Neighborhood Blight Indices, Impacts on Property Values and Blight Resolution Alternatives

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Abstract

We examine the impacts of blight on neighborhoods in Memphis, TN and present cost-effective blight abatement solutions. Based on a blight survey for each property within the city of Memphis completed in January 2016. Using the blight survey and a logit model, we construct a blight index for each neighborhood. Neighborhood blight indices ranging between 1 and 5 facilitates to the understanding of blight problem costs by measuring the impact of neighborhood blight on property sales prices indicating that prices are significantly negatively related to both the neighborhood index and individual property blight score. Further, by applying factor analysis and Shapley-Owen Value decomposition methodologies, we further define the blight drivers and economic factors associated neighborhood blight further clarifying approaches for addressing neighborhood blight and providing alternative resolution for blight problems.

Neighborhood Blight Indices, Impacts on Property Values and Blight Resolution Alternatives

1. Introduction

Neighborhood blight may be identified by abandoned or poorly maintained real properties, often characterized by overgrowth, litter, abandoned vehicles, junk or dumping. Blighted properties are frequently tax delinquent, where taxes owed may be greater than either market or appraised value, may be available for tax sale by the Shelby County Trustee or already may be the responsibility of the Shelby County Land Bank. See Figure 1 for pictures of blighted properties and Figure 2 for examples of blighted neighborhoods in Memphis.

Blight levels for individual properties as well as neighborhood blight levels are difficult to quantify; however, we use the results of a blight survey for each property within the Memphis city limits completed in January 2016. We use this survey to empirically estimate a neighborhood blight index for each neighborhood that may be used in assessing the impact of blight on property values and facilitates regional planning aimed at the eradication of blight.

//////// Insert Figures 1 and 2 ////////

The Neighborhood Preservation, Inc. in Memphis recently developed the "Memphis Neighborhood Blight Elimination Charter," where the Charter is intended to serve as a coordinating framework containing a set of principles and values that Memphis holds regarding blighted and nuisance properties. The blight survey of Memphis real estate properties completed in January 2016 provides data to facilitate accomplishing some of the objectives of this Charter. Teams of individuals canvassed essentially all properties in Memphis, collecting and quantifying data on each property's physical condition. Data collected for each property include a blight rating between 1 (non-blighted) and 5 (highly blighted), overgrown vegetation, trash on property, broken windows, bad siding, junk and old cars on property, etc.

We validate the predictive accuracy of the survey data's quantified descriptions for each property in predicting the survey team's assigned blight index value using logit regression. Results for the logit regression are very good with essentially all individual property characteristics data collected being highly statistically significant. Thus we substantiated the accuracy and consistency of the survey team's data collection and assessments of individual property blight scores.

Subsequently, we aggregate individual property blight scores (ranging from 1 to 5) into unique neighborhood average blight scores, thus creating a continuous distribution of neighborhood blight scores across neighborhoods or a Neighborhood Blight Index. Therefore, a neighborhood blight index close to one (1) would identify a neighborhood that has no or very little evidence of blight; whereas, a neighborhood blight index nearly 5 would indicate a neighborhood with essentially all properties being blighted.

Based on the neighborhood blight index created for each Memphis neighborhood, we examine the impact of blight, using OLS models, positing that effects of both spatial distribution and spatial clustering of blight affects housing values. We find negative impacts of neighborhood blight on housing values that increase incrementally with the degree of each neighborhood's blight index as well as the blight index for individual properties. We are confident that we are the first to quantify blight and study its significance as a price component in municipality housing valuation.

Additionally, we decompose each independent factor's, factors being clusters of independent variables, contribution to the OLS coefficient of determination (R^2) by applying factor analysis and the Shapley-Owen methodology. We find that the neighborhood blight index, in conjunction with other neighborhood characteristics, possess a high level of explanatory power predicting property values.

2. Literature Review

Breger (1967) is one of the first to identify and analyze causes of blight. He defines blight as the critical stage in the functional or social depreciation of real property beyond which its existing condition or use is unacceptable to the community. He divided vacant land into three categories: structurally unemployed land for which the cost needed to make it productive is greater than the present value of the yield from any productive use; frictionally unemployed land which arises in the absence of perfect and costless information about present and future prices, quantities and qualities; and land held in reserve for the future use.

More recent studies addressing blight also endeavor to define the significant elements driving blight. Morandé, Petermann and Vargas (2010) investigate blight determinants of vacant urban land in Santiago Chile, concluding that variables impacting the probability of land being vacant are: the distance to nearest underground subway station, the surface area that could be recovered, whether the site is in a conservation area or surrounded by listed houses, the block's population density, the quality of edification, the neighborhood criminality level, and the site's area (width and length).

It is revealed that population mobility and factors that affecting mobility may be important driving forces of blight. For example, Baum-Snow (2007) studies effects of interstate highways on city populations finding that construction of new limited access highways contribute to central city population declines. Cullen and Levitt (1999) find causality between city depopulation and rising crime rates, playing an important driver of urban blight. Brueckner and Helsley (2009) also focus on urban blight showing that corrective policies shifting population from the suburbs to the city center may lead to higher levels of reinvestment in central-city housing, therefore reducing blight.

3. Data and Methodology

3.1. Data

We combine several different data sets in developing our panel data. Blight data are obtained from the blight survey data and the Shelby County Trustee's office, which covers only the city of Memphis. As previously indicated survey data includes individual single family blight data including street addresses and blight scores (a scale of 1 to 5) for each property, where 1 defines properties with no blight and 5 is assigned to significant blight properties. All unique blight scores for properties within previously defined and relatively more homogenous neighborhoods are averaged to determine a unique blight index for each neighborhood. In addition to blight scores, other individual property characteristics are aggregated and averaged to their respective neighborhoods resulting in unique neighborhood characteristic variables. Other blight related variables, in addition to those collected in the blight survey, include whether each neighborhood property is current or delinquent in ad valorem taxes, available for tax sale and/or has been placed in the Shelby County Land Bank.

The individual property blight survey data, completed in January, 2016, was used in an Ordered Logit Model to validate the accuracy and consistency of the survey individual blight scores and other physical characteristics collected and quantified in the survey. Other individual property physical characteristics were found to accurately and statistically significantly predict individual property survey blight scores assigned the survey team. Thus, results indicate that the survey team accurately and consistently collected individual property data consistent with assigned blight scores.

Given that the incidences of blight in Memphis vary significantly across neighborhoods, we posit that neighborhood blight and other unique neighborhood demographics and attributes significantly influences property values. To measure impacts of neighborhood as well as individual property data on property values, we average individual property survey blight scores to establish unique neighborhood blight indices. We subsequently use each neighborhood's blight index in conjunction with other individual property attributes.

The dependent variable in our OLS model is sale prices for properties sold on or after January 2015 that were obtained from the Shelby County Assessor. As shown below in the results section, the regression coefficient for the neighborhood blight index indicates the impact of blight on surrounding neighborhood property values.

Data from the Shelby County Assessor's Office also contains other characteristics of individual property including: square feet of total living area, number of bedrooms, full baths, half baths, square feet of land, number of stories, age, physical condition, whether there is a garage, pool, fireplaces, and number of family rooms etc.

Median household income, ethnicity and education level, at block group geographic boundary levels and aggregated to unique neighborhoods, are obtained from American Community Survey (ACS) 5-year estimates at U.S. Census Bureau. We introduce these demographic factors as proxies for each neighborhood's social/economic status.

Based on zoning code in the Assessor data, we remove neighborhoods with less than 12 parcels and require that at least 90% of neighborhood properties are single family residences as defined by the Zoning Code. Finally, we apply the following steps below to configure our sample using the Shelby County Assessor's 2016 dataset:

1) Remove sales dated prior to January 1, 2015;
2) Remove duplicated records where sales records haves different parcel IDs but same transaction number;

3) Remove sales that involves only land;

4) Remove parcels with more than one recorded dwelling.

Our final sample contains 8,143 house sales records between January 2015 and March 2016 within total of 494 Memphis neighborhoods.

3.2. Methodology

Ordered Logit Model - Equation (1) denotes an Ordered Logit Model that validates the accuracy and consistency of survey data by regressing individual property blight indices, as the dependent variable, on other physical property variables collected by the survey team. A Logit model, equation (1), is applied since individual blight scores for each property are discrete variables, j, with 1 meaning excellent and 5 dilapidated. The probability of each property falling into one of these five categories is shown in equation (2).

$$\log\left(\frac{\pi_i^j}{\pi_i^0}\right) = \alpha^j + \sum_{K=1}^{k} \beta_k^j x_{ki} \tag{1}$$

$$\Pr(Y_1 = y_{1,\ldots\ldots,} Y_k = y_k) = \begin{cases} \dfrac{n!}{y_j!\ldots.y_k!}\pi_1^0\ldots\pi_k^{C-1} & , when \sum_{j=1}^{k} y_j = n \\ 0, otherwise \end{cases} \tag{2}$$

Where vector y_k represents the discrete categories of the blight index, ranging from 1 to 5.

OLS Hedonic Model - The hedonic OLS model relating each surveyed property's sale price to each property's factors/attributes takes the following form:

$$P = \beta X + \varepsilon \tag{3}$$

Or specifically,

$$P_{jt} = \beta_1 SurveyBlightScore_j + \beta_2 NeighborhoodBlightIndex + \beta_n X_n + \varepsilon$$

Where, P_{ij} is the actual sale price for property i in neighborhood j; X_n is a matrix of explanatory variables, excluding the previously calculated *NeighborhoodBlightIndex*, but including physical characteristics/attributes of individual single family properties for both the individual surveyed property data and the neighborhood, n, locational indicators, neighborhood indicators, and time indicators; β_n is the vector of parameters, and ε is the error term. The variables of particular interests are β_1 and β_2.

Factor analysis - We use factor analysis to determine the number and identification of orthogonal factors important in predicting sale prices. Factor analysis presumes that covariance terms among the explanatory variables predicting property selling prices may be captured by several unobserved, orthogonal factors. The application of factor analysis is based on the presumption that underlying factors, such as neighborhood characters, individual property characters and residents' demographics are not necessarily correlated. Factors are rotated in order to determine each factor's unique/orthogonal explanation power variable covariances. We evaluate factor loadings, coefficients existing in the factors matrix, for each independent variable. Factor loadings may reveal different orthogonal attributes predicting sale prices. Factor loadings can be considered as standardized regression weights by which the underlying factors are multiplied in computing participant scores on the observe variables. Additionally, factor loadings also document the correlation coefficients between an observed variable and its underlying unobserved factor. Finally, factor loadings represent the explanatory power of the underlying factors in predicting variability of observed variables.

Shapley-Owen Value - Based on the factor analysis results, we identify the structure/identification of factors predicting property sales prices. We then use Shapley-Owen Values to indicate each factor's contribution to the coefficient of variation (R^2) or each factor's ability to explain total OLS variation.[1] Using the Shapley-Owen's approach, we decompose an OLS model's overall goodness of fit as measured by R^2 into partial R_i^2, where $R^2=\sum_i R_i^2$.

The Shapley Values measure the marginal change in R^2 when new regressors are added to the model. Theoretically decomposing the R^2 in an OLS model with N regressors requires calculations of all pairwise regressor R^2 values or 2^N submodels. The partial R_i^2 for regressor *i* is computed as:

$$R_i^2 = \sum_{T \subseteq Z\{x_i\}} \frac{K!(N-K-1)!}{N!}[R^2(T \cup \{x_i\}) - R^2(T)] \tag{4}$$

Where, T is the submodel with K regressors but without regressor x_i, and $T \cup \{x_i\}$ is the same model but includes x_i. The set Z contains all the submodels with combinations of regressors.

Shapley Values may be calculated from the variance-covariance matrix. The Owen Value is an extension of Shapley Values, computed for groups of regressors that may have relatively high factor loadings. We employ Shapley-Owen Value in decomposing our OLS model to determine the explanatory power of each group of regressor as identified by factor analysis loadings in previous step.

IV. Results

4.1. Summary Statistics

Table 1 shows our variable descriptions used in our later models. Table 2 displays variable sample summary statistics, where the average and standard deviation for property selling prices are \$101,657 and \$121,133, respectively, where the highest sale price is \$2,750,000. The average and standard deviation for individual property Blight Scores are is 1.781 and 0.750, where the

[1] Shapley-Owen Value (SOV) is developed by Owen and Shapley (1989) from spatial voting games theory. It can be applied to identify the contribution of a particular regressor to the overall explanation of variation in an OLS model.

median of Blight Scores is 2. This suggests that more than half of sample properties are in relatively good condition with only slight levels for no blight. The average and standard deviation for neighborhood Blight levels is 1.751 and 0.43, respectively, where the median neighborhood Blight Index is 1.771 with a maximum of 3.039, indicating, given our survey data, that neighborhood with blight score around 3 represent the most serious blight problem.

//////// Insert Table 1 and 2 Here ////////

4.2. Blight Index – Ordered Logit Model

We use an Ordered Logit Model to predict survey data blight scores, indicating each property's physical condition, as the dependent variable and the associated individual property attributes as predictors. Predictors, as recorded by the survey team, are the outside appearance of each property such as over vegetation, litter, trash, dumping, fallen tree, graffiti and other predictor variables such as if the property has broken windows, damaged shed or garage, damaged fence, damaged roof, etc. Logit model results are reported in Table 3, where, as previously mentioned, all physical condition variables are statistically significant indicating that individual property characteristics recorded by the blight survey team accurately predicts the assigned blight score. Deterioration of each of the blight characteristic measures is reflected in the assigned blight score.

//////// Insert Table 3 Here ////////

4.3. The determinants of property sale prices – OLS model

Table 4 reports OLS regression results, where sales price are regressed on individual property blight scores, the neighborhood blight indices and control variables. Individual property blight scores from the survey data, one of the variable of interest, and neighborhood blight indices, the average blight score for all properties in each neighborhood. Three models with different control variables are reported. Model 1 includes all housing attributes from the Assessor's data and neighborhood physical and demographic characteristics, such as percentages of properties in the Shelby County land bank or available for tax sale, the percentage of owner occupied houses and the percentage of vacant land. Model 2 controls for neighborhood social/economy characteristics from ACS Census Bureau, such as median house income, ethnicity and residents' education level, etc. Model 3 controls for only data collected on each property in the blight survey. Results for Model 1 indicate that the individual property *Blight Score* and the neighborhood *Blight Index* both significantly and negatively impact sale prices. Most neighborhood characteristics and the social/economic characteristics are significant determinants of price. For example, both the neighborhood percentage of White and Asian and percentage of the neighborhood population attaining higher education degrees positively impact sale prices. However, there is no indication of any significant relation between sale price and many of the blight survey recorded variables. Thus, these variables are unreported in Models 2 and 3.

//////// Insert Table 4 Here ////////

Model 2 includes control variables obtained from the Shelby County Assessor including: house characteristics such as squared feet of living area, number of bedrooms, number of full bathrooms, number of half bathrooms, squared feet of land, number of stories, age of a house, condition of a house and grade of a house. Model 3 includes interaction effects on sales prices between the house condition and squared feet of living area on house sales price. The coefficient estimates of individual property *Blight Score* and neighborhood *Blight Index* shown in Table 4, Models 1, 2, and 3 are negative and statistically significant, at least, at the 5% confidence level, revealing a strong negative relationship between blight and property sale prices. R^2s for the three models are 0.492, 0.747, and 0.792, respectively, implying good fitting models.

4.4 The Orthogonal factors - Factor analysis

Factors affecting property sales prices are multitudinous. Previously, all three models used at least 25 explanatory variables that are shown to be statistically and significantly explain property sale prices. However, many of these explanatory variables may be correlated with each other, thus presenting the possibility of multicolinearity. As a result, we perform a factor analysis to estimate the number and impact of orthogonal underlying factors and factor loadings affecting sale prices. Factor loadings identify each variable's explanatory power with respect to each orthogonal factor, allowing us to determine the number of independent factors affecting property values.[2] We use a varimax rotation to estimate orthogonal factors, where results are reported in Table 5. We observe 5 orthogonal common factors from the variables used in the OLS model. Table 5, Panel B shows the results of Rotated Factor Pattern, which is also known as standardized regression coefficients, documenting the pattern loadings representing the particular contribution of each factor to the variance of the perceived variables.

//////// Insert Table 5 Here ////////

To identify the connotation of each factor, we select meaningful variables with factor loadings greater than 0.5 for each of the five factors. The first common factor, which contains the highest explanatory power for the model variance, is associated with four house characteristics, including squared feet of living area, number of bedrooms, number of full bathrooms, and property grade. Factor 2 is composed of neighborhood characteristics: percentage of vacant land, percentage of single family (defined by Land Use Code), and percentage of neighborhood properties in the Shelby County land bank or available for tax sale. There are 4 meaningful variables contributing

[2] Since dummy variables of house condition are highly correlated with each other and the variables of grade, these dummy variables are omitted in the factor analysis and the following Shapley-Owen Value computation.

to Factor 3, including blight score for individual property, neighborhood blight index, percentage of owner occupied properties, and average median house income. Factor 4 reflects residents' demographics variables, ethnicity, and education level. Factor 5 reveals two property characteristics: number of stories and number of half bathrooms. Interestingly, none of these variables have high loadings for more than one factor, thus none of them are deleted.

4.5. The contribution to coefficient of determination – Shapley-Owen Value

Given the results from factor analysis reported in Table 5, we assign the explanatory variables into 6 groups and employ a Shapley-Owen Value methodology to determine each group's contribution to the explained variation of the model as measured by R^2. Table 6, Panel A shows the construction of each groups. The six groups of independent variables are Bligh associated with Owner Occupied and House Income, Demographics, Property Characters 1, Property Characters 2, Neighborhood Characters, and Others. Table 6, Panel B, using only the variable representing one of the six factors, reports the regression results, indicating that all explanatory variables are statistically predictors property sales prices.

//////// Insert Table 6 Here ////////

Table 6, Panel C depicts the marginal contributions made by each variable group to the model's R^2. The group representing House Characteristics shows highest contribution of 0.267, where House Characteristics are: squared feet of living area, number of bedrooms, number of full bathrooms, and grade of the property. The group associated with Owner Occupied and House Income makes marginal contribution of 0.148, which is the same contribution as the group associated with Demographics. Thus, Table 6 results confirm that blight problems, both for individual properties and for neighborhoods, play significant roles in explaining property values.

V. Blight Drivers and Blight Resolution Stratagems

Table 6, Shapley-Owen Values assist in identifying possible drivers of neighborhood blight, where identification of blight drivers may assist in formulating stratagems for blight resolution.

Blight drivers, including social, demographic and other neighborhood characteristics, empirically shown above to be associated with blight include: neighborhoods with high percentage of rentals rather than owner occupied housing, lower neighborhood median household incomes, lower percentage of neighborhood residence with higher education degrees, less educational opportunities with less access to good schools and lower education levels, lower neighborhood percentages of Asian or white residence, and higher percentages of neighborhood properties that are tax delinquent, available for tax sale or are already in the Shelby County land bank, higher proportion of properties in poor repair, poorly maintained and with unkept yards. Thus, blight resolution and blight prevention need to focus on these, and potentially other drivers.

VI. Conclusion

Unfortunately, the City of Memphis, TN contains a number of blighted communities; however, the amalgam of blighted and unblighted neighborhoods serves as an excellent laboratory to study the drivers, prevention and potential resolution of neighborhood blight. Thus, we investigate the blight problem drivers and potential resolution approaches in Memphis, Shelby County, Tennessee by first applying an Ordered Logit Model to validate the accuracy and consistency of the Memphis property blight survey completed in January, 2016. We regress the blight survey team's assigned blight score for each property's physical conditions recorded by the survey team using a Logit model.

Logit Model results indicate that data collected by the survey team accurately predicts and is consistent with the survey team's blight score assigned to each property. We construct a blight index for each neighborhood based on the average individual property blight scores for each neighborhood. We then employ OLS regressions examining the impact of both individual property blight and neighborhood blight on Sales Price for properties selling in the neighborhood to determine the impact of blight. We control for each neighborhood's social/economy characteristics, such as median house income, ethnicity, and residents' education level, and for individual property characteristics, such as square feet of living space, number of bedroom, stories, et al. As posited, we find that both individual property blight as recorded by the blight survey team and the neighborhood blight index significantly and negatively impact property sale prices.

We use Factor Analysis to determine underlying factors and their loadings with observed variables, including blight, affecting sale prices. Using factor loadings, we segment variables into five groups. Using the variables from the five different group, we use the Shapley-Owen decomposition methodology to determine each group's contribution to the OLS coefficient of determination as measured by R^2. This methodology provides superior empirical explanations of neighborhood blight and provides insights into the drivers and potential resolution strategies.

For a jurisdiction to accomplish blight resolution and blight preservation attention needs to focus on drivers and factors that blight. We have identified some of the drivers and factors associated with neighborhood blight to be: neighborhoods with high percentage of rentals rather than owner occupied housing, lower neighborhood median household incomes, lower percentage of neighborhood residence with higher education degrees, less educational opportunities with less access to good schools and lower education levels, lower neighborhood percentages of Asian or white residence, and higher percentages of neighborhood properties that are tax delinquent, available for tax sale or are already in the Shelby County land bank, higher proportion of properties in poor repair, poorly maintained and with unkempt yards.

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Figure 1. Examples of Blighted Properties

Figure 2. Examples of Blighted Neighborhoods

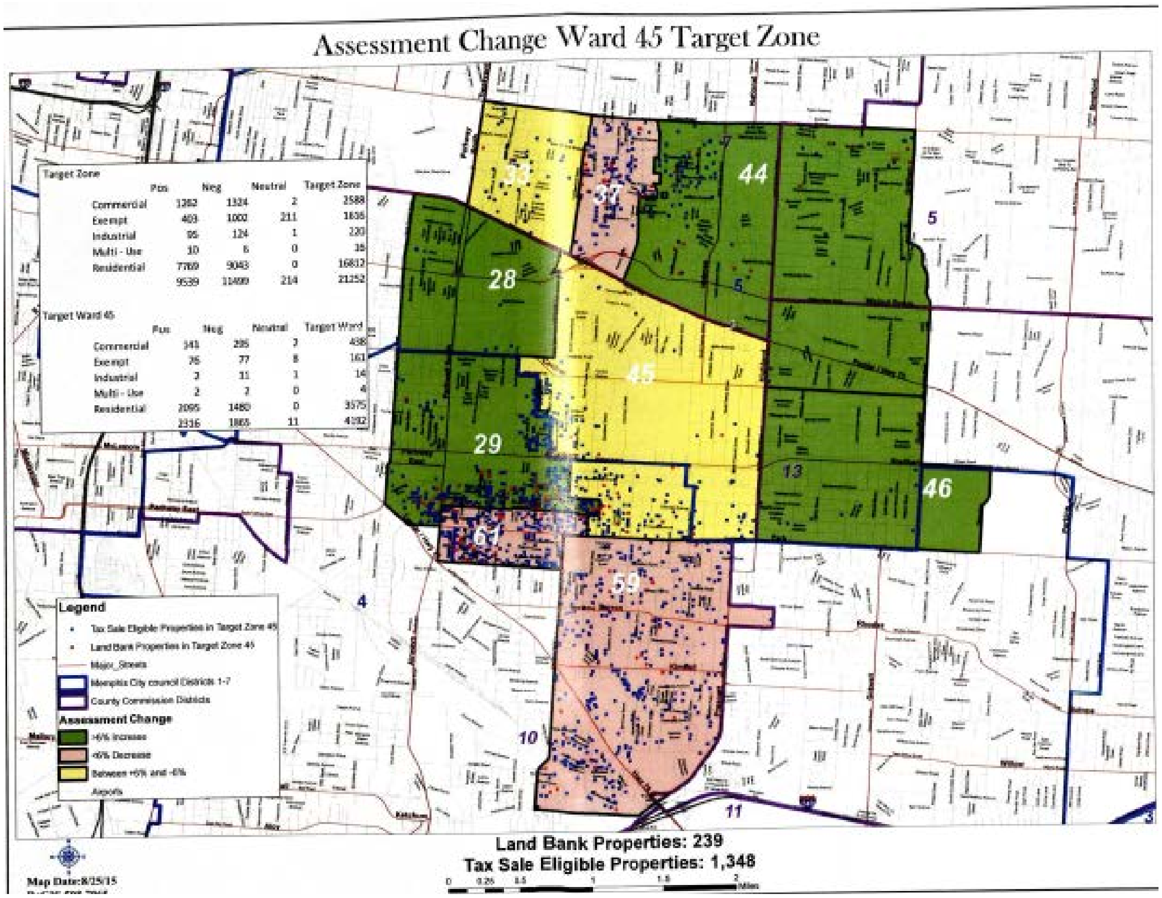

Table 1. Variable Descriptions

Variables	Description
Blight Score(Individual)	
Blight Index	
occupancy_PartOccupied	An occupancy indicator with 1 meaning partially occupied and 0 other
occupancy_PossUnoccupie	An occupancy indicator with 1 meaning possibly unoccupied and 0 other
occupancy_Unoccupied	An occupancy indicator with 1 meaning unoccupied and 0 other
occupancy_NoStructure	An occupancy indicator with 1 meaning no structure and 0 other
Litter_none	A litter indicator with 1 meaning no sign of litter and 0 other
litter_Low	A litter indicator with 1 meaning low level of litter and 0 other
litter_Medium	A litter indicator with 1 meaning medium level of litter and 0 other
litter_High	A litter indicator with 1 meaning high level of litter and 0 other
Vegetation	An indicator variable with 1 meaning overgrown vegetation and 0 normal
Trash	An indicator variable with 1 meaning trash/debris presented at the time of survey
Dumping	An illegal dumping indicator with 1 meaning yes and 0 no
Tree	A fallen tree indicator with 1 meaning yes and 0 no
Construction	An indicator variable with 1 meaning active construction on property and 0 normal
Rent	An indicator variable with 1 having rent/sale sign and 0 none
Vehicle	An abandoned vehicle indicator with 1 meaning yes and 0 none
Siding	A damaged siding indicator with 1 meaning yes and 0 none
Painting	An indicator variable with 1 meaning the property needs painting and 0 none
fire_none	An indicator variable with 1 meaning no fire damage and 0 other
fire_minor	An indicator variable with 1 meaning minor fire damage and 0 other
fire_major	An indicator variable with 1 meaning major fire damage and 0 other
fire_collapsed	An indicator variable with 1 meaning collapsed due to fire and 0 other
roof_minor	An indicator variable with 1 meaning minor roof damage and 0 other
roof_major	An indicator variable with 1 meaning major roof damage and 0 other
roof_none	An indicator variable with 1 meaning no roof damage and 0 other
Roof	Damaged roof indicators with categories damaged roof, minor, major and none
Windows	A broken windows indicator with 1 meaning yes and 0 none
Shed	A damaged shed/garage indicator with 1 meaning yes and 0 none
Graffiti	A graffiti indicator with 1 meaning yes and 0 none
Porch	A damaged porch indicator with 1 meaning yes and 0 none
Foundation	An indicator variable with 1 meaning visible cracks in foundation and 0 none
Fences	A damaged fence indicator with 1 meaning yes and 0 none
Entry	An indicator with 1 meaning open to casual entry and 0 none
Boarded	An indicator with 1 meaning the property is boarded and 0 normal
Other	An indicator with 1 meaning that the property has other issue and 0 without issues
Percent_inlandbk	Percentage of properties in land bank for each neighborhood
STD_rating	Standard deviation of individual property blight scores for each neighborhood
Percent_OwnerOccupied	Percentage of properties owner occupied for each neighborhood
Mean_MedianIncome	Median householder income for each neighborhood
Mean_eduLow	Percentage of low education level (lower than high school) population for each
Mean_eduHigh	Percentage of high education level (Masters, Professional and Doctorate) population

Mean_White	Percentage of White people population for each neighborhood
Mean_Asian	Percentage of Asian people population for each neighborhood
Mean_AssessedValue	Average assessed value of all the single families in each neighborhood
Mean_BaseArea	Average square feet of base area for the single families in each neighborhood
Mean_LivingArea	Average square feet of living area for the single families in each neighborhood
Percent_UnOccupied	Unoccupancy rate for each neighborhood
Percent_Vegetation	Overgrown vegetation existing rate for each neighborhood
Percent_Trash	Trash existing rate for each neighborhood
Percent_Dumping	Dumping existing rate for each neighborhood
Percent_FallenTree	Fallen tree existing rate for each neighborhood
Percent_ActiveConstructio	Active construction existing rate for each neighborhood
Percent_OnRent	For rent/sale sign existing rate for each neighborhood
Percent_AbVehicle	Abandoned vehicle existing rate for each neighborhood
Percent_Siding	Damaged siding existing rate for each neighborhood
Percent_Painting	Need of painting existing rate for each neighborhood
Percent_Windows	Broken windows existing rate for each neighborhood
Percent_Shed	Damaged shed/garage existing rate for each neighborhood
Percent_Graffiti	Graffiti existing rate for each neighborhood
Percent_Porch	Damaged porch existing rate for each neighborhood
Percent_Foundation	Visible cracks in foundation existing rate for each neighborhood
Percent_Fences	Damaged fence existing rate for each neighborhood
Percent_Entry	Open to casual entry existing rate for each neighborhood
Percent_Boarded	Boarded rate for each neighborhood
Percent_Other	Other issues existing rate for each neighborhood

Table 2 Summary Statistics

Variable	N	Mean	Std Dev	Minimum	Median	Maximum
Price	8,143	$114,513	$130,276	$2	$85,000	$2,750,000
Blight Score(Individual)	8,143	1.754	0.749	1.000	2.000	5.000
Blight Index (Neighborhood)	8,143	1.732	0.435	1.000	1.756	3.039
Percent Tax&landbank	8,143	0.059	0.091	0.000	0.020	0.655
Percent OwnerOccupied	8,143	0.716	0.141	0.053	0.724	1.000
Percent Single (Land Use Code)	8,143	0.932	0.099	0.097	0.972	1.000
Percent Vacantland	8,143	0.036	0.070	0.000	0.013	0.569
Pecent Asian&White	8,143	0.446	0.349	0.000	0.381	1.000
Percent HighEducation	8,143	0.306	0.226	0.000	0.239	0.915
Mean MedianIncome	8,143	$52,374	$24,577	$12,616	$48,578	$171,176
Percent OnRent	8,143	0.013	0.009	0.000	0.012	0.125
LivingArea	8,143	1,757	820	560	1,528	10,585
Bedrooms	8,143	3.134	0.705	1.000	3.000	8.000
FullBaths	8,143	1.783	0.688	1.000	2.000	7.000
HalfBaths	7,677	0.231	0.441	0.000	0.000	3.000
Land	8,143	11,393	7,651	1,800	9,875	217,800
Stories	8,143	1.182	0.336	1	1	3
Age	8,143	51.197	22.281	0	54	159
Unsound	8,143	0.003	0.052	0	0	1
VeryPoor	8,143	0.002	0.048	0	0	1
Poor	8,143	0.022	0.148	0	0	1
Fair	8,143	0.419	0.493	0	0	1
Average	8,143	0.329	0.470	0	0	1
Good	8,143	0.177	0.382	0	0	1
VeryGood	8,143	0.031	0.174	0	0	1
Excellent	8,143	0.017	0.128	0	0	1
Grade	8,138	31.807	5.969	10	30	70

Table 3 Blight Index

An Ordered Logit Model is performed. The dependent variable is the blight index defined as 1, 2, 3, 4, and 5 with 1 meaning excellent and 5 meaning severely dilapidated. The explanatory variables are described in Table 1.

	Estimates	SDE	Chi-Square
vegetation	0.763***	0.027	827.1
trash	0.475***	0.031	237.2
dumping	0.702***	0.112	39.48
tree	0.621***	0.087	50.48
construction	0.361***	0.078	21.56
rent	-0.733***	0.046	254.8
vehicle	0.795***	0.048	270.3
siding	1.202***	0.024	2,487
painting	1.748***	0.018	9,932
windows	1.057***	0.060	308.1
shed	1.036***	0.053	379.7
graffiti	0.369***	0.148	6.24
porch	0.583***	0.037	244.0
foundation	0.441***	0.043	103.6
fences	0.441***	0.046	90.68
entry	0.771***	0.091	71.13
boarded	1.120***	0.042	803.2
other	1.268***	0.406	9.78
litter_none	-1.750***	0.063	772.0
litter_Low	-0.452***	0.064	49.16
litter_Medium	-0.273***	0.071	14.76
occupancy_NoStructur	-0.640***	0.117	30.11
occupancy_Occupied	-1.466***	0.034	1,897
occupancy_PartOccupi	-1.076***	0.073	218.1
occupancy_PossUnoccu	-0.690***	0.047	218.6
fire_none	1.397***	0.137	104.1
fire_minor	2.633***	0.182	210.1
fire_collapsed	2.595***	0.265	95.73
roof_none	-2.276***	0.033	4,728
roof_minor	-1.055***	0.036	866.0

Table 4

Table reports results for OLS regressions using property sale prices, P_{jt}, as the dependent variable.

$$P_{jt} = \beta_1 SurveyBlightScore_j + \beta_2 NeighborhoodBlightIndex + \beta_3 X_n + \varepsilon$$

Model 1 includes all explanatory variables, including individual property Blight Scores and neighborhood Blight Indices, Model 2 controls for neighborhood social/economy characteristics, such as median house income, ethnicity, and residents' education level and Model 3 controls for variables recorded in the Blight survey.

	Model 1		Model 2		Model 3	
	β	P-value	β	P-value	β	P-value
Intercept	88,144	0.103	-98,420	0.000	-68,709	0.000
Blight Score	-8,412	0.000	-5,439	0.000	-5,786	0.000
Blight Index	-8,473	0.042	-9,248	0.001	-5,552	0.033
Percent	-45,178	0.048	49,238	0.002	14,031	0.346
Percent	138,053	0.000	-33,095	0.001	-9,159	0.324
Percent Single (Land	-220,652	0.000	-14,334	0.391	-26,197	0.093
Percent Vacantland	-44,951	0.211	-51,004	0.041	-57,807	0.013
Percent	22,730	0.000	46,219	0.000	36,180	0.000
Percent	100,035	0.000	75,496	0.000	71,397	0.000
Mean MedianIncome	1.87	0.000	0.40	0.000	0.43	0.000
Percent OnRent	594,385	0.000	-37,901	0.642	-12,407	0.870
vegetation	-2,805	0.654				
trash	7,895	0.257				
dumping	16,849	0.518				
tree	716	0.965				
construction	12,003	0.174				
rent	-4,900	0.252				
vehicle	-4,930	0.731				
siding	-911	0.881				
painting	-4,485	0.305				
windows	3,233	0.783				
shed	2,294	0.843				
graffiti	23,705	0.465				
porch	-2,317	0.799				
foundation	6,333	0.574				
fences	-4,017	0.699				
entry	2,262	0.900				
boarded	2,335	0.756				
other	-17,701	0.467				
litter_none	7,252	0.573				
litter_Low	6,583	0.619				
litter_Medium	11,437	0.442				
occupancy_Occupied	-217	0.992				
occupancy_PartOccu	5,207	0.845				
occupancy_PossUno	-146	0.995				

occupancy_Unoccup	-2,335	0.917				
fire_none	15,338	0.696				
fire_minor	19,336	0.698				
fire_Major	14,870	0.758				
roof_none	-1,532	0.836				
roof_minor	2,793	0.741				
LivingArea			48.90	0.000	24.26	0.000
Bedrooms			-7,711	0.000	-3,421	0.006
FullBaths			17,350	0.000	16,257	0.000
HalfBaths			10,214	0.000	8,709	0.000
Land			0.94	0.000	0.94	0.000
Stories			-17,522	0.000	-10,045	0.000
Age			400	0.000	490	0.000
Unsound			-37,924	0.003		
VeryPoor			-27,991	0.040		
Poor			-7,624	0.112		
Average			-3,373	0.124		
Good			-6,129	0.066		
VeryGood			97,279	0.000		
Excellent			241,846	0.000		
Grade			3,115	0.000	1,967	0.000
SF_unsound					-29.09	0.000
SF_vpoor					-20.75	0.016
SF_poor					-7.64	0.011
SF_avg					6.57	0.000
SF_good					11.47	0.000
SF_vgood					46.15	0.000
SF_excellent					86.45	0.000
N	8,143		7,672		7,672	
Adjusted R^2	0.492		0.747		0.792	

Table 5 Factor Analysis

Panel A Orthogonal Transformation Matrix

	1	2	3	4	5
1	0.600	-0.395	-0.543	0.360	0.243
2	0.539	0.817	0.076	-0.015	0.191
3	-0.324	0.314	-0.174	0.823	-0.298
4	0.192	-0.254	0.801	0.436	0.259
5	0.456	-0.115	0.164	-0.055	-0.865

Panel B Rotated Factor Pattern

	Factor1	Factor2	Factor3	Factor4	Factor5
percent_vacantland	-0.002	0.915	0.109	-0.162	-0.036
Blight Score	-0.152	0.147	0.548	-0.121	-0.079
STORIES	0.484	-0.030	-0.137	0.056	0.493
LivingArea	0.843	-0.051	-0.200	0.215	0.314
Percent_eduHigh	0.305	-0.079	-0.468	0.711	0.054
Percent_single_LUC	0.034	-0.907	-0.172	0.009	0.047
Blight Index	-0.293	0.274	0.718	-0.203	-0.120
Percent_OwnerOccupied	0.450	-0.232	-0.570	0.360	0.151
Mean_MedianIncome	0.419	-0.217	-0.557	0.474	0.114
Percent_OnRent	0.028	-0.040	-0.010	0.198	0.044
mean_AsianWhite	0.113	-0.156	-0.312	0.757	0.009
percent_tax_landbk	-0.168	0.739	0.360	-0.265	-0.073
Bedrooms	0.660	-0.086	-0.103	-0.002	0.240
FullBaths	0.769	-0.148	-0.322	0.004	0.004
HalfBaths	0.166	-0.056	-0.091	0.078	0.582
Land	0.454	0.063	-0.072	0.123	0.001
age	-0.181	0.334	0.376	0.415	-0.208
grade	0.679	-0.204	-0.405	0.215	0.314

Panel C Variance Explained by Each Factor

Factor1	Factor2	Factor3	Factor4	Factor5
3.322	2.630	2.431	1.913	0.950

Table 6 Shapley-Owen Value

Panel A The groups of Shapley-Owen model

Variable	Group
Blight Score	Blight_Occupied_Income
Bligh Index	Blight_Occupied_Income
Percent_OwnerOccupied	Blight_Occupied_Income
Mean_MedianIncome	Blight_Occupied_Income
Percent_eduHigh	Demographic
mean_AsianWhite	Demographic
LivingArea	House_Character1
Bedrooms	House_Character1
FullBaths	House_Character1
grade	House_Character1
STORIES	House_Character2
HalfBaths	House_Character2
percent_vacantland	Neighborhood_Character
Percent_single_LUC	Neighborhood_Character
percent_tax_landbk	Neighborhood_Character
Percent_OnRent	Others
Land	Others
age	Others

Panel B Estimation

	Estimate	Std_Error	Z_Score	P_Value
intercept	-104,453	18,876	-5.534	0.000
Blight Score	-5,082	1,073	-4.735	0.000
Blight Index	-8,944	2,644	-3.382	0.001
Percent_OwnerOccupied	-76,417	9,225	-8.284	0.000
Mean_MedianIncome	0.588	0.057	10.39	0.000
Percent_eduHigh	69,520	6,201	11.21	0.000
mean_AsianWhite	58,811	3,264	18.02	0.000
LivingArea	60.71	2.041	29.74	0.000
Bedrooms	-10,998	1,296	-8.488	0.000
FullBaths	20,303	1,683	12.06	0.000
grade	4,384	254.9	17.20	0.000
STORIES	-27,605	2,655	-10.40	0.000
HalfBaths	14,706	1,815	8.102	0.000
percent_vacantland	-110,884	23,637	-4.691	0.000
Percent_single_LUC	-49,171	16,269	-3.022	0.003
percent_tax_landbk	108,648	14,630	7.426	0.000

Percent_OnRent	191,492	80,257	2.386	0.017
Land	1.003	0.107	9.374	0.000
age	482.1	44.97	10.72	0.000

Panel C Shapley-Owen Value

Group	Contribution to R^2
Blight_Occupied_Income	0.148
Demographic	0.148
House_Character1	0.267
House_Character2	0.049
Neighborhood_Character	0.039
Others	0.057
R^2 Sum	0.707
R^2 Full	0.707