Equitable Urban Revitalization and Access to Amenities*

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Abstract:

Stemming urban decline and exodus from the city is a pertinent issue facing policymakers. The success of any effort to address these issues depends on the equitability of the process, which is especially important in lower-income minority neighborhoods disproportionately affected by issues of environmental degradation. Using a unique set housing activity data coupled with neighborhood level data on demographics and the environment, we examine the effect of a targeted urban revitalization effort in Baltimore, Maryland via a quasi-experimental design. We find neighborhoods funded by the program have higher housing sales than short-listed unfunded neighborhoods, with increases in house renovations seen in neighborhoods with multiple funded projects. We also find that high levels of poverty, crime, and brownfields within each neighborhood affect the outcome of the revitalization effort.

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I) Introduction

Efforts to stem urban decline and exodus from the city have long been at the forefront of the conversation for policymakers. Nowhere is this more pertinent than in the former manufacturing cities of the Rust Belt, where city populations have shrunk significantly despite growing urban populations. Residents are moving out of the cities and into suburban communities, leading to differential growth across space in the urban environment. To reverse this trend, cities have renewed focus on enticing residents to return to the city, but much of this policy operates with limited meaningful economic analysis.

One of the fundamental issues confronting urban redevelopment efforts is the issue of durable housing (Glaeser and Gyourko, 2005). In cities with a shrinking population, this durability can lead to an oversupply of housing. This oversupply cannot meet the underlying demand for housing, which causes the surplus housing to deteriorate. This deterioration of the housing stock further suppresses demand and can contribute to long-lasting cycles of urban decline and renewal that may last upwards of one hundred years (Rosenthal, 2008). Altering the natural decline and renewal cycles to minimize the former and hasten the latter is a clear goal of urban policymakers and planners. The success of urban revitalization efforts also hinges on ensuring the process actually helps the areas that are suffering the most from urban decline, i.e. the process is fair and equitable. This is particularly important in lower-income minority neighborhoods who are disproportionately affected by issues of environmental degradation (UCC, 1987) and vacancy (Silverman et al., 2012). Understanding the total weight of these issues is thus a priority for urban policymakers especially as scarce public resources are dedicated to addressing them. Misguided policy, however, could exacerbate these cycles, leading to suboptimal outcomes for both the city and its residents.

Previous work on urban redevelopment has traditionally focused on the decisions of individual landowners regarding the timing and intensity of redevelopment, which follows from the basic urban model (Brueckner, 1980; Wheaton, 1982). Redevelopment will happen when the price of land in current use is exceeded by the price of land in its redeveloped use, minus the cost of conversion. Much of the empirical work on residential redevelopment focuses on the role price plays on the redevelopment decision (see Rosenthal & Helsley, 1994; Dye & McMillan, 2007; McMillen & O'Sullivan 2013) establishing the importance of expectations for the future path of land and house values, which are, in part, a function of the anticipated future state of the neighborhood.

Merging issues of environmental inequity into urban redevelopment typically has focused on brownfields and remediation (Schoenbaum, 2002; McCarthy, 2009) or proximity to environmental negatives (Dale et al., 1999; McCluskey and Rausser, 2001; McCluskey and Rausser, 2003) and the resulting effect on house prices. This particular stream of work fits comfortably into the environmental gentrification stream of the environmental justice literature but so to would work focused on urban redevelopment that considers outcome equity and the role environmental goods play in the success of redevelopment. If the removal of explicitly environmental locally undesirable land uses (LULUs) can affect house prices, one would expect similar outcomes on the redevelopment of blighted vacant structures that can contribute to environmental degradation through lead contamination (Sayre and Katzel, 1979; Lanphear et al., 2002).

Previous environmental justice studies have shown the robust relationship between the disproportionate impact LULUs have on poor and minority groups. Minority groups are disproportionately affected by the location of facilities that contribute to pollution or the increased risk of impaired health outcomes (Bullard, 1990; Oakes et al., 1996; Pastor et al., 2001, Apelberg et al., 2005; Depro et al., 2015). Much of this work operates on the outright discrimination or coming to the nuisance model of firm location and/or household sorting (see Banzhaf, 2012 for a detailed explanation of the different "models" of environmental justice). This approach may be inadequate to address the issues at the intersection of urban revitalization and environmental justice, where underlying land-use decisions that contribute to environmental inequality (*i.e.* lack of building code enforcement, underinvestment, zoning decisions) stem from governmental failure enforce its standards equally across the city. One could argue if these outcomes are from an underlying decision process wherein decisions benefit groups with higher political capital, which is what Viscusi and Hamilton (1999) find, but the overarching issue is a lack of equitable policy on behalf of the government.

Bringing environmental justice issues into the urban front has been of interest to other fields, especially as they relate to urban revitalization efforts. Schweitzer and Stephenson Jr. (2007) argue that a failure to understand that "uneven geographical development" is the driving force behind the injustice issues, both environmental and social, facing urban populations. This uneven geographical development stems from both geographical constraints and the rise of suburbs but also the historical endogenous land development decisions. This is echoed in work by Wilson et al. (2008) who note that planning and zoning decisions contribute to uneven development through fragmentation. While our work does not explicitly attempt to address all of these issues, we do focus on the role urban revitalization efforts have on stimulating the housing market and how the effect is heterogeneous across diverse city neighborhoods.

This paper empirically estimates the effect of an urban revitalization effort in Baltimore, Maryland on neighborhood level housing sales and renovations. The Vacants to Value (V2V) initiative, described in detail in the next section, targets vacant lots and properties through wholesale cleanup and demolition, removing excessive housing stock and converting the land into temporary open space before additional development occurs. We exploit the demolition portion and the unique nature of the V2V program, to develop a natural experiment with three distinct groups: funded neighborhoods, unfunded but short-listed neighborhoods, and unfunded and unlisted neighborhoods. We also explore how underlying neighborhood characteristics, specifically poverty, crime, parks, brownfields, and public transportation accessibility interact with each of these groups.

Utilizing a unique dataset of neighborhood level demographic, amenity, and housing data from 2013 through 2015, we find that housing renovations are 200 percent higher in neighborhoods with multiple V2V interventions while housing sales are between 4.8 and 45 percent higher in neighborhoods with at least one funded site. We also find that high levels of poverty and crime can dampen the effects of the urban revitalization efforts. Neighborhoods with significant acreage designed as brownfields also have higher levels of housing sales if they are the recipient of V2V funding.

This work is a distinct turn from the traditional environmental justice literature, moving beyond the issues of hazardous waste cleanup and air pollution, and focusing instead on the role urban revitalization efforts play on environmental justice and equity across socio-demographic groups. Our contribution lies in the fact we are one of the first to explore urban revitalization efforts through the environmental justice framework with a unique micro-set of data not typically found in the economic literature.

II) Redevelopment efforts in Baltimore and Vacants to Value

Baltimore, Maryland presents an ideal location for studying the impacts of city-led efforts aimed at urban revitalization. The population of Baltimore shrunk nearly 34 percent since a peak in 1960 despite a 60 percent increase in the population of the surrounding metro region. This is causing significant issues in the residential housing market with vacant lots and vacant housing – an estimated 14,000 vacant properties at last city count – and environmental health related issues. As a former industrial city with a deep-water port, Baltimore continues to feel the after-effects of its history as an industrial hub with approximately 4% of all available land in the city in brownfield status (Baltimore Brownfields Initiative, 2014).

One of the bigger issues facing the city stems from the legacy of lead, especially in the context of rampant vacancy. The deteriorating vacant properties contribute to very high levels of lead exposure for nearby residents with adverse health effects on the populace (Barry-Jester, 2015). The problem is so acute within both Maryland and Baltimore that the state has mandated students in designated "at-risk" areas to undergo blood lead level testing before starting public school, leading to the testing of nearly 100,000 students a year. In Baltimore City alone, where the entire city is designated as "at-risk", over 65,000 children had elevated blood lead levels since testing began in 1993 (Maryland Department of the Environment, 2013).

To bring about urban renewal and address the issues, both health and economic, imposed by vacancy, Baltimore began a unique blight elimination program in 2010 called Vacants to Value (V2V). It is a comprehensive city-led effort to revitalize neighborhoods that specifically targets areas of high vacancy through increased code enforcement, providing homebuyer incentives, expediting the sale of city-owned properties, and promoting green and sustainable communities (Jacobson, 2015). One of the centerpieces of the program is the use of targeted demolition of vacant properties in distressed areas. This is the most noticeable of the V2V program activities, as wholesale block-level demolition of non-public housing is extremely uncommon and, to the best of our knowledge, never before used as part of an urban renewal plan at any scale. It is the demolition portion of the project that is of particular importance and the focus of this paper. While the program itself provides a suite of policy actions across the city, only the demolition portion is spatially explicit.

In 2013, the program created a short-list of possible demolition sites in targeted neighborhoods based upon Baltimore's 2011 Housing Market Topology (HMT), a large-scale housing study created by and for the city to help identify and strategically match limited public resources in neighborhoods to encourage revitalization. The HMT functions by using cluster analysis to define the housing market in each neighborhood on a five-point scale[1] based upon underlying issues of vacancy, occupancy rates, and population decline. For the set of neighborhoods scoring in the lowest category, a preliminary list of targeted areas for block-level demolitions within each neighborhood was created as a means to revitalize the market by removing excessive housing stock.

[1] Regional Choice, Middle Market Choice, Middle Market, Middle Market Stressed, and Stressed.

From the initial shortlist, selected projects were funded during the study period. This selection for funding was exogenously determined by city planners and only subject to being on the initial shortlist (*i.e.* no projects were funded that were not on the initial shortlist). While funding was a factor in project initiation, generally speaking, projects were not selected based on cost and projects are equally dispersed throughout the city contingent upon initial placement on the shortlist, as we demonstrate in the next section. Some neighborhoods had multiple projects funded during the study period while others had no funded projects during the period despite multiple shortlisted projects.

III) Data

As our central research question relies upon determining the effectiveness of the V2V program, we collect a wide range of data from each of the different neighborhoods in Baltimore. Our work aggregates data from a wide range of sources and is best grouped into four distinct groups, which we detail in turn.

The first set of data we collect is socio-demographic information on the neighborhoods themselves. Baltimore has 278 distinct city-defined neighborhoods of which 247 are residential neighborhoods.[2] The average population in each neighborhood is a little over 2,500 people. This puts each neighborhood as roughly the same size as a U.S. Census Block Group but there is tremendous variation in neighborhood size across the city. The largest single neighborhood, Frankford, has over 17,000 residents according to the most recent U.S. Census estimates, while the smallest, Blythewood had a population of just 72 people. We collect data on each

[2] The remaining neighborhoods consist of industrial areas, large city parks, and one business park, all of which have no residents. These are dropped from our central analysis but create dummy variables for neighborhoods that border areas with brownfield sites, which include several industrial areas.

neighborhood’s residential composition, including racial and age breakdowns, in addition to data on each neighborhoods housing stock, including vacancy rate. The source for this detailed information in each neighborhood comes from the 2010 U.S. Census and from the five-year American Community Survey (ACS) estimates spanning 2006-2010, created for the city due to a special request from the Department of Planning to the Census Bureau. We provide a comprehensive list of the socio-demographic data in Table 1 with key summary statistics.

The neighborhood data is nearly complete for all 247 residential neighborhoods but some neighborhoods have key data necessary for our analysis missing. These include information on the education level in each neighborhood from the ACS – percentage with high school degree or higher and percentage with a bachelor’s degree or higher – which is missing from nine neighborhoods and information on household income and the percentage of the population living under the poverty line, missing from eight neighborhoods. Rather than drop these neighborhoods from our analysis due to the missing data, we instead take a population weighted average of the data from the surrounding neighborhoods and use this as an estimate for the missing data.

The second set of data we collect is amenity data for each neighborhood. We collect data on the number of light-rail and subway stops in each neighborhood, the amount of parkland and proximity to Baltimore’s largest parks and coastline, in addition to information on brownfields within each neighborhood, and crime information. For the transportation data, we utilize GIS shapefiles available from the Baltimore’s Open Data website and map light-rail and subway locations to each neighborhood. We obtain a shapefile with all of the city maintained parks from the same website and dissolve the park data layer into the neighborhood layer, which allows us to calculate both the number of individual parks in each neighborhood and the percentage of parkland per total area in the neighborhood.

For the brownfield data, we utilize the Brownfield Master Inventory (BMI), available from the Maryland Department of the Environment. The BMI is the master list of all declared or suspected – reported but not verified – brownfield sites in the entire state. We restrict our brownfields of interest to only those within the City of Baltimore and utilize ArcGIS to geolocate each of the sites in Baltimore into their requisite neighborhoods. We then tally the number of brownfield sites in each neighborhood and the total acreage of all the sites. As shown in Table 1, there is approximately one listed brownfields for every residential neighborhood in Baltimore, with an average size per brownfield of 7.5 acres. All told, approximately 4.3% of all the non-industrial land in Baltimore has brownfield status. This speaks both to the legacy of environmental neglect in Baltimore but also to the systemic underlying environmental issues pushing against efforts to revitalize city.

To calculate our crime rates, we collect the daily reported crime statistics for 2013 through 2015 from the Baltimore Police Department, which provides the type, date, and general location of the crime, including the neighborhood. Baltimore Police define nine different types of crimes with each type having several subcategories based on the crime itself. We follow convention from the Federal Bureau of Investigation (United States Department of Justice, 2013) and divide the nine types of crimes into two categories, violent and property crimes.[3] We then take the average of both crimes types over the three year period, divide by the neighborhood

[3] Violent crimes consist of homicide, rape, robbery, and aggravated assault while property crimes consist of burglary, larceny, arson, and auto theft. The Baltimore crime statistics also have a miscellaneous category for shootings that do not fall under any other category. We do not include these as part of the violent crime category, in order to remain consistent with FBI guidelines. This means that the violent crime numbers are lower than they would be if miscellaneous shootings were included.

population, and multiply by 1,000 to standardize the crime rates.[4] Table 2 provides some detail on the crime rates in each neighborhood and compares the neighborhood average to the city's crime rates as a whole and to the U.S. crime rates. The differences in the neighborhood average crime rates and the city-wide crime rates stem largely from the missing zero resident neighborhoods, which have very low violent crime rates, as one would expect.

Our third set of collected data is information on housing sales[5] and renovation activity within Baltimore. We obtain housing sale records from 2013 through 2015 from Maryland PropertyView, a database created by the Maryland Department of Planning that contains housing and parcel information as well as GIS parcel data. We then geolocate each housing sale into its requisite neighborhood and create a count of the housing sales per year in each neighborhood. We are also able to distinguish between houses sold for owner occupancy versus houses sold as rental properties from a unique identifier for the latter property type. The average neighborhood had just under 22 housing renovations and 139 housing sales over our three year period, as seen in table 3.

Similarly, we acquire all filed housing permits from the Housing Authority of Baltimore City (HABC). This data includes the address of each permit in addition to the issue date, the expiration date, and the neighborhood in which the address is located. Despite not explicitly labeling the renovations by a unique code, we are able to identify renovation activity though the permit description field which is the part of the physical permit where the work to be done is described. Once we have created a short list of renovations, we match the addresses from the

[4] We average the crime rates over a longer period in order to mitigate the effect of a spike in crime rates that occurred in 2015. We choose to use 1,000 instead of 100,000 as the means of standardizing the crime rates as our unit of observation is at a sub-city level.

[5] Housing sales include detached single-family houses in addition to apartments, condominiums, and attached single-family house sales.

permit file to a master list of all housing parcels within Baltimore and retain only the renovation activity that is matched to a residential parcel.[6] As the V2V program is focused on revitalizing neighborhoods through stimulating the housing market by removing excessive housing stock, we want to examine the effect of the program on residential renovation activity only. This is not to discount the possibility of V2V having a positive effect on non-residential renovation activity, as it could lead to an increase in neighborhood desirability which would, in turn could cause residents of the city to resort across neighborhoods. We leave this question open for future research.

Our final set of data is on the V2V program itself. As mentioned in the previous sections, the V2V program created a preliminary list of targeted areas in 2012 and funded a small set of them in 2013 with additional areas funded in 2014. We tag each targeted area into its requisite neighborhood and create a series of treatment groups based upon membership into the following three groups: never neighborhoods, preliminary neighborhoods, and funded neighborhoods. These are simply the neighborhoods that did not make the preliminary list, the neighborhoods that made the list but were unfunded, and the neighborhoods funded at some point. We create an additional set of dummy variables for neighborhoods that saw multiple V2V projects funded, as seen in Table 3. All told, 49 neighborhoods made the short-list and 29 were funded during the first two years[7] of the program.

Figures 1-4 show the geographic distribution of the V2V activity across Baltimore, with triangles indicating short-listed projects in each neighborhood and circles indicating funded projects in each neighborhood and overlaid with population density, poverty, vacancy and

[6] Housing renovations include the same property types gathered for housing sales.
[7] Information on funding for 2015 is not currently available.

violent crime rates, respectively. As the maps shows, the activity is clustered in certain parts of the city, which is expected as these are also the areas with high population density and areas where the housing market has frictions due to issues of crime and vacancy.

IV) Identification strategy and implementation

Our goal is to determine the effectiveness of V2V program led demolitions on stimulating the housing market within each neighborhood, as measured by the number of renovations and housing sales. Due to the design of the program, it presents the opportunity to construct a natural experiment with distinct groups: funded sites in neighborhoods and unfunded but shortlisted sites in neighborhoods (which we call preliminary), with unlisted neighborhoods as a control group. The control group, as currently constructed, includes neighborhoods that received the lowest rating on the aforementioned Baltimore Housing Market Topology study but also neighborhoods that scored higher. Clearly, our control group is not perfect for our study, as the better control group would be the neighborhoods who received the lowest rating in the HMT but had zero projects making the initial list.[8] However, our control group does still receive the non-demolition benefits of the V2V program – increased code enforcement, homebuyer benefits, streamlining the sale of city owned housing – so it does still serve as an imprecise control.

The key to the identification strategy we utilize is establishing that the underlying characteristics between the neighborhoods that saw V2V demolition activity – our treated group – do no differ from the preliminary list neighborhoods that were unfunded during the study period. In table 4, we examine the difference in the means between the two groups across a

[8] We have requested the neighborhood designation from the city but do not currently have the complete results of the HMT. Once the data is received, it will be incorporated into a future version of this manuscript.

mixture of neighborhood level variables. We see that the funded neighborhoods have, on average, slightly higher population density, violent crime rates, number of brownfields, public transit accessibility[9], owner occupancy rates, vacancy rates, and number of parks. However, the difference in the means between the groups is not significantly different from zero. The only variables whose means do differ in our treated and untreated group are percent black, percent white, and vacant lot[10] percentage. The treated groups do tend to have a higher percentage of black residents with a lower percentage of white residents, which is not necessarily surprising for a city like Baltimore where black residents outnumber white residents two to one. We do not believe this jeopardizes the identification strategy in any way, as black residents make up the overwhelming majority in both the treated and untreated neighborhoods.

Since we have established the underlying characteristics of our groups are sufficiently similar to allow for our chosen identification strategy, we empirically implement our first models as shown below with our three different variables of interest:

$$\boldsymbol{Renovations_{it} = \alpha + \beta_X X_i + +\theta Pre + \rho Fund + \epsilon_{it}} \tag{1}$$

$$\boldsymbol{Sales_{it} = \alpha + \beta_X X_i + +\theta Pre + \rho Fund + \epsilon_{it}} \tag{2}$$

$$\boldsymbol{Sales\_nonrental_{it} = \alpha + \beta_X X_i + +\theta Pre + \rho Fund + \epsilon_{it}} \tag{3}$$

where the number of renovation, sales and sales of non-rental housing in neighborhood *i* in year *t* is a function of the underlying neighborhood control variables (demographic makeup and

[9] We measure public transit accessibility as a binary variable that receives a one if the neighborhood has a light-rail or subway stop anywhere in the neighborhood. We do not include bus stops in this version of the manuscript due to a data availability issues.

[10] Vacant lot percentage is the number of empty lots in the neighborhood classified as vacant by the city divided by the total number of lots in that neighborhood. This differs from the vacancy rate, which is simply the number of residential units that are vacant. Vacant lot percentage includes residential lots but also some number of commercial and industrial lots as well. We erred on the side of inclusion by keeping in all vacant lots instead of selecting only residential lots.

amenity variables) and the binary treatment variables ***Pre*** and ***Fund***. ***Pre*** takes a value of one if the neighborhood made the short list for V2V demolition funding and ***Fund*** takes a value of one if the neighborhood had a site selected.

Since we our dependent variables are count variables, the conventional starting point would be with a simple Poisson model. However, we have concerns that our data may suffer from overdispersion. As a check against this concern, we run two different tests on our data that are both reported in Table 5. The first is a simple mean and variance comparison for our variables of interest, based on the underlying fact that in the Poisson distribution, they should be equal. It is quite clear that this does not hold for any of our dependent variables, indicating this may not be the appropriate distribution. As a secondary test, we run models (1)-(3) with the Poisson distribution and report the goodness of fit statistic in the last column of Table 5. The goodness of fit test is significant at the one percent level ($p<0.01$), indicating we have overdispersion in our data and the Poisson model is not appropriate. While the issues of overdispersion could be addressed by utilizing a robust standard error correction with the Poisson model as is suggested by Cameron and Trivedi (2009), we instead utilize a negative binomial model, which can handle overdispersion in count data. Our data is also panel in nature as we have observations of counts for each neighborhood in each yearly period of observation. This allows us to utilize a panel count model with robust standard errors, which we do so with a pooled approach due to the short panel nature of the data (Cameron and Trivedi, 2013).

We also develop a secondary set of models to explore the effect of certain neighborhood characteristics and amenities on our treated and untreated groups. We are particularly interested in the role of poverty and crime on housing market activity in addition to our amenities data, *i.e.*

brownfield sites, transit accessibility, and park space. We modify our basic equations from above as follows (we show the results for the sales equations only, as the right hand side of the model is uniform across each dependent variable):

$$\boldsymbol{Sales_{it} = \alpha + \beta_X X_i + +\theta_1 Pre + \theta_2 Pre * Pov + \ \rho_1 Fund + \rho_1 Fund * Pov + \epsilon_{it}} \tag{4}$$

$$\boldsymbol{Sales_{it} = \alpha + \beta_X X_i + +\theta_1 Pre + \theta_2 Pre * Crime + \ \rho_1 Fund + \rho_1 Fund * Crime + \ \epsilon_{it}} \tag{5}$$

$$\boldsymbol{Sales_{it} = \alpha + \beta_X X_i + +\theta_1 Pre + \theta_2 Pre * Brown + \ \rho_1 Fund + \rho_1 Fund * Brown + \epsilon_{it}} \tag{6}$$

$$\boldsymbol{Sales_{it} = \alpha + \beta_X X_i + +\theta_1 Pre + \theta_2 Pre * Park + \ \rho_1 Fund + \rho_1 Fund * Park + \epsilon_{it}} \tag{7}$$

$$\boldsymbol{Sales_{it} = \alpha + \beta_X X_i + +\theta_1 Pre + \theta_2 Pre * Trans + \ \rho_1 Fund + \rho_1 Fund * Trans + \epsilon_{it}} \tag{8}$$

In equation (4), we create a dummy variable for all neighborhoods with a poverty rate greater than or equal to 40 percent – the standard designation for extreme poverty utilized by the U.S. Census – which we then interact this with both the ***Pre*** group and the ***Fund*** group. Equation (5) examines the role of high violent crime rates on our outcome variables, which we define as a violent crime rate more 2.5 times the citywide average. In Equation (6), we create an interaction term for neighborhoods that have total brownfield acres greater than the city average of 7.52 acres while in equation (7), we create an interaction for neighborhoods with park space less than the average for all neighborhoods – the percentage of land in the neighborhood designated as a park. Finally, equation (8) is a simple interaction between the transit accessibility dummy variable and the two groups of interest.

V) Estimation results and discussion

We estimate the first set of models in Table 6, which arise from equations 1-3. Focusing first on model 1 and on our variables of interest, we find that neighborhoods designated on the short list for V2V funding see no effect on the total number of housing renovations. We also find that our treated group, the funded neighborhoods, likewise sees no effect on the renovation level. We do see a strong positive effect for a subgroup of our main treated variable, the neighborhoods that had multiple V2V projects funded. For this group, we find that housing renovations increased by 200 percent[11] for this set of neighborhoods. This particular result indicates that renovation activity may not be spurred along by a simple one-time investment into the neighborhood by the city, as it may not be a sufficient signal to spur homeowner reinvestment in their own property. Rather, the stronger signal of multiple occurrences of investment indicates that the city is sufficiently investing into the area rather than a simple one-off event.

In model 2, our outcome variable changes to the number of housing sales in each neighborhood and we see a similar story as before with the preliminary group seeing no effect from making the short list. We do find a positive result significant at the five percent level with funded projects, with housing sales in these neighborhoods up by over 45 percent with no additional effect found for multiple project neighborhoods. Model 2 indicates that the V2V program may be spurring a housing market turnaround as intended.

The results of non-rental housing sales in model 3 paints a more complicated story, as here we find statistically significant results for both the preliminary and funded groups, at the one and ten percent levels, respectively, but with point estimates in the opposite directions.

[11] Using the standard conversion of e^(coefficient).

Neighborhoods on the initial list see non-rental housing sales that are 69.3 percent lower than non-short listed neighborhoods but that effect is reversed for those neighborhoods that have a funded project. Here, housing sales are 74.1 percent higher, which means the net effect in these neighborhoods would be a 4.8 percent increase in housing sales. The total effect is an order of magnitude lower than the model that looks at all housing sales[12] but is still indicative of the V2V project stimulating demand in the market in these neighborhoods. However, all is not well in the non-funded markets, as they do not receive the positive funding effect offset thus housing sales are just generally depressed in that area, conditional on initial list placement. If we interpret this result from an individual asset holder's perspective – the homeowner – the decrease in housing sales makes intuitive sense. If one expects that the value of your asset may increase in the future, say for example by an increased demand for housing as supply decreases via demolitions, that asset would be held into the next period. Therefore, homeowners may simply be waiting for clarity on the location of future V2V projects.

We now turn to discussing the results from a select number of the control variables from all three of the previous models, starting with the sociodemographic variables. We find that poverty rate is negative and statistically significant at high levels in all of our models. A one-unit change in the poverty rate in a neighborhood leads to 1.265 percent change in the number of renovations, a 0.176 percent change in housing sales, and a 0.415 percent change in non-rental housing sales. We see similar outcomes with the violent crime rate, but with a bigger effect on the sales models. Intuitively, this makes sense, as high crime areas are less attractive to prospective homebuyers. We also see a marked difference in the point estimates between all housing sales and non-rental housing sales.

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[12] As with many cities, Baltimore has a large rental market, so it would be expected that rental investment groups would attempt to buy into areas of the city where they expect future land rents to increase.

Curiously, we see a positive effect for housing vacancy in all of the models, with a large effect in the renovation model. Though this may be counter to initial expectations, it could be partially explained by an increased number of residential units available for renovation or sale at a discounted or some underlying differences in housing values in each neighborhood not accounted for in our models. Further work may be warranted to explain this strange result.

Moving to the amenities and environmental control variables, we do not find a consistent effect for transportation accessibility across the models. For the case of stadium[13] proximity, we see a negative effect for both housing sales models, possibly driven by congestion and noise effects of a busy area. We find an interesting and mixed set of results for parks, with a single positive effect in the all-sales model for proximity to one of Baltimore's major parks but no effect in the non-rental sales model. The number of parks in a neighborhood corresponds to an increase in both renovations and sales but the effect of the amount of parkland is actually negative across all models. At best, this paints an interesting picture of differential effects of parks between neighborhoods. These effects may be driven by the data construction, as we treat all parks as equal in the parks variable, which may not hold in all cases, given the result from the major park adjacency variable. Underlying park-level attributes have been shown to affect the value of parks in previous work (see Livy and Klaiber, 2016). With the brownfield variables, we find only a single consistently significant variable across all models, which is the number of brownfield acres in each neighborhood. Curiously, the sign flips from negative in the renovation model to positive in the sales models.

V.i) Interaction model results and discussion

[13] The stadiums are Camden Yards, home of the Baltimore Orioles, and M&T Bank Stadium, home of the Baltimore Ravens. Both are located in the same neighborhood, which is non-residential with a heavy commercial component.

We report the results of equations (4) and (5) in Table 7. We group the each of the equations together in the table, thus models 4.1 through 4.3 utilize equation (4) each with a different dependent variable while models 5.1 through 5.3 utilize equation (5) in a similar manner. With our poverty interaction models, we only find significant results on our interaction variables with renovations. Our previous finding that renovations are over 200 percent higher in neighborhoods with multiple funded projects remains but a few curious results crop up on the interaction terms. Both are significant at the one percent level but point in different directions. High poverty neighborhoods on the preliminary list see 438 percent higher levels of renovations but funded projects in these areas have 83 percent lower renovations. Considering we do not see similar behavior in the companion sales models, these results are likely spurious and an artifact of the data.

On the crime interaction models, we find two significant results, both at the five percent level and both in one of the sales models. In the all-sales model (5.2), high violent crime neighborhoods that have funded V2V projects see a 56 percent increase in housing sales. This effect is large enough to offset the general decline in sales found in our earlier models. In the non-rental sales model (5.3), we find a large effect associated with the preliminary listed high crime neighborhoods. Both results give some indication that the V2V program may be improving the housing market in these high crime areas if but only marginally.

In our first set of amenity models, we model interactions with V2V neighborhoods and neighborhoods with higher than average brownfield acreage. In the all-sales model (6.2), we find that the interaction of our treated group has a large value that is significant at the one percent level. This set of neighborhoods has house sales that are 373 percent higher and over 300 percent higher than funded neighborhoods alone. This may be some indication that these areas could be primed for future environmental gentrification, conditional on brownfield remediation. However, it may be driven more by the rental market than the owner-occupied market, as the results in model 6.3 do indicate.

Our park-poor interaction model yields only a single interesting result in the non-rental sales model (7.3) where we see this set of neighborhoods has an increased level of housing sales. The rest of the park variables are generally consistent with the previous models, but the previous significance on the amount of parkland variable is no longer significant. This does give us some further indication that underlying characteristics of parks in the neighborhoods may be partially driving that particular result.

Our final set of models examines public transit accessibility with our V2V neighborhoods. The results from model 8.3 immediately spring forward, as we find a large positive effect related to transit accessibility and funded V2V neighborhoods and a smaller negative effect related to accessibility and unfunded neighborhoods. The first result would be expected, as housing sales would naturally be higher in areas more easily accessible but the other results dampen that particular finding. Perhaps the correct interpretation would be that public transit accessibility present a mixed bag of blessing in any neighborhood that buyers and sellers may value differently.

VI) Concluding thoughts and future work

This paper provides one of the first examinations of the effects of an urban revitalization program that utilizes block-level demolition as a renewal strategy through an environmental justice framework. Armed with a unique dataset of housing market data, neighborhood demographic and environmental attribute data, and a natural experimental design, we find that the neighborhoods funded by the program had higher housing sales than similar short-listed neighborhoods that were unfunded. We also find increased renovation activity in neighborhoods with multiple funded projects. Extending our basic model to include interaction amongst variables of interest, we find that higher poverty rates depressed renovation activity while high crime rates influence housing sales negatively. Funded neighborhoods with large brownfield sites generally have more housing sales as do those with higher levels of transit accessibility.

Our results do indicate that this particular urban revitalization effort has been a qualified success in its short existence but we cannot conclusively state that these findings will hold as the program ages. The initial positive effects may dampen with time, especially if programmatic changes happen in the future. Despite our hesitations of drawing strong conclusions, our work does show that targeted demolitions may be a valid renewal strategy in urban neighborhoods with excessive housing supply, high crime, and generally failing housing markets.

We believe that this work helps advance the frontier of environmental justice research into a new realm of analysis through examining equity issues in urban revitalization efforts and we hope it is the first of many works to move in that direction. While these topics have received recent attention from researchers in other fields, economists have yet to explore this important area to provide meaningful policy guidance for urban decision-makers. As cities seek to renew their cores, they must also ensure that these efforts equally benefit all residents, regardless of their socio-economic group.

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Figures and Tables

Figure 1: V2V program and population density

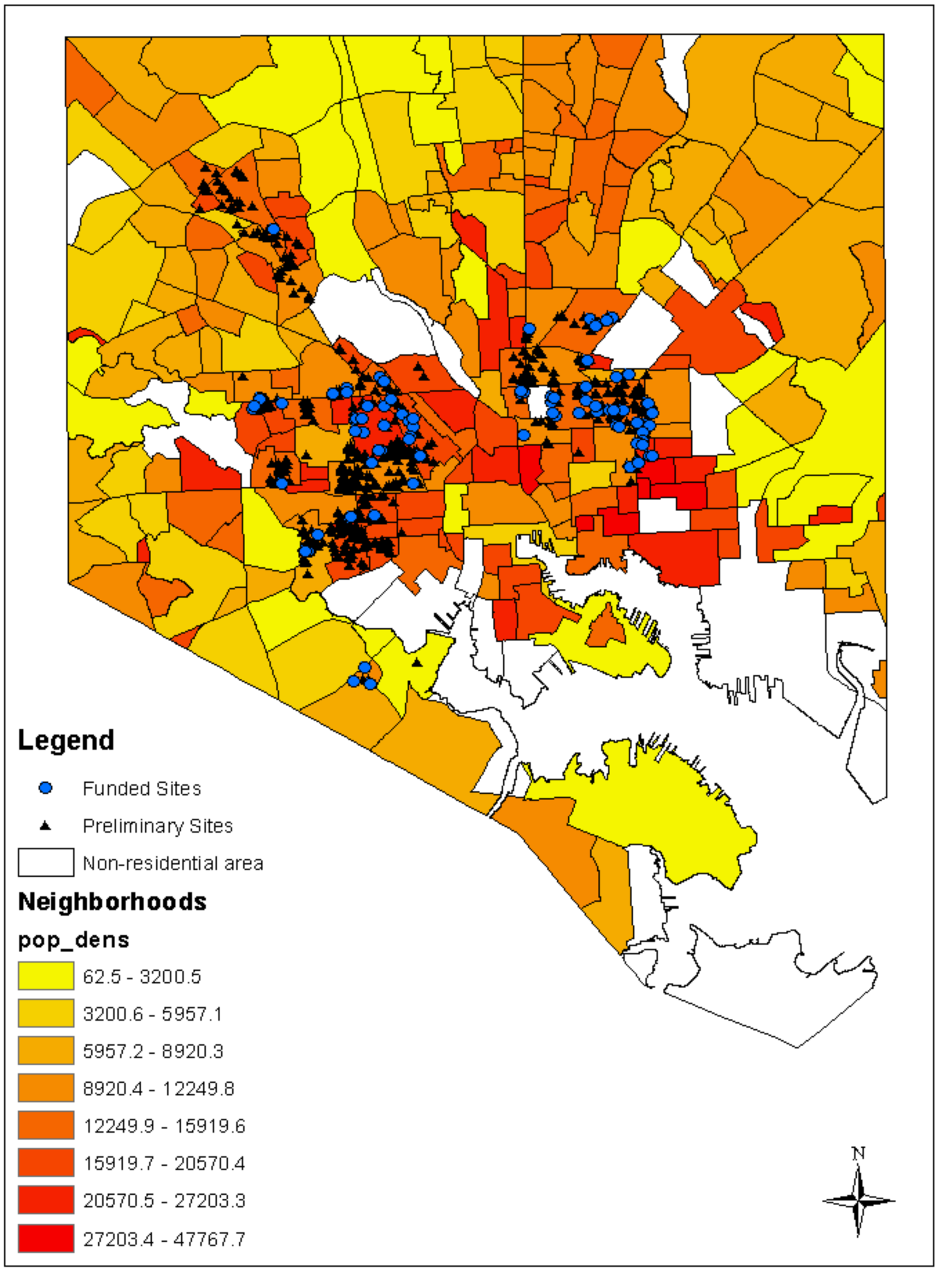

Figure 2: V2V program and poverty rate

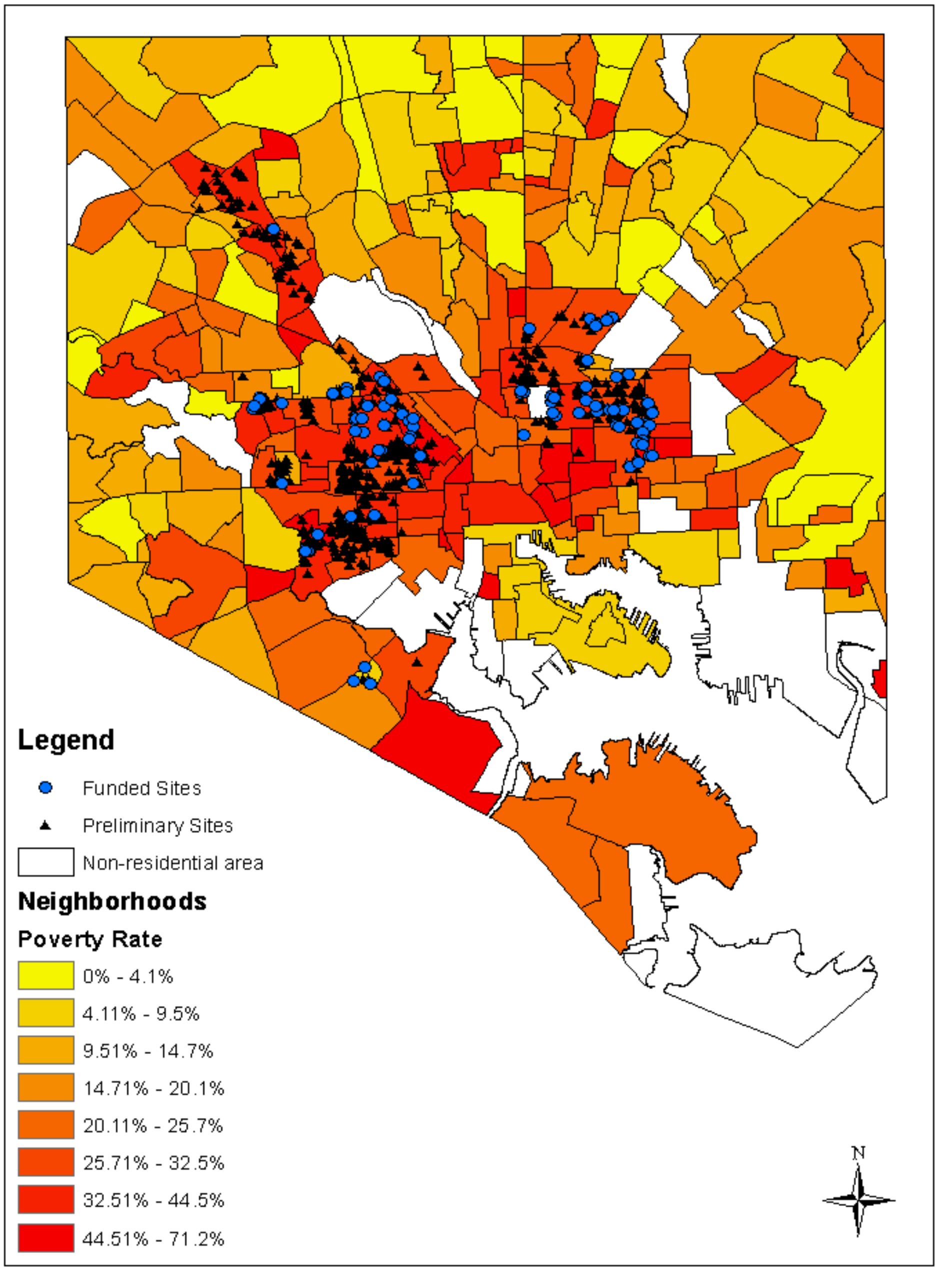

Figure 3: V2V program and vacancy rate

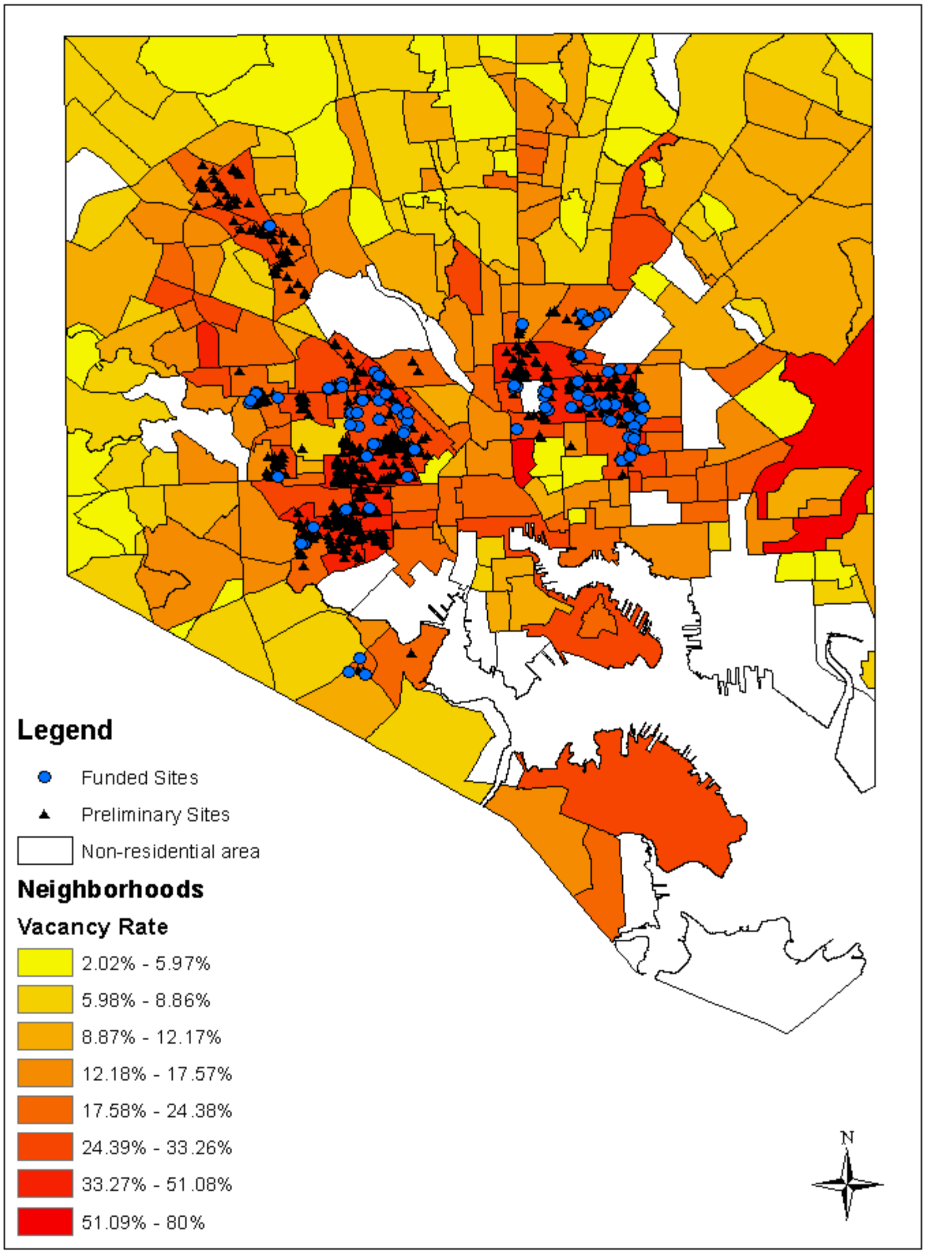

Figure 4: V2V program and violent crime rate

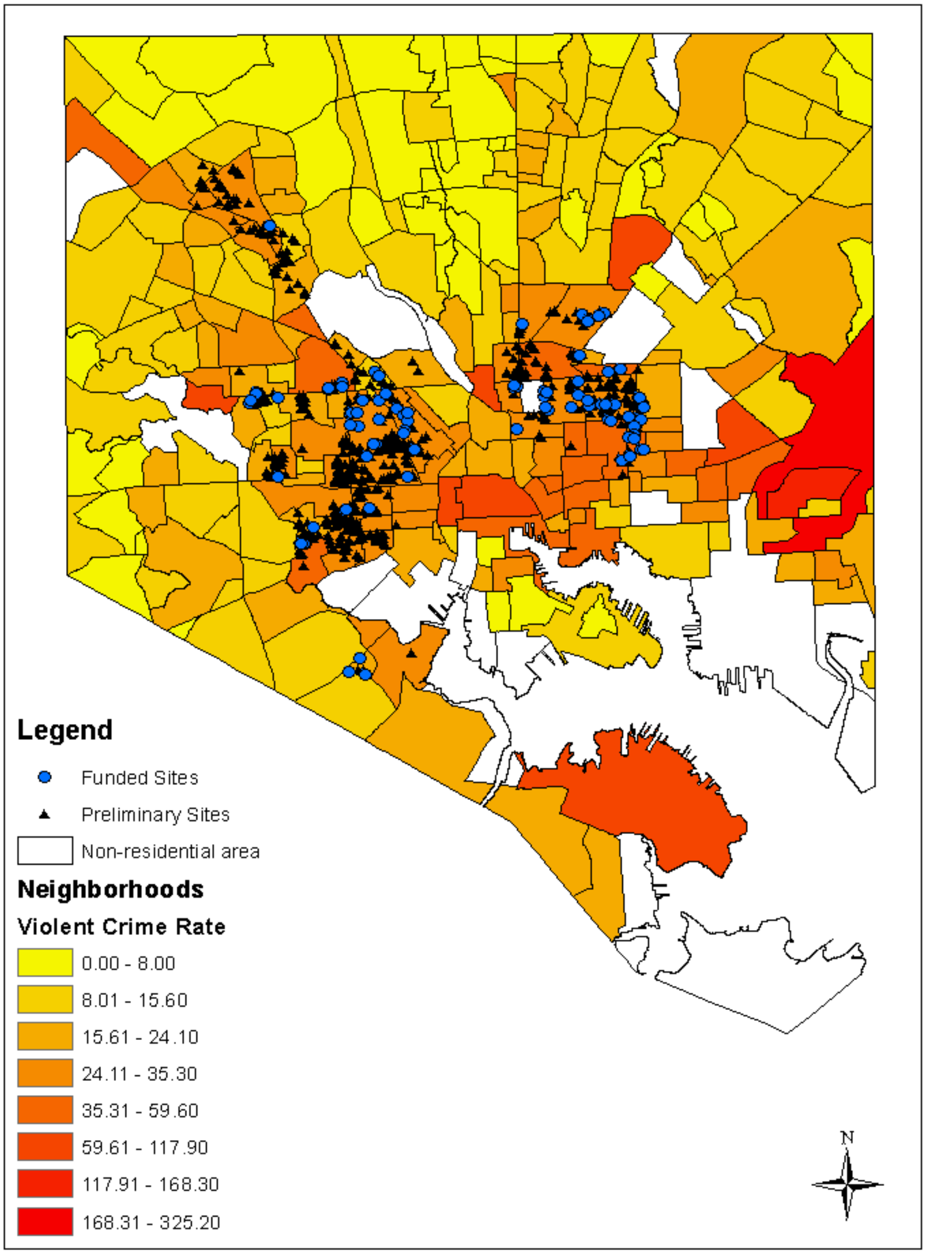

Table 1: Summary statistics of key variables

Baltimore Neighborhood Characteristics (n=247)				
Variable	**Mean**	**Std. Deviation**	**Min**	**Max**
population	2,511	2,402	72	17,694
black (%)	0.309	0.321	0.00258	0.944
white (%)	0.625	0.360	0	0.985
hispanic (%)	0.0413	0.0633	0.00279	0.413
male	1,182	1,152	38	8,056
female	1,329	1,285	34	9,638
age0_4	166.5	182.9	2	1,383
age5_11	201.1	231.4	0	1,734
age12_14	81.20	93.18	0	794
age15_17	91.51	103.0	1	873
age18_24	316.0	434.5	1	3,989
age25_34	418.9	526.3	2	4,835
age35_44	309.6	311.7	4	2,269
age45_64	632.2	600.9	2	4,675
age65ovr	294.0	282.9	0	1,687
under 25 (%)	0.334	0.102	0.0572	0.779
% over 65 (%)	0.125	0.0633	0	0.451
hh income ($)	44,081	26,035	7,668	191,042
poverty rate (%)	21.41	14.40	0	71.20
high school degree (%)	0.7753	0.1431	0.24	1
college degree (%)	0.2595	0.2394	0	0.991
hh size	2.440	0.399	1	3.439
owner occupany (%)	0.432	0.208	0	0.949
vacancy rate (%)	0.158	0.112	0.0202	0.800
Amenity Data				
# of parks	1.368	2.180	0	26
parkland (%)	0.0471	0.0960	0	0.731
# of brownfields	1	3.363	0	41
brownfield acres	7.520	45.13	0	645.7
transit accessible	0.105	0.308	0	1
adj waterfront	0.0567	0.232	0	1
adj to stadium	0.0202	0.141	0	1
adj to major park	0.146	0.354	0	1
adj to industrial park	0.154	0.362	0	1
adj brownfield acres	56.20	176.6	0	1,065

Table 2: Crime rate comparison

Crime Rates			
Variable	**Neighborhood Avg.**	**Baltimore**	**United States Avg.**
Violent Crime Rate	28.38	13.7	3.67
Property Crime Rate	50.42	48.49	26.65

Note: Neighborhood crime rates are the average crime rates from 2013-2015, as detailed in text, and converted to crimes per 1,000 people. Baltimore and United States crime rates are two year averages from 2013-2014. 2015 data is not currently available.

Table 3: Transactions and program status

Housing Transactions and V2V Program				
Variable	**Mean**	**Std. Deviation**	**Min**	**Max**
2013 Renovations	7.543	13.04	0	145
2014 Renovations	7.943	13.62	0	152
2015 Renovations	7.130	11.79	0	116
all renovations	21.75	29.73	0	200
2013 Housing Sales	43.22	55.47	0	581
2014 Housing Sales	58.62	110.1	0	1,473
2015 Housing Sales	37.14	45.84	0	389
all sales	139.0	173.0	0	1,482
2013 Housing Sales (non-rental)	34.09	54.72	0	581
2014 Housing Sales (non-rental)	47.67	110.4	0	1,473
2015 Housing Sales (non-rental)	29.78	44.05	0	389
all sales no rental	111.5	173.2	0	1,482
	N	% of total neighborhoods		
preliminary V2V	49	20%		
funded V2V	29	12%		
multiple funded V2V	19	8%		

Table 4: Treatment group t-tests

Group Mean Diffences, treated vs untreated			
Variable	Preliminary	Funded	Difference
	Mean	Mean	
population density	14017.16	14541.72	-524.55
number of brownfields	0.35	0.38	-0.029
public transit accessible	0.1	0.103	-0.0034
percent black	0.86	0.94	-0.073*
percent white	0.093	0.031	0.062*
poverty rate	0.304	0.299	0.0056
household income	27840.5	30539	-2698.5
owner occupancy rate	0.266	0.293	-0.027
vacancy rate	0.265	0.289	-0.023
vacant lot percent	0.092	0.142	-0.0496**
number of parks	2	2.62	-0.62
percent park acrerage	0.034	0.024	0.0099
violent crime rate	36.77	37.42	-0.66
property crime rate	43.75	43.53	0.22

Table 5: Overdispersion tests

Variable	Mean	Variance	Poisson Goodness of Fit Statistic
Renos	21.75	881.55	4558.149***
Sales	138.98	29853.78	24406.69***
Sales non-rental	111.53	29910.82	22462.79***

Table 6: Main model results

Variable (negative binomial regression)	(Model 1) Renos	(Model 2) Sales	(Model 3) Non-Rental Sales
preliminary v2v	**-0.298**	**-0.0149**	**-1.179*** **
	(0.187)	(0.129)	(0.202)
funded v2v	**-0.0389**	**0.376** **	**0.554* **
	(0.199)	(0.158)	(0.304)
multiple v2v	**0.693*** **	**0.243**	**0.0559**
	(0.198)	(0.166)	(0.314)
under18	-0.467	0.610	-0.432
	(0.848)	(0.930)	(0.981)
over 65	-1.026	-2.137***	-2.225***
	(0.807)	(0.638)	(0.703)
poverty rate	-1.265***	-0.176*	-0.415***
	(0.445)	(0.102)	(0.123)
hh income	3.98e-06	0.0595	0.151
	(3.06e-06)	(0.0947)	(0.129)
owner occ rate	-0.270	0.291	-0.0129
	(0.368)	(0.200)	(0.226)
vacancy rate	3.566***	0.476***	0.736***
	(0.682)	(0.0882)	(0.119)
avg vio crime rate	-0.0105***	-1.619***	-2.255***
	(0.00319)	(0.400)	(0.435)
avg prop crime rate	0.000934	-2.08e-06	-2.99e-06
	(0.00103)	(2.41e-06)	(2.51e-06)
bachelors %	0.268	-0.0129***	-0.0215***
	(0.405)	(0.00308)	(0.00347)
hs %	-1.891***	-0.00200	0.00244**
	(0.529)	(0.00143)	(0.00121)
vacant lot %	-0.0352***	0.338	-0.128
	(0.00382)	(0.393)	(0.419)
majorparkadjacent	0.134	2.238***	-0.272
	(0.115)	(0.549)	(0.659)
number of parks	0.160***	0.636*	0.543
	(0.0373)	(0.365)	(0.387)
parkland %	-1.457***	-1.477***	-1.407**
	(0.439)	(0.467)	(0.555)
trans access	-0.395***	0.00469	0.00889*
	(0.117)	(0.00460)	(0.00459)
stadiumadjacent	-0.314	-0.0446***	-0.0501***
	(0.230)	(0.00414)	(0.00503)
number of listed brownfield sites	0.559***	-0.278	-0.0447
	(0.113)	(0.498)	(0.532)
brownfield acres	-0.00566**	0.138***	0.0983**
	(0.00270)	(0.0319)	(0.0385)
adjacent brownfield acres	0.00831*	0.00201	0.000859
	(0.00432)	(0.00206)	(0.00145)
Constant	3.313***	5.103***	5.954***
	(0.555)	(0.495)	(0.600)
Observations	741	741	741

Note: *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Table 7: Crime and poverty models

	Interaction variable: Poverty Rate			Interaction variable: Violent Crime Rate		
Variable (negative binomial regression)	(Model 4.1) Renos	(Model 4.2) Sales	(Model 4.3) Non-Rental Sales	(Model 5.1) Renos	(Model 5.2) Sales	(Model 5.3) Non-Rental Sales
interaction with preliminary	**1.477***** (0.454)	**0.437** (0.342)	**-0.662** (0.776)	**0.414** (0.302)	**0.0212** (0.264)	**0.938**** (0.421)
interaction with funded	**-1.790***** (0.559)	**-0.582** (0.410)	**0.640** (0.912)	**0.412** (0.274)	**0.446**** (0.199)	**-0.465** (0.316)
preliminary v2v	**-0.557***** (0.173)	**-0.0824** (0.133)	**-1.129***** (0.216)	**-0.524***** (0.199)	**-0.252** (0.168)	**-0.883***** (0.301)
funded v2v	**0.187** (0.180)	**0.428***** (0.160)	**0.506** (0.312)	**-0.277** (0.243)	**0.411*** (0.220)	**-0.0512** (0.397)
multiple v2v	**0.746***** (0.222)	**0.271** (0.177)	**0.0641** (0.335)	**0.593***** (0.187)	**0.185** (0.177)	**0.0921** (0.295)
under18	-0.758 (0.839)	0.551 (0.939)	-0.336 (0.991)	-0.708 (0.841)	0.438 (0.941)	-0.545 (0.971)
over 65	-1.088 (0.812)	-2.148*** (0.641)	-2.188*** (0.714)	-0.895 (0.815)	-2.152*** (0.637)	-2.286*** (0.698)
poverty rate	-1.313*** (0.451)	-1.614*** (0.428)	-2.195*** (0.447)	-1.265*** (0.429)	-1.561*** (0.399)	-2.203*** (0.435)
hh income	3.80e-06 (3.05e-06)	-2.11e-06 (2.42e-06)	-2.87e-06 (2.51e-06)	3.95e-06 (2.99e-06)	-2.05e-06 (2.40e-06)	-2.84e-06 (2.49e-06)
owner occ rate	-0.110 (0.364)	0.386 (0.400)	-0.148 (0.425)	-0.216 (0.365)	0.337 (0.396)	-0.0983 (0.417)
vacancy rate	4.240*** (0.667)	2.448*** (0.576)	-0.375 (0.691)	3.267*** (0.683)	1.961*** (0.562)	-0.274 (0.657)
avg vio crime rate	-0.0107*** (0.00314)	-0.0130*** (0.00307)	-0.0214*** (0.00347)	-0.0139*** (0.00337)	-0.0132*** (0.00305)	-0.0218*** (0.00342)
avg prop crime rate	0.000683 (0.00103)	-0.00216 (0.00146)	0.00249** (0.00121)	0.00186* (0.00105)	-0.00199 (0.00151)	0.00244** (0.00122)
bachelors %	0.135 (0.397)	0.612* (0.368)	0.571 (0.391)	0.0850 (0.406)	0.556 (0.367)	0.506 (0.382)
hs %	-1.604*** (0.507)	-1.406*** (0.474)	-1.462*** (0.563)	-1.666*** (0.502)	-1.381*** (0.457)	-1.372** (0.545)
vacant lot %	-0.0359*** (0.00362)	-0.0444*** (0.00414)	-0.0501*** (0.00499)	-0.0383*** (0.00491)	-0.0464*** (0.00432)	-0.0506*** (0.00516)

majorparkadjacent	0.180	0.0681	0.139	0.159	0.0759	0.119
	(0.115)	(0.0943)	(0.133)	(0.112)	(0.0941)	(0.129)
number of parks	0.163***	0.138***	0.0985**	0.170***	0.140***	0.0921**
	(0.0392)	(0.0321)	(0.0391)	(0.0390)	(0.0322)	(0.0384)
parkland %	-1.524***	-0.277	-0.0399	-1.439***	-0.226	-0.0332
	(0.442)	(0.502)	(0.531)	(0.461)	(0.509)	(0.535)
trans access	-0.326***	-0.162	-0.416***	-0.412***	-0.170	-0.377***
	(0.116)	(0.103)	(0.125)	(0.119)	(0.104)	(0.123)
stadiumadjacent	-0.325	0.281	-0.00451	-0.272	0.323	0.00807
	(0.234)	(0.196)	(0.230)	(0.245)	(0.206)	(0.231)
number of listed brownfield sites	0.603***	0.489***	0.725***	0.499***	0.439***	0.717***
	(0.111)	(0.0889)	(0.119)	(0.112)	(0.0881)	(0.116)
brownfield acres	-0.00550**	0.00202	0.000853	-0.00588*	0.00212	0.00101
	(0.00259)	(0.00206)	(0.00144)	(0.00306)	(0.00198)	(0.00144)
adjacent brownfield acres	0.00817*	0.00491	0.00902**	0.0106**	0.00550	0.0106**
	(0.00434)	(0.00472)	(0.00457)	(0.00414)	(0.00454)	(0.00464)
Constant	3.039***	5.021***	5.970***	3.248***	5.125***	5.953***
	(0.555)	(0.497)	(0.615)	(0.522)	(0.484)	(0.598)
Observations	741	741	741	741	741	741

Note: *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Table 8: Amenities models

	Interaction variable: Brownfields			Interaction variable: Parkland			Interaction variable: Transit Accessibility		
	(Model 6.1)	(Model 6.2)	(Model 6.3)	(Model 7.1)	(Model 7.2)	(Model 7.3)	(Model 8.1)	(Model 8.2)	(Model 8.3)
Variable (negative binomial regression)	**Renos**	**Sales**	**Non-Rental Sales**	**Renos**	**Sales**	**Non-Rental Sales**	**Renos**	**Sales**	**Non-Rental Sales**
interaction with preliminary	**0.152**	**-0.747****	**-0.428**	**-0.124**	**0.268**	**-0.402**	**-0.412**	**-0.758****	**-1.869*****
	(0.483)	(0.370)	(0.391)	(0.408)	(0.244)	(0.336)	(0.396)	(0.351)	(0.458)
interaction with funded	**0.988***	**1.318*****	**-1.252****	**0.219**	**-0.342**	**1.446****	**-0.115**	**0.0728**	**1.525****
	(0.534)	(0.503)	(0.623)	(0.474)	(0.354)	(0.640)	(0.583)	(0.425)	(0.652)
preliminary v2v	**-0.301**	**0.0666**	**-1.136*****	**-0.211**	**-0.201**	**-0.918*****	**-0.272**	**0.0485**	**-1.082*****
	(0.203)	(0.138)	(0.221)	(0.404)	(0.218)	(0.292)	(0.199)	(0.136)	(0.206)
funded v2v	**-0.0211**	**0.332****	**0.518***	**-0.195**	**0.624****	**-0.534**	**-0.0539**	**0.336****	**0.477**
	(0.204)	(0.158)	(0.309)	(0.431)	(0.302)	(0.561)	(0.206)	(0.159)	(0.307)
multiple v2v	**0.590*****	**0.209**	**0.0966**	**0.666*****	**0.269**	**-0.156**	**0.752*****	**0.315***	**0.0810**
	(0.207)	(0.167)	(0.315)	(0.218)	(0.183)	(0.327)	(0.209)	(0.171)	(0.329)
under18	-0.622	0.482	-0.397	-0.492	0.617	-0.314	-0.491	0.434	-0.445
	(0.850)	(0.939)	(0.985)	(0.842)	(0.925)	(0.982)	(0.841)	(0.949)	(0.980)
over 65	-0.992	-2.167***	-2.246***	-1.032	-2.132***	-2.271***	-1.055	-2.158***	-2.216***
	(0.813)	(0.643)	(0.702)	(0.808)	(0.639)	(0.705)	(0.806)	(0.640)	(0.701)
poverty rate	-1.167***	-1.541***	-2.271***	-1.269***	-1.601***	-2.140***	-1.196***	-1.548***	-2.238***
	(0.450)	(0.405)	(0.437)	(0.441)	(0.407)	(0.444)	(0.443)	(0.401)	(0.441)
hh income	4.41e-06	-1.96e-06	-3.21e-06	3.94e-06	-1.97e-06	-3.07e-06	4.04e-06	-2.01e-06	-3.03e-06
	(3.07e-06)	(2.42e-06)	(2.51e-06)	(3.05e-06)	(2.41e-06)	(2.53e-06)	(3.05e-06)	(2.41e-06)	(2.49e-06)
owner occ rate	-0.284	0.346	-0.0992	-0.260	0.321	-0.0685	-0.207	0.410	-0.0720
	(0.368)	(0.393)	(0.420)	(0.366)	(0.395)	(0.422)	(0.369)	(0.399)	(0.419)
vacancy rate	3.463***	2.002***	-0.303	3.611***	2.118***	-0.272	3.556***	2.209***	-0.229
	(0.711)	(0.562)	(0.684)	(0.653)	(0.566)	(0.668)	(0.677)	(0.544)	(0.668)
avg vio crime rate	-0.0105***	-0.0128***	-0.0211***	-0.0105***	-0.0128***	-0.0214***	-0.0104***	-0.0125***	-0.0214***
	(0.00320)	(0.00306)	(0.00347)	(0.00319)	(0.00308)	(0.00346)	(0.00316)	(0.00303)	(0.00339)
avg prop crime rate	0.00108	-0.00202	0.00227*	0.000904	-0.00196	0.00246**	0.000886	-0.00248	0.00214*
	(0.00106)	(0.00145)	(0.00122)	(0.00104)	(0.00143)	(0.00121)	(0.00103)	(0.00156)	(0.00127)
bachelors %	0.207	0.590	0.558	0.256	0.651*	0.548	0.242	0.613*	0.537
	(0.405)	(0.366)	(0.388)	(0.407)	(0.365)	(0.390)	(0.403)	(0.365)	(0.388)
hs %	-1.848***	-1.415***	-1.382**	-1.854***	-1.552***	-1.309**	-1.887***	-1.512***	-1.473***
	(0.530)	(0.459)	(0.551)	(0.534)	(0.483)	(0.558)	(0.530)	(0.473)	(0.556)
vacant lot %	-0.0356***	-0.0448***	-0.0498***	-0.0353***	-0.0447***	-0.0504***	-0.0351***	-0.0446***	-0.0500***
	(0.00393)	(0.00415)	(0.00502)	(0.00380)	(0.00416)	(0.00509)	(0.00383)	(0.00414)	(0.00499)

majorparkadjacent	0.143	0.0925	0.158	0.139	0.0563	0.146	0.145	0.0770	0.163
	(0.115)	(0.0961)	(0.130)	(0.115)	(0.0967)	(0.127)	(0.115)	(0.0944)	(0.130)
number of parks	0.162***	0.136***	0.0949**	0.160***	0.138***	0.105***	0.164***	0.139***	0.0975**
	(0.0378)	(0.0318)	(0.0391)	(0.0374)	(0.0319)	(0.0393)	(0.0388)	(0.0325)	(0.0391)
parkland %	-1.461***	-0.295	-0.0594	-1.468***	-0.251	-0.0394	-1.447***	-0.237	-0.0449
	(0.443)	(0.493)	(0.526)	(0.442)	(0.505)	(0.540)	(0.442)	(0.504)	(0.524)
trans access	-0.383***	-0.162	-0.414***	-0.394***	-0.169	-0.425***	-0.310**	-0.0425	-0.287**
	(0.118)	(0.102)	(0.122)	(0.117)	(0.103)	(0.123)	(0.122)	(0.115)	(0.123)
stadiumadjacent	-0.309	0.289	-0.00986	-0.314	0.297	-0.00754	-0.310	0.309	-0.00339
	(0.234)	(0.201)	(0.225)	(0.230)	(0.201)	(0.229)	(0.231)	(0.200)	(0.224)
number of listed brownfield sites	0.540***	0.471***	0.754***	0.562***	0.465***	0.751***	0.557***	0.465***	0.720***
	(0.115)	(0.0898)	(0.119)	(0.113)	(0.0884)	(0.122)	(0.115)	(0.0885)	(0.116)
brownfield acres	-0.00626*	0.00232	0.00102	-0.00559**	0.00198	0.000914	-0.00535**	0.00221	0.00139
	(0.00380)	(0.00225)	(0.00154)	(0.00266)	(0.00202)	(0.00146)	(0.00265)	(0.00204)	(0.00158)
adjacent brownfield acres	0.00877**	0.00508	0.00877*	0.00822*	0.00469	0.00841*	0.00813*	0.00431	0.00983**
	(0.00431)	(0.00455)	(0.00458)	(0.00434)	(0.00460)	(0.00462)	(0.00447)	(0.00464)	(0.00466)
Constant	3.302***	5.096***	5.925***	3.285***	5.169***	5.801***	3.264***	5.122***	5.970***
	(0.552)	(0.493)	(0.600)	(0.559)	(0.507)	(0.606)	(0.560)	(0.504)	(0.612)
Observations	741	741	741	741	741	741	741	741	741

Note: *, **, *** indicate significance at the 10, 5, and 1 percent levels, respectively.