and Cleveland Neighborhood Progress provided the raw datasets. Each dataset was cleaned and aggregated to quarterly time-series, where appropriate.

Postal vacancy sites are vacant single-family properties where USPS mail carriers noted uncollected mail for 90 days or more. Sheriff sale auctions were limited to those properties that sold for more than $0. Total usable area of each property were provided in annual property characteristics snapshots. We use this variable as a proxy for the total livable area of each property, as total livable area was not an available indicator. Rehabilitation projects included any projects that received a loan under the Housing Enhancement Loan Program (HELP), were projects of the Opportunity Homes (OpHo) program or Slavic Village Recover Project (SVRP), or were Cuyahoga County Land

Bank renovation projects. Green infrastructure projects included in this analysis were those that were part of the Northeast Ohio Regional Sewer District (NEOSRD) initiatives. Land use on green space, commercial areas and residential areas were used to provide additional context.

These indicators were compiled on a quarterly basis for each treatment and control block at two geographies: 1) the Census block-level, and 2) within a ¼ mi. of each treatment and control block.

To evaluate the impact of greening interventions, the following approximations for social and economic outcomes were used:

- Public safety as measured by the prevalence of aggravated assaults, burglaries, and simple assaults,
- Economic development as measured by the hedonic price response[13] in single-family home sale prices,
- Changes in total construction cost and number of approved building permits, and
- Changes to the number of tax delinquent properties and the amount (i.e., dollar-value) delinquent.

Historical records were obtained for crime incidents, tax delinquency and property transfers for all locations and parcels in Cleveland. To isolate sales of specifically single-family dwellings, annual property characteristics were joined with data on sales transfers and filtered for single-family homes. We identified all building permits that were approved during the study period and summarized the total number and construction costs for all permits. Tax delinquent parcels were identified as parcels that had a total net delinquent balance greater than $0.

Quarterly outcomes data were compiled to two geographies: 1) for treatment and control blocks included in the matching process and 2) within 1/8th mi. of the centroid of each matched treatment and control block.

[13] "Hedonic" refers to the process by which the price of a good, like housing, is estimated as a function of its constituent components (number of bathrooms, bedrooms, granite countertops, etc.) given the willingness to pay for that good in a market.

Description	Data Use	Relevant Variables	Spatial Resolution	Temporal Coverage	Data Source
Reimagining Cleveland greening projects	Treatment	type of greening, grant amount	Parcel	2011-2013; all interventions	CNP / CWRU
90-day postal vacancy	Matching	single and multi-family vacancy	Parcel	2008-2015; quarterly	CNP / CWRU
Demolition history	Matching	demolition binary	Parcel	2000-2016; all demolitions	CNP / CWRU
Foreclosure filings	Matching	disposition type, amount	Parcel	2006-2016; all foreclosures	NEO-CANDO
Sheriff sale auctions	Matching	foreclosure binary	Parcel	2000-2016; all auctions	NEO-CANDO
Land bank transfers	Matching	transfer binary	Parcel	2009-2016; all transactions?	NEO-CANDO
Total usable area in property	*Matching*	square feet of usable space	Parcel	2000-2015; annual	NEO-CANDO
Rehabilitations					
HELP loans	*Matching*	loan amount, loan approval date	Parcel	2012-2015; all loans	CNP / CWRU
OpHo acquisitions	*Matching*	total development costs, acquisition date	Parcel	2007-2012; all acquisitions	CNP / CWRU
SVRP projects	Matching	total development costs, rehab completion date	Parcel	2013-2015	CNP / CWRU
Lank Bank renovations	Matching	disposition date	Parcel	2010-2016; all rehabs	CNP / CWRU
Green Infrastructure	Matching	grant amount	Parcel	2009-2015	NEOSRD
Land use					Cuyahoga County FTP
Distance to green space land use	Matching	land use type	Sub-parcel	2014	Cuyahoga County FTP
Percent commercial land use	Matching	land use type	Sub-parcel	2014	Cuyahoga County FTP
Neighborhood	Matching	neighborhood name	Neighborhood	2012	Cleveland Open Data
Approved building permits	Outcome	number, total construction cost	Parcel	2005-2015; all permits	CNP / CWRU
Tax delinquency	Outcome	amount delinquent	Parcel	2010-2015; quarterly	CNP / CWRU
Crime events	Outcome	aggravated assaults, non-aggravated assaults, burglaries	Point-level	2007-2015; all incidents	CNP / CWRU
Sales transfers	Outcome	sale price	Parcel	2000-2015; all sales	CNP / CWRU

Notes: CNP = Cleveland Neighborhood Progress, CWRU = Case Western Reserve University, NEO-CANDO = Northeast Ohio Community and Neighborhood Data for Organizing, FTP = File Transfer Protocol

Table 2.1: Datasets used for this study

3. Research Design

This study hypothesizes that the Reimagining Cleveland vacant land greening program generated positive spatial spillover effects that increased economic development outcomes and reduced crime.

When studying this hypothesis, it is not enough to ask if outcomes improved after the greening occurred. It may be that a non-greening influence caused the improvement. While pre and post treatment comparisons are important, in order to identify the specific effect of the Reimagining Cleveland program, comparisons must be made between treated areas that were greened and control areas that are comparable but did not experience greening.

The best way to ensure apples-to-apples comparisons is to run an experiment by randomly allocating greening across space such as the work described in Garvin et al. (2013). An experiment helps to ensure that study conclusions are not biased by the presence of confounding factors. For a variety of institutional reasons, non-profits and governments typically do not have the option to randomize in an experimental context. Because the Reimagining Cleveland greening intervention was not randomly allocated, the goal of our analysis is to design a 'quasi-experiment' that addresses the possibility for 'selection bias'.

Selection bias arises because the criteria used to allocate greening interventions across space is not observed in the data. This can be problematic. If CNP decided to invest in "underserved" or "transitioning" areas, for example, and this strategy goes unaccounted for in our research design, the resulting evaluation may be biased because we may be making comparisons to neighborhoods that were not considered by CNP stakeholders.

There are several options for developing a quasi-experimental research design. First, we attempted but were unsuccessful in retrieving a list of all locations where stakeholders applied for but did not receive a Reimagining intervention. These areas might have constituted an interesting control group. We were also unable to acquire a qualitative description of the selection criteria describing how these investments were allocated across the City.

Instead, to select an adequate control group, we turned to an econometric technique referred to as the 'Propensity score'[14] which attempts to match study areas to control group candidates based on a series of observable characteristics in the data. The motivation is by matching treated areas with a comparable cohort of control areas, it may be possible to overcome selection bias when outcomes are compared.

When choosing variables to match on, despite not having CNP's selection criteria, we tried to consider the institutional goals that CNP stakeholders would have wanted to address when they located the intervention. The focus was on baseline, pre-treatment characteristics that would have influenced the decision to green. These characteristics

[14] Rosenbaum & Rubin (1983); Caliendo & Kopeinig (2008)

include distance to green space; number of green infrastructure projects in the area; percent commercial land use in the immediate area; single-family vacancy; demolitions; number of foreclosures; number of sheriff sales; number of land bank dispositions; total usable area on the block; number of rehabs; total amount of loan dollars toward rehabs. We also required that every treated block was matched with a control block in the same neighborhood and allowed for the possibility that the same control unit could be matched more than once.

In order to judge the quality of our matches, variable means were compared before and after matching using a statistic called 'standardized mean difference'. The idea is that before matching, when apples and oranges comparisons are made, large average differences in these variables should be observed between treatment and control groups. However, when we match to make apples-to-apples comparisons, we should expect that these differences largely disappear. The results section reports variable means and standardized mean differences both before and after matching.

Once we have confidence in our matches, we can begin to explore our stated hypothesis. Again the motivation is to test for significant differences in outcomes both before and after a lot is treated and between control and treatment groups. To do so, we join outcome data to our control and treatment lots for four time periods – once in the quarter proceeding the intervention and for one, two and four quarters after the intervention. This helps to understand not only the effect of the intervention but if these effects are sustained over time. In addition to differences over time, we are equally interested in differences across space. As such, differences are analyzed at two spatial scales. The first collects data at the census block level and the second does so within a 1/8 mi. radius around each greening intervention[15].

We estimate several forms of what is commonly referred to as a 'difference-in-difference' regression[16], which is explicitly designed to measure differences in outcomes between pre and post treatment time periods and between control and treatment groups. Specifically, the regression compares the average change in the treatment group with the average change in the control group and asks whether these differences are statistically significant. The concept of statistical significance in this context refers to across (treatment/control) group differences that cannot be explained by random chance alone. These differences are estimated while controlling for the quarter of the greening event, its neighborhood as well as additional related variables[17]. We also account for the number of Reimagining Cleveland greening interventions in the area. Unfortunately, sample size limitations prevent us from providing estimates for different types of greening interventions.

[15] We experimented with ¼ mi. buffers but became concerned that at this geography, treated areas would overlap.

[16] Donald & Lang (2007)

[17] The difference-in-difference model takes the form:

$$Y_{it} = \beta_0 + \beta_1 Treatment_i + \beta_2 Post_t + \beta_3 (Treatment * \ Post)_{it} + \ \varepsilon_{it}$$

Where Y_{it} represents an outcome of interest on parcel *i* at time *t*. $Treatment$ is a dummy variable denoting treatment and control parcels; $Post$ is a dummy variable denoting the pre and post treatment time period $Treatment * \ Post$ is an interaction between the two and ε_{it} is the error term. The coefficient on the interaction, β_3, is interpreted as the difference in outcomes between control and treated groups after the intervention occurred relative to the pre-treatment time period.

It is important to note that mechanically these models attempt to identify differences on average. Thus if greening led to a noteworthy change in one neighborhood but not in another, the model would not treat this difference as significant.

These regressions estimate coefficients for several notable variables including a pre-treatment fixed effect, a treatment/control fixed effect and the interaction of the two. While the two former coefficients are interpretable, they are not particularly useful in this context. What is useful and what we do interpret is the multiplicative interaction which if significant, states the magnitude difference in outcomes between control and treated land after the intervention occurred relative to the pre-treatment time period.

We begin by estimating differences for home sales prices. For the remaining regressions we switch to aggregate and average outcomes. As an example, for crime outcomes, the total number of crimes at the block and 1/8th mi. radius are analyzed. For continuous outcomes, linear regression is used, but when counts are the dependent variable, negative binomial regressions are employed. This statistical approach is uniquely designed to deal with count data.

Variable	Variable Means (Unmatched)	Variable Means (Matched)		Matched Difference in Means	Standardized Mean Difference Unmatched	Standardized Mean Difference Matched
	Control	*Treatment*	*Control*	*p-value*		
n	51935	104	101			
Distance to green space	1095.09 (758.88)	899.82 (580.34)	897.85 (611.89)	0.981	0.31	0.003
Percent commercial land use	9.76 (17.29)	7.24 (10.43)	8.31 (14.90)	0.553	0.176	0.084
Single family housing vacancy	48.94 (55.96)	50.55 (71.42)	52.76 (54.91)	0.806	0.069	0.035
Number of demolitions	0.96 (1.55)	1.30 (1.60)	1.86 (2.26)	0.042	0.124	0.288
Number of foreclosures	4.85 (4.00)	6.49 (3.75)	6.50 (4.54)	0.987	0.234	0.002
Number of sheriff sales	1.22 (1.46)	1.07 (1.51)	1.33 (1.47)	0.22	0.105	0.173
Number of land bank dispositions	0.50 (1.01)	1.49 (2.30)	1.52 (2.09)	0.898	0.307	0.018
Amount of developable area	555367.29 (334519.99)	598032.75 (295337.24)	617000.73 (327942.55)	0.666	0.363	0.061
Number of rehabilitations	0.14 (0.44)	0.20 (0.47)	0.19 (0.44)	0.877	0.089	0.022
Total amount of loan dollars for rehabs	1379.68 (19385.14)	148.51 (1492.56)	3265.72 (28602.37)	0.275	0.024	0.154
Number of green infrastructure project:	0.00 (0.06)	0.00 (0.00)	0.00 (0.00)	--	--	--

Table 4.1: Results of the propensity score matching procedure

4. Results

Propensity matching results

Table 4.1 shows the results of the propensity score matching procedure used to match control and treatment blocks. Column 2 shows variable means for each block Citywide not included in the treatment. Column 3 shows the variable means for the treatment group blocks. Note their differences are quite substantial, but after the matching process, the means for the control group (Column 4) are much smaller and comparable to that of the treatment group. This shows that matching helped to create comparable control and treatment groups. As a check, Column 6 shows standardized mean differences when this comparison is made in an unmatched context and Column 7 shows how these differences are reduced after matching occurs.

It is reasonable to ask if the differences between control and treatment blocks are relatively high. The literature typically suggests that a standardized mean difference less than 0.1 is preferable[18]. In the unmatched context, just 3 of the ten variables reach this threshold. Column 7 shows the standardized mean difference after matching. 7 of the 10 variables used for matching have standardized mean differences less than the 0.1 threshold. We then analyze post-matching difference in means t-tests (Column 5) for each variable and find, judging by the p-values, that 9 of 10 variables show no statistically significant differences between control and treatment groups. We are therefore, reasonably convinced that apples-to-apples comparisons in outcomes can be made. Figure 4.1 shows the control and treated matches in each neighborhood. Note that there are several instances where a single control unit was matched to more than one treatment.

Regression results

With comparable treatment and control groups in hand, greening effects can now be estimated in a regression context. In order to gain some perspective, outcomes over the course of the study period are visualized. Figure 4.2 shows the time series trend for all outcomes throughout the study period. These trends are then visualized separately for treatment and control groups. Figure 4.3 shows the time series in green for treated blocks and in red for control blocks.

Figure 4.2 shows that citywide trends for aggravated assault and simple assault remained flat but for burglary, the trend decreased dramatically. With respect to the economic development outcomes, tax delinquency and home prices remained relative flat while permits increased dramatically.

Figure 4.3 shows that overall, control and treatment blocks exhibited comparable time series trends. For aggravated assaults, tax delinquencies and home prices however, there are some noticeable differences in outcomes. The purpose of the regressions however, is to ask if these differences are driven specifically by greening interventions.

[18] Harder et al. 2010; Austin (2011)

The results of the regressions are now discussed. Note that while several controls are employed in the regression, associated coefficients are not included in the regression results below. Full regression tables can be found in Appendix 1. Here we take each outcome in turn and discuss the results.

	Block geography			1/8 mi. geography		
	1Q Post	2Q Post	4Q Post	1Q Post	2Q Post	4Q Post
Economic Development						
Home prices	-0.538	0.358	-0.386	-0.406*	-0.386	-0.382
	(0.614)	(0.551)	(0.643)	(0.245)	(0.244)	(0.269)
Tax delinquent amount	0.061	-0.673	-0.304	0.259	-0.492	-0.375
	(0.543)	(0.575)	(0.546)	(0.321)	(0.363)	(0.272)
Number of tax delinquent properties	0.105	-0.027	-0.108	0.165	0.009	-0.046
	(0.172)	(0.18)	(0.17)	(0.118)	(0.134)	(0.108)
Building permit amount	0.436	0.115	0.577	0.772	-1.137	0.302
	(0.796)	(0.72)	(0.759)	(0.879)	(0.89)	(0.86)
Number of building permits	0.161	-0.036	0.035	0.268	0.145	0.318*
	(0.315)	(0.318)	(0.332)	(0.183)	(0.176)	(0.184)
Crime						
Aggravated assaults	-1.039	0.299	-0.794	-0.542**	0.490*	-0.161
	(0.712)	(0.753)	(0.68)	(0.266)	(0.272)	(0.257)
Simple assaults	-0.132	-0.348	-0.309	0.022	0.085	-0.072
	(0.3)	(0.304)	(0.297)	(0.148)	(0.153)	(0.15)
Burglaries	-0.539	-0.492	-0.103	-0.256	-0.176	0.102
	(0.352)	(0.366)	(0.338)	(0.164)	(0.155)	(0.171)

*p < 0.1 **p < 0.5 *** p < 0.01

Table 4.2: Estimated difference in difference interactions regression coefficients and standard errors by outcome, geography and post-treatment time period

Home prices, permits and delinquency

We estimated difference-in-difference regressions on the log of home prices including a host of traditional hedonic variables that control for the physical characteristics of the house[19]. We also control for other relevant data we were able to collect including Homestead Exemptions and tax abatements. Finally, we control for the number of greening interventions on the block as well as quarter and neighborhood fixed effects[20].

We found only one instance of very weak significance. Home price difference-in-differences are significant at the 0.1 level (p-value = 0.099) for sales one quarter after the treatment within 1/8th of a mile of a greening intervention. The model estimates that on average, post treatment home prices are 66% *less* than pre-treatment when compared to control areas. With the weak significance in mind, it worth considering that 95% confidence intervals on this estimate suggest that these differences could range

[19] This includes lot frontage and depth, number of bedrooms, bathrooms and property condition

[20] 'Fixed effects' refer to variables used to control for differences in time and across neighborhoods.

between 41% less and 8% *more*. As such we do not consider estimates with such weak significance worth considering. Note that the sample sizes for these regressions were very small, particularly at the block level (Appendix 1). We removed a great many sales that had home prices near $0. These could have been non-arms-length transactions or simply a reflection of how messy administrative data is.

We find no significant differences for tax delinquency, either for the number of tax delinquent properties or for the total tax delinquency in dollars. We also find no difference in the number or total cost of building permits issued to properties around greened land. These findings suggest that it is unlikely that the Reimagining Cleveland program has a sustained economic development impact on property markets in Cleveland.

Aggravated assaults, simple assaults & burglaries

Regressions on crime outcomes were estimated by aggregating crime events to block and 1/8th mi. buffers around greening interventions. The amount of developable area in the given geographical unit, the total number of Reimagining Cleveland interventions in the area as well as quarter and neighborhood fixed effects were controlled for.

No evidence is found to suggest significant differences with respect to burglaries and simple assaults. However, the models do suggest that greening may have led to a reduction in aggravated assaults. The pertinent regression estimates that on average, areas within 1/8mi of greening interventions experienced a 58% reduction in aggravated assaults one quarter after the intervention relative pre-post trends in the control group. This result is significant at the 0.05 level (p-value = 0.0415). The 95% confidence intervals on this estimate are wide, suggesting the average assault reductions could be as low as 34% or as high as 98%. It also worth noting that this effect becomes weakly significant two quarters after the intervention (p-value = 0.0719) and insignificant four quarters after the intervention (p-value = 0.53).

This result may mean that the Reimagining Cleveland greening intervention did have an effect on public safety outcomes, but that this effect was not sustained over time. Notably, the data used for this analysis does not observe the extent to which these greening sites were maintained. Thus, it could be that the behavior-altering effect of greening is in fact short-lived or that these sites fell into disrepair and that had an effect on outcomes.

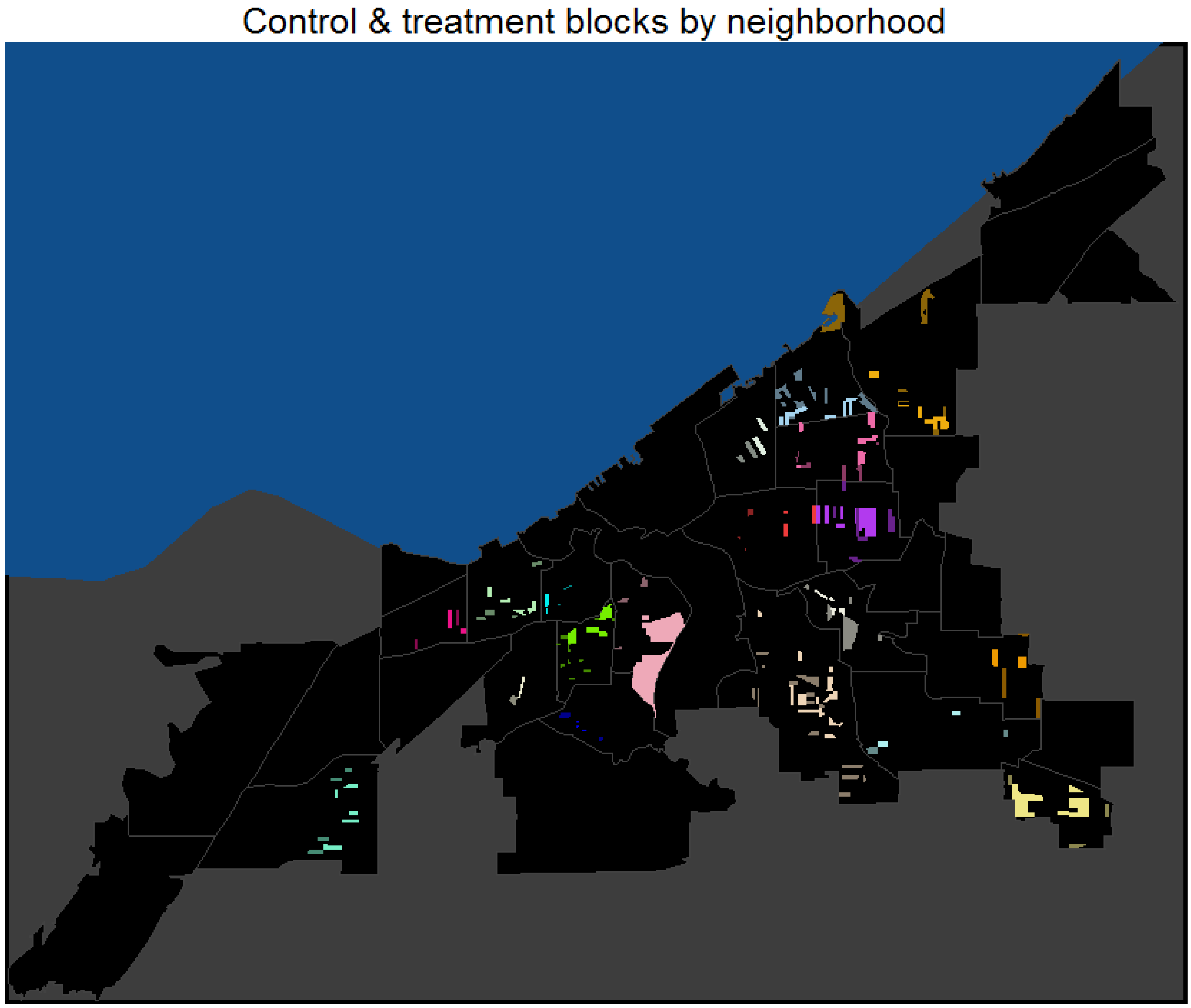

Figure 4.1: Matched treatment blocks (darker shades) & control blocks (lighter shades) by neighborhood

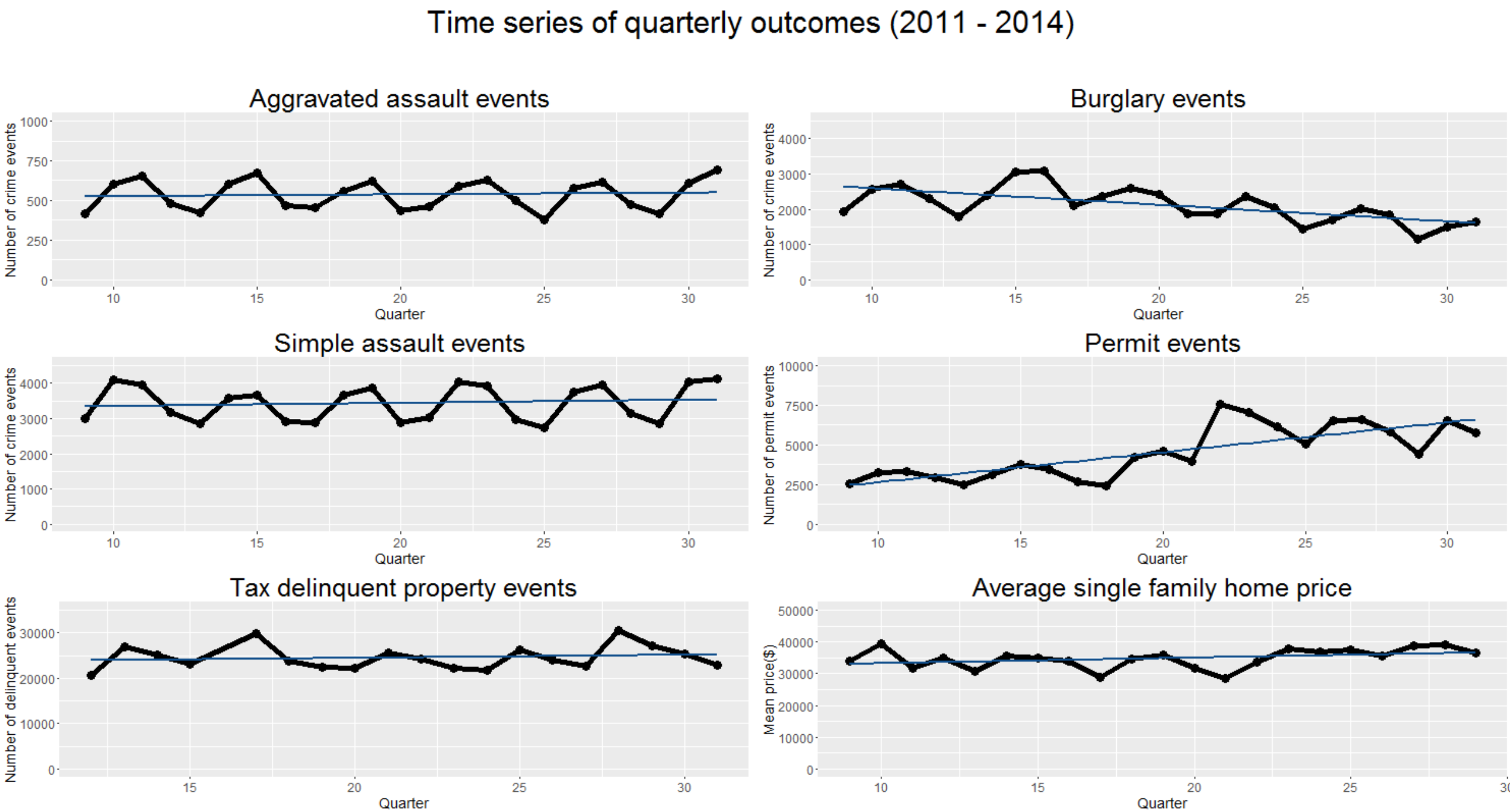

Figure 4.2: Time series of outcomes throughout study period

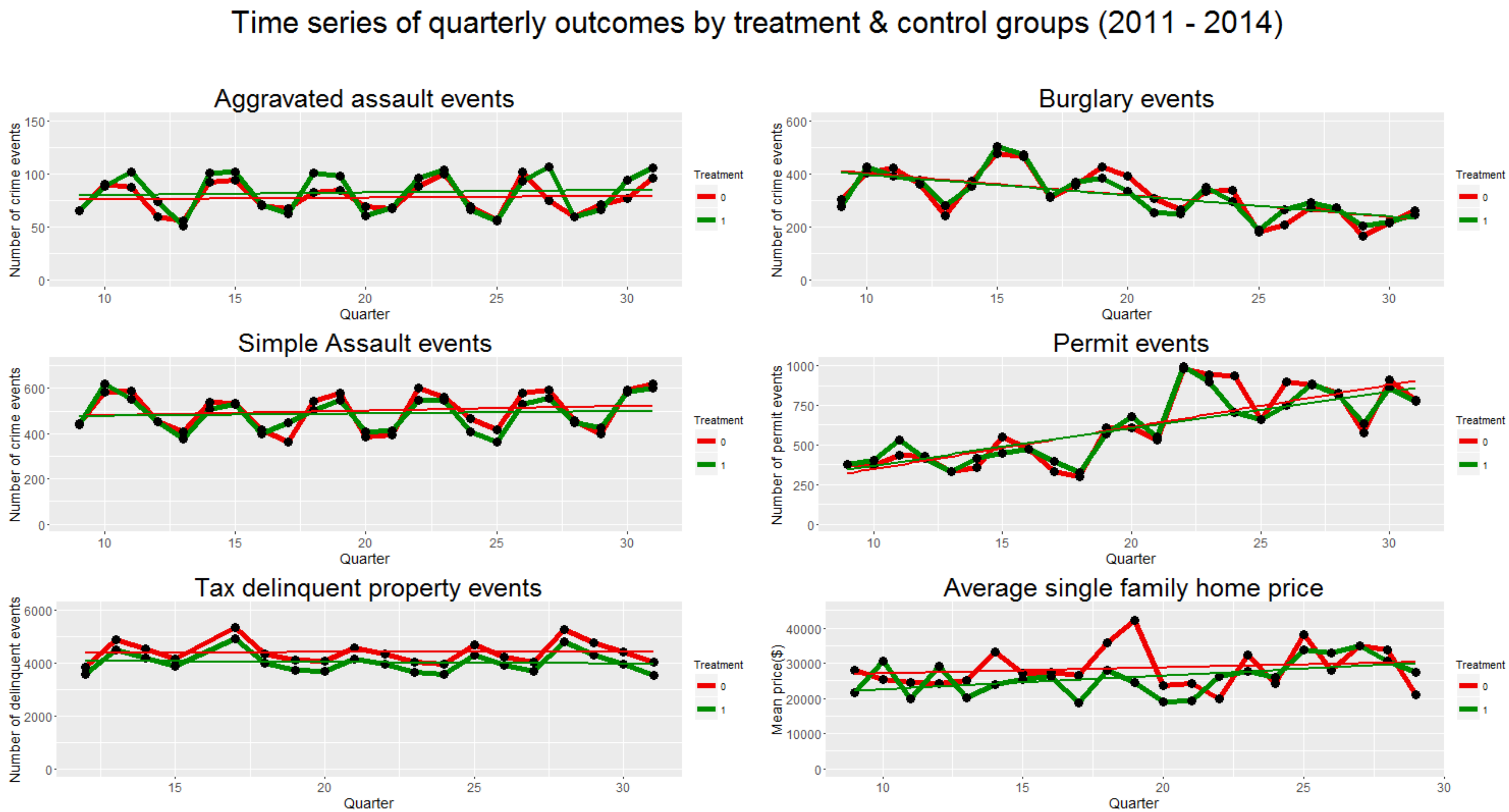

Figure 4.3: Time series of outcomes throughout study period by treatment and control group

5. Conclusions

This report finds evidence that the Reimagining Cleveland greening program had an effect on aggravated assaults in the short term. With respect to the remaining outcomes for which no effects were estimated, it is important to note that no effects does not mean negative effects. More so, these conclusions exist within the context of the research design which could be improved upon with added information about how vacant land parcels were selected for greening.

How do these findings square with the literature? Branas et al. (2011) found significant reductions in assaults and no effect on burglaries in Philadelphia[21]. It is important to note however, that these differences were not estimated to exist once the greening treatment was randomly allocated as it was in Garvin et al. (2013), a study that also took place in Philadelphia. While we did not estimate any significant economic development differences herein, Heckert & Mennis (2012) found statistically significant home price effects in Philadelphia.

At the onset of this report we asked if these findings were generalizable to other cities. Thus far, work from Philadelphia and this study from Cleveland is not enough to conclude whether in general, greening programs have an effect on the outcomes studied in this analysis. In addition, Philadelphia and Cleveland, despite their industrial past are far from comparable. Cleveland was not as resilient as Philadelphia in the wake of the Great Recession and Philadelphia has benefited a great deal more from new investment in formerly blighted neighborhoods.

Greening vacant land is still a valuable intervention in post-industrial cities because of its cost effectiveness. If greening leads to any social, economic or environmental benefit, even if they are marginal, it is worth the minimal upfront investment. The trick for planners is to discover the appropriate scale at which these interventions have a pronounced effect. It may be that to have a significant effect in a city like Cleveland, far more than 236 parcels have to be greened. For all of these reasons, more research is needed from more cities.

As discussed above, this analysis only estimated the effect of certain indirect benefits. The direct benefits of the Reimagining Cleveland greening program are incredibly important. These include increasing social cohesion and helping neighborhoods plan for sustainability. In other cities, green infrastructure is being used to nullify the negative effects of stormwater runoff and scholars have for years, touted the role that urban greening plays on a host of health and wellbeing outcomes[22].

If CNP continues the program and wishes to evaluate the social impacts of greening, they may consider developing a survey that asks residents and business owners

[21] These authors found modest effects for burglaries for one neighborhood when the dataset was split by neighborhood and separate regressions were estimated.
[22] Schilling & Logan (2008) for a review.

surrounding both control and treated lots both before and after the greening if they value the intervention and to what end.

Even with additional research however, proponents of greening should be concerned about securing funding, particularly from city councils which seem to be preoccupied by cost/benefit ratios. For these legislators, recreational and health benefits may not capture the same attention as crime and home price spillovers. New vacant land greening programs may require continued investment on behalf of the Third Sector, which has found a niche providing vital community resources when city managers are hesitant to do so.

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Appendix 1: Regression tables

Outcome Variable: Single family home sale prices

	log sale prices - Block geography			log sale prices - Within 1/8th mile of blocks		
	1Q Post Treatment	**2Q Post Treatment**	**4Q Post Treatment**	**1Q Post Treatment**	**2Q Post Treatment**	**4Q Post Treatment**
	9.409***	10.255***	10.360***	9.248***	9.370***	9.190***
	(1.328)	(1.026)	(1.358)	(0.489)	(0.451)	(0.484)
Usable area: parcel	-0.00001	0.0003	0.002***	0.001***	0.001***	0.001***
	(0.001)	(0.0004)	(0.001)	(0.0002)	(0.0002)	(0.0002)
Frontage	-0.0004	-0.002	-0.001	-0.0003	-0.001	-0.002
	(0.007)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)
Depth	0.003	0.008	-0.002	0.002	0.0001	0.002
	(0.007)	(0.005)	(0.006)	(0.002)	(0.001)	(0.002)
Property condition good or excellent	1.111**	0.054	0.19	0.432**	0.566***	0.508***
	(0.454)	(0.399)	(0.442)	(0.187)	(0.184)	(0.189)
Age of home	-0.003	-0.019**	-0.022**	-0.011***	-0.011***	-0.011***
	(0.007)	(0.007)	(0.01)	(0.002)	(0.003)	(0.003)
# of bedrooms	-0.221	-0.023	-0.219	-0.035	0.084	-0.068
	(0.197)	(0.205)	(0.246)	(0.063)	(0.081)	(0.085)
# of bathrooms	0.079	-0.548	-0.064	0.179	-0.099	-0.088
	(0.373)	(0.417)	(0.399)	(0.154)	(0.15)	(0.166)
Homestead exemption?	0.085	0.053	0.137	0.087	0.082	0.446*
	(0.753)	(0.627)	(0.573)	(0.219)	(0.244)	(0.25)
Tax abatement?	0.766	1.585***	0.67	0.333*	0.443**	0.416**
	(0.61)	(0.546)	(0.649)	(0.191)	(0.176)	(0.192)
Total reimag. projects	-0.703	-0.661*	-0.235	-0.072	-0.106	0.008
	(0.521)	(0.37)	(0.455)	(0.168)	(0.15)	(0.081)
1 quarter post intervention	-0.383			0.018		
	(0.469)			(0.172)		
2 quarters post intervention		-0.254			0.232	
		(0.404)			(0.169)	
4 quarters post intervention			-0.044			0.239
			(0.509)			(0.205)
Treatment	1.154	1.476**	0.697	0.186	0.321	0.237
	(0.923)	(0.665)	(0.789)	(0.29)	(0.27)	(0.233)
1 quarter post * Treatment	-0.538			-0.406*		
	(0.614)			(0.245)		
2 quarters post * Treatment		0.358			-0.386	
		(0.551)			(0.244)	
4 quarters post * Treatment			-0.386			-0.382
			(0.643)			(0.269)
Observations	71	67	63	248	255	228
R^2	0.657	0.807	0.708	0.452	0.463	0.459
Adjusted R^2	0.332	0.602	0.375	0.349	0.363	0.347

*p < 0.1 **p < 0.5 *** p < 0.01

Note: Quarter and neighborhood fixed effects not shown

Outcome Variable: Tax Delinquency Amount

	Log tax delinquency amount - Block geography			Log tax delinquency amount - Within 1/8th mile of blocks		
	1Q Post Treatment	**2Q Post Treatment**	**4Q Post Treatment**	**1Q Post Treatment**	**2Q Post Treatment**	**4Q Post Treatment**
Intercept	4.553***	4.371***	4.015***	7.758***	7.666***	7.400***
	(0.782)	(0.83)	(0.789)	(0.471)	(0.535)	(0.398)
Usable area: block	0.0002	0.0003	0.0003*			
	(0.0002)	(0.0002)	(0.0002)			
Usable area: 1/8 Mi.				0.0001*	0.0001*	0.0001
				(0.00004)	(0.00005)	(0.00004)
Total reimag. projects	0.095	0.073	0.065	0.02	0.039	0.033
	(0.16)	(0.169)	(0.161)	(0.094)	(0.107)	(0.08)
1 quarter post intervention	-0.12			-0.33		
	(0.387)			(0.229)		
2 quarters post intervention		-0.061			-0.191	
		(0.41)			(0.258)	
4 quarters post intervention			0.473			0.549***
			(0.39)			(0.195)
Treatment	1.018**	1.473***	1.513***	-0.21	0.161	0.059
	(0.465)	(0.493)	(0.467)	(0.275)	(0.311)	(0.232)
1 quarter post * Treatment	0.061			0.259		
	(0.543)			(0.321)		
2 quarters post * Treatment		-0.673			-0.492	
		(0.575)			(0.363)	
4 quarters post * Treatment			-0.304			-0.375
			(0.546)			(0.272)
Observations	410	410	410	410	410	410
R^2	0.25	0.25	0.19	0.43	0.43	0.33
Adjusted R^2	0.187	0.182	0.12	0.381	0.378	0.273

**p < 0.1   **p < 0.5   *** p < 0.01*

Note: Quarter and neighborhood fixed effects not shown

Outcome Variable: Count of Tax Delinquent Homes

	Tax delinquent properties - Block geography				Tax delinquent properties - Within 1/8th mile of blocks		
	1Q Post Treatment	**2Q Post Treatment**	**4Q Post Treatment**		**1Q Post Treatment**	**2Q Post Treatment**	**4Q Post Treatment**
Intercept	0.486*	0.359	0.577**		2.369***	2.230***	2.455***
	(0.258)	(0.277)	(0.255)		(0.178)	(0.203)	(0.162)
Usable area: block	0.0002***	0.0003***	0.0002***				
	(0.00005)	(0.0001)	(0.00005)				
Usable area: 1/8 Mi.					0.0001***	0.0001***	0.0001***
					(0.00001)	(0.00002)	(0.00001)
Total reimag. projects	0.065	0.082*	0.083*		0.027	0.022	0.032
	(0.047)	(0.049)	(0.047)		(0.034)	(0.039)	(0.031)
1 quarter post intervention	-0.128				-0.192**		
	(0.128)				(0.085)		
2 quarters post intervention		-0.057				-0.119	
		(0.132)				(0.095)	
4 quarters post intervention			0.174				0.083
			(0.125)				(0.077)
Treatment	0.502***	0.500***	0.473***		0.009	0.1	0.074
	(0.145)	(0.152)	(0.145)		(0.1)	(0.114)	(0.091)
1 quarter post * Treatment	0.105				0.165		
	(0.172)				(0.118)		
2 quarters post * Treatment		-0.027				0.009	
		(0.18)				(0.134)	
4 quarters post * Treatment			-0.108				-0.046
			(0.17)				(0.108)
Observations	410	410	410		410	410	410
Akaike Inf. Crit.	2,329.98	2,350.39	2,393.16		3,474.95	3,546.10	3,467.71

**p < 0.1 **p < 0.5 *** p < 0.01*

Note: Quarter and neighborhood fixed effects not shown

Outcome Variable: Building Permit Cost

	Log building permit cost - Block geography				Log building permit cost - Within 1/8th mile of blocks		
	1Q Post Treatment	**2Q Post Treatment**	**4Q Post Treatment**		**1Q Post Treatment**	**2Q Post Treatment**	**4Q Post Treatment**
Intercept	0.642	0.938	0.085		4.144***	6.298***	5.501***
	(1.146)	(1.039)	(1.097)		(1.29)	(1.315)	(1.258)
Usable area: block	0.001**	0.001***	0.001***				
	(0.0002)	(0.0002)	(0.0002)				
Usable area: 1/8 Mi.					0.0002**	0.0003***	0.0001
					(0.0001)	(0.0001)	(0.0001)
Total reimag. projects	0.479**	0.431**	0.522**		-0.129	0.007	-0.063
	(0.234)	(0.212)	(0.223)		(0.258)	(0.262)	(0.252)
1 quarter post intervention	0.512				-0.196		
	(0.567)				(0.626)		
2 quarters post intervention		-0.192				0.177	
		(0.513)				(0.634)	
4 quarters post intervention			-0.027				0.791
			(0.542)				(0.616)
Treatment	0.216	0.251	0.388		1.266*	0.708	0.929
	(0.682)	(0.617)	(0.65)		(0.752)	(0.763)	(0.734)
1 quarter post * Treatment	0.436				0.772		
	(0.796)				(0.879)		
2 quarters post * Treatment		0.115				-1.137	
		(0.72)				(0.89)	
4 quarters post * Treatment			0.577				0.302
			(0.759)				(0.86)
Observations	410	410	410		410	410	410
R^2	0.13	0.16	0.12		0.16	0.16	0.13
Adjusted R^2	0.061	0.088	0.046		0.091	0.087	0.054

**p < 0.1 **p < 0.5 *** p < 0.01*

Note: Quarter and neighborhood fixed effects not shown

Outcome Variable: Count of Building Permits

	Building permits - Block geography			Building permits - Within 1/8th mile of blocks		
	1Q Post Treatment	**2Q Post Treatment**	**4Q Post Treatment**	**1Q Post Treatment**	**2Q Post Treatment**	**4Q Post Treatment**
Intercept	-1.428***	-1.845***	-1.653***	0.455	0.748***	0.566**
	(0.485)	(0.543)	(0.532)	(0.284)	(0.265)	(0.281)
Usable area: block	0.0003***	0.0003***	0.0003***			
	(0.0001)	(0.0001)	(0.0001)			
Usable area: 1/8 Mi.				0.0001**	0.0001***	0.0001**
				(0.00002)	(0.00002)	(0.00002)
Total reimag. projects	0.198**	0.163*	0.174**	0.044	0.012	0.044
	(0.079)	(0.083)	(0.086)	(0.052)	(0.05)	(0.052)
1 quarter post intervention	0.503**			0.309**		
	(0.235)			(0.13)		
2 quarters post intervention		0.494**			0.264**	
		(0.235)			(0.124)	
4 quarters post intervention			0.528**			0.377***
			(0.246)			(0.132)
Treatment	0.115	0.213	0.117	-0.225	-0.08	-0.178
	(0.275)	(0.277)	(0.287)	(0.159)	(0.153)	(0.16)
1 quarter post * Treatment	0.161			0.268		
	(0.315)			(0.183)		
2 quarters post * Treatment		-0.036			0.145	
		(0.318)			(0.176)	
4 quarters post * Treatment			0.035			0.318*
			(0.332)			(0.184)
Observations	410	410	410	410	410	410
Akaike Inf. Crit.	1,143.55	1,078.72	1,114.58	2,077.88	2,014.23	2,112.33

**p < 0.1 **p < 0.5 *** p < 0.01*

Note: Quarter and neighborhood fixed effects not shown

Outcome Variable: Aggravated Assaults

	Aggravated assaults - Block geography			Aggravated assaults - Within 1/8th mile of blocks		
	1Q Post Treatment	**2Q Post Treatment**	**4Q Post Treatment**	**1Q Post Treatment**	**2Q Post Treatment**	**4Q Post Treatment**
Intercept	-3.980***	-3.737***	-4.785***	-0.764*	-0.823*	-1.021**
	(1.198)	(1.016)	(1.242)	(0.418)	(0.423)	(0.443)
Usable area: block	0.0002	-0.0001	0.0002			
	(0.0001)	(0.0002)	(0.0001)			
Usable area: 1/8 Mi.				-0.00001	-0.00002	-0.00001
				(0.00003)	(0.00003)	(0.00003)
Total reimag. projects	0.252*	0.255*	0.290**	0.042	0.031	0.046
	(0.142)	(0.138)	(0.113)	(0.068)	(0.068)	(0.064)
1 quarter post intervention	0.897			0.188		
	(0.593)			(0.184)		
2 quarters post intervention		0.229			-0.522**	
		(0.671)			(0.213)	
4 quarters post intervention			1.273**			0.193
			(0.585)			(0.186)
Treatment	0.819	0.661	0.551	0.003	0.115	-0.089
	(0.629)	(0.615)	(0.628)	(0.221)	(0.219)	(0.221)
1 quarter post * Treatment	-1.039			-0.542**		
	(0.712)			(0.266)		
2 quarters post * Treatment		0.299			0.490*	
		(0.753)			(0.272)	
4 quarters post * Treatment			-0.794			-0.161
			(0.68)			(0.257)
Observations	410	410	410	410	410	410
Akaike Inf. Crit.	304.23	307.08	327.71	864.66	826.01	901.29

**p < 0.1 **p < 0.5 *** p < 0.01*

Note: Quarter and neighborhood fixed effects not shown

Outcome Variable: Simple Assaults

	Simple assaults - Block geography			Simple assaults - Within 1/8th mile of blocks		
	1Q Post Treatment	**2Q Post Treatment**	**4Q Post Treatment**	**1Q Post Treatment**	**2Q Post Treatment**	**4Q Post Treatment**
Intercept	-1.339***	-0.818**	-1.642***	0.168	0.452*	0.106
	(0.432)	(0.396)	(0.446)	(0.246)	(0.246)	(0.258)
Usable area: block	0.0001	0.0002**	0.0001			
	(0.0001)	(0.0001)	(0.0001)			
Usable area: 1/8 Mi.				0.00005***	0.00003	0.00001
				(0.00002)	(0.00002)	(0.00002)
Total reimag. projects	0.160**	0.109	0.06	0.058	-0.007	-0.002
	(0.065)	(0.078)	(0.072)	(0.041)	(0.045)	(0.044)
1 quarter post intervention	0.386			0.223**		
	(0.241)			(0.106)		
2 quarters post intervention		0.308			0.035	
		(0.239)			(0.11)	
4 quarters post intervention			0.667***			0.300***
			(0.236)			(0.108)
Treatment	0.580**	0.548**	0.690***	0.007	0.094	0.045
	(0.253)	(0.259)	(0.261)	(0.128)	(0.132)	(0.131)
1 quarter post * Treatment	-0.132			0.022		
	(0.3)			(0.148)		
2 quarters post * Treatment		-0.348			0.085	
		(0.304)			(0.153)	
4 quarters post * Treatment			-0.309			-0.072
			(0.297)			(0.15)
Observations	410	410	410	410	410	410
Akaike Inf. Crit.	889.96	851.06	935.71	1,895.09	1,861.52	1,912.83

**p < 0.1 **p < 0.5 *** p < 0.01*

Note: Quarter and neighborhood fixed effects not shown

Outcome Variable: Burglaries

	Burglaries - Block geography			Burglaries - Within 1/8th mile of blocks		
	1Q Post Treatment	**2Q Post Treatment**	**4Q Post Treatment**	**1Q Post Treatment**	**2Q Post Treatment**	**4Q Post Treatment**
Intercept	-1.356***	-1.732***	-2.077***	0.21	0.492**	0.077
	(0.487)	(0.562)	(0.586)	(0.265)	(0.242)	(0.296)
Usable area: block	0.00004	0.0001	-0.00003			
	(0.0001)	(0.0001)	(0.0001)			
Usable area: 1/8 Mi.				0.00002	0.00001	0.00002
				(0.00002)	(0.00002)	(0.00002)
Total reimag. projects	0.064	0.04	0.04	-0.033	-0.064	-0.122**
	(0.115)	(0.113)	(0.107)	(0.053)	(0.053)	(0.06)
1 quarter post intervention	0.405			0.392***		
	(0.279)			(0.117)		
2 quarters post intervention		0.203			0.186*	
		(0.29)			(0.111)	
4 quarters post intervention			0.129			0.064
			(0.278)			(0.125)
Treatment	0.700**	0.730**	0.646**	0.136	0.191	0.213
	(0.312)	(0.318)	(0.294)	(0.148)	(0.14)	(0.154)
1 quarter post * Treatment	-0.539			-0.256		
	(0.352)			(0.164)		
2 quarters post * Treatment		-0.492			-0.176	
		(0.366)			(0.155)	
4 quarters post * Treatment			-0.103			0.102
			(0.338)			(0.171)
Observations	410	410	410	410	410	410
Akaike Inf. Crit.	718.37	683.30	722.36	1,647.06	1,562.17	1,590.37

**p < 0.1   **p < 0.5   *** p < 0.01*

Note: Quarter and neighborhood fixed effects not shown

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