An Analysis of the Correlations Between Vacant Properties, Police Incidents/Crime, and Property Values in the City of Minneapolis, Minnesota Using Geographic Information Systems and Regression Analysis for the Year 2015

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Abstract

Vacant properties are often viewed as targets of unwanted attention from criminals. It is debated whether crime influences the location of these vacant properties, but it is also suggested that they are codependent. This study seeks to identify if a correlation exists between the variables vacant properties, crime, and the mean property values calculated per neighborhood of Minneapolis, Minnesota. Data from the year 2015 is used in this analysis. ArcGIS analysis tools, such as Ordinary Least Squares (OLS) and Exploratory Regression, are used to evaluate correlations which might suggest a relationship between property values, crime incidents, and vacant properties per neighborhood. Spatial Autocorrelation and Pearson's Correlation are also utilized to further analyze the variables. Other variables that might contribute to correlation are discussed, such as urban renewal efforts in the form of gentrification, greening of open space, and crime types. Past studies regarding the correlation of vacant houses, crime, and property values suggest a correlation. This study searched for a properly specified model to confirm correlation between the variables but did not identify any obvious or strong correlation between variables.

Introduction

Vacant lots and abandoned properties are perceived as places that attract crime. They are also perceived to be a product of crime. Vacant properties are found to be unkempt, unaesthetic, and a magnet for illegal activity such as prostitution, drugs, and violent crime (Garvin, Cannuscio, and Branas, 2013). This research investigates if a correlation exists between crime, vacant properties, and property values in the City of Minneapolis, Minnesota for the year 2015.

Garvin *et al*. (2013) investigated the idea that turning vacant lots and properties into vibrant community spaces decreased crime in the surrounding areas. Although open space, vacant properties, and crime have evidence of congruence, it is questioned whether they are codependent or independent (Whelan, 2015).

This study seeks to aid in the identification of effects of crime on property values and the occurrence of vacant or abandoned property. Vacant properties can be described as commercial

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or residential properties that are uninhabited, blighted, or not maintained. The properties can include both buildings and vacant lots.

Philadelphia

There are numerous studies, mostly conducted in Philadelphia, to assess efforts to green the blighted open spaces in hopes of limiting or deterring crime. The greening of vacant lots was conducted in Philadelphia and consisted of two groups, lots that were greened and non-greened (Kraut, 1999). Greening is defined as "cleaning the lots, planting grass and trees, and building a wooden fence around the perimeter" Garvin *et al.* (2013). Garvin *et al.* (2013) conducted an in-depth study, similar to others in Philadelphia, about the difference between actual crime and perceptions of crime.

Kraut (1999) displayed the facts about a notorious slum lord named Samuel Rappaport who owned numerous amounts of vacant properties in Philadelphia. It was reported that Rappaport owned many properties, let them sit, and had intentions of selling later. This, in effect, created blight and distress in the surrounding neighborhood (Kraut, 1999).

Moreover, it is also noted that properties owned by Rappaport located within the center of the city were magnets for devious activities comprised of graffiti, broken windows, and the presence of "drug dealers and derelicts" (Kraut, 1999).

Garvin *et al.* (2013) conducted another in depth analysis of the issue of vacant properties in Philadelphia. The study considered the perceptions and crime ratings before and after the greening of an open area. They conducted interviews of the residents, and after the trial period, interviewed the residents again for a thorough explanation of their perception of change. The purpose was to deliver primary evidence supporting the notion that greening vacant lots and or open space may result in better public perception of crime and the actual reduction of crime that is violent (Garvin *et al.*, 2013).

A limitation was the failure to have a standard distance around the area of study (Garvin *et al.*, 2013). Another weakness was the fact that it was challenging to conclude interviews with all residents who initially signed up for the study; only 21 of the 29 participants engaged in the follow-up interviews that were scheduled after a three-month period (Garvin *et al.,* 2013).

Twin Cities, Minnesota

In a study conducted by Nega, Wei-Hsin, and Vrtis (2010), an Open Space Index (OSI) analysis was performed using statistics and geographic information science (GIS). They set out to investigate the distribution of open space within the Twin Cities Region of Minnesota comparing factors such as race, economic status, and land availability. The study utilized the OSI, which essentially calculated the volume of land that would be categorized as open or unused (Nega *et al.,* 2010).

Their method of OSI calculation measured the smallest distance between an area of interest and an already existing area of infrastructure. Their calculations were made using GIS (Nega *et al.*, 2010).

Their overall findings concluded that there were indeed inconsistencies in the spatial distribution of open public space, economic status, and minority populations within the Twin Cities (Nega *et al.,* 2010).

Locations of Vacant Properties

Per Kraut (1999), in Hanging Out the No Vacancy Sign: Eliminating the Blight of Vacant Buildings from Urban Areas, vacant buildings are at the root of the cause of blighted and unkempt neighborhoods and urban areas. This phenomenon could be attributed to the ill attention to upkeep and/or to the property not being inhabited at all (Kraut, 1999). Kraut (1999) implied problem land owners, such as Rappaport, are sometimes deemed to be the root cause of the blighted properties because their lack of attention and scheming, tax evading ways.

Blight Attracts Crime

Whelan (2015) reported findings in Philadelphia, PA of homes that the State of Pennsylvania required to be maintained. Such requirements included ordinances that say owners must not board up windows and doors on blocks in the city that have an “occupancy rate higher than 80 percent” (Whelan, 2015). Furthermore, it was reported that the appearance of property has a direct impact on the property value, crime, and perceptions of the neighborhood.

Whelan (2015) noted changes following the improvement of the blighted properties. “Within a year of the repairs, the area around those houses saw an estimated 19 percent reduction in assaults and a 39 percent reduction in gun assaults” (Whelan, 2015). The crime data for Whelan’s (2015) study was collected from the Philadelphia police department over a two-year span. This data compared the homes that were improved with those that were not, or the control properties.

In contrast with the findings of a reduction of crime, Garvin *et al.* (2013) found evidence which displayed an increase in the amount of crime, however slight. Garvin *et al.* (2013) used a buffered, half-mile area to study the amount of crimes taking place around certain vacant properties before and after greening them. Garvin *et al.* (2013) stated the crime level “before greening and after greening was 31.2% and 33.8%, respectively” (Garvin *et al.,* 2013). Garvin *et al.* (2013) concluded a test result with Chi-square was not significant enough to pursue another study at a larger scale.

Crime and Property Values

Other factors related to neighborhood perceptions of crime and safety or property devaluation include the presence of known criminals, such as sex offenders (Linden and Rockoff, 2008). Linden and Rockoff (2008) presented findings that suggested a correlation of lower property values near homes of registered sex offenders in Mecklenburg County, North Carolina. Their methods included a hedonic estimation methodology and offered statistical evidence of the correlation.

It was estimated that properties located near a registered sex offender, within 0.1 to 0.3 miles, were valued at roughly $5,500 less than properties farther away (Linden and Rockoff, 2008). Findings also suggested the values of properties beyond 0.3 miles were not decreased and there seemed to be less of an overall effect from the presence of registered sex offenders. Linden and Rockoff (2008) concluded that the general public does not want to live near a registered sex offender and avoids potential criminal activity.

Crime rates are hypothesized to influence overall “urban public revenues” (Naroff, Hellman, and Skinner, 1980). Naroff *et al.* (1980) observed the City of

Boston, Massachusetts and argued crime affects property values, which would then translate into a tax base, and ultimately aid in the ability of the city to fight crime. Furthermore, it is also stated that property values are determined by the services the government offers its citizens, such as schools and other public service packages (Naroff *et al.*, 1980). Both Naroff *et al.* (1980) and Linden and Rockoff (2008) would lend support to the idea that an increase in property value and taxes would translate into lower crime and blighted neighborhoods. One question that arises from their findings is whether the levels of crime are based on actual or perceived crime (Naroff *et al.*, 1980).

Mead (2000) found that crime follows the path of least resistance, thus further supporting the findings of Naroff *et al.* (1980) that higher property values and taxes are paid by the rich to avoid the poor. Mead (2000) also exemplified that society is constructed and manipulated to keep the wealthy and the poor separated (Mead, 2000), which in effect exacerbates the effects of crime and poverty.

Ihlanfeldt and Mayock (2010) produced evidence supporting the idea that crime and housing property values are inversely and directly related. An example is given regarding criminals, which discussed the implications that crime may be worse in neighborhoods that already have low property values.

Authors suggested health and safety issues correlate with locations of blighted and vacant properties (Branas, Cheney, MacDonald, Tam, Jackson, and Ten Have, 2011). Additionally, it is observed that the placement of blighted properties affects the surrounding populations and crime of the areas. Other authors support this assessment, such as Whelan (2015).

It is also noted that criminals tend to commit criminal activity closer to where they live, so therefore lower income areas are said to automatically attract crime (Ihlanfeldt and Mayock, 2010). It was found statistically significant that the two main forms of crime that showed any effect on housing values were aggravated assault and robbery (Ihlanfeldt and Mayock, 2010).

Whelan (2015) reported that the good or well-groomed appearance of a property improved perceptions of crime and overall crime rates in the areas studied. Garvin *et al.* (2013) suggested the same findings as Whelan (2015) and Branas *et al*. (2011), that the cleaning up and greening of the vacant properties significantly changed the perception, safety, and overall appearance and property values of a neighborhood.

Methods

Data

The location of this study consisted of the 87 neighborhoods in Minneapolis as shown in Figure 1. The Minneapolis neighborhoods, street centerlines, city boundary, property values for 2015, and crime for 2015 were all gathered from Open Data Minneapolis (City of Minneapolis Open Data, 2016).

Data for vacant properties in Minneapolis was acquired from the City of Minneapolis Vacant Building Registration, which was produced by the City of Minneapolis Department of Regulatory Services (2016). The year used for analysis was 2015, which was queried from the master list containing years spanning from 2010 to the present year, 2017. There was a total of 81 vacant properties for 2015. Figure 2 displays the locations of the 81 vacant properties.

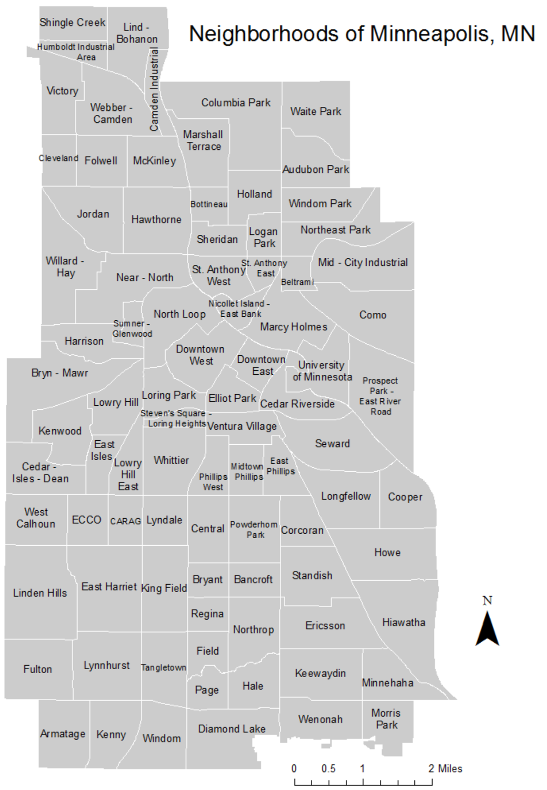

Figure 1. The 87 Neighborhoods that comprise Minneapolis, Minnesota.

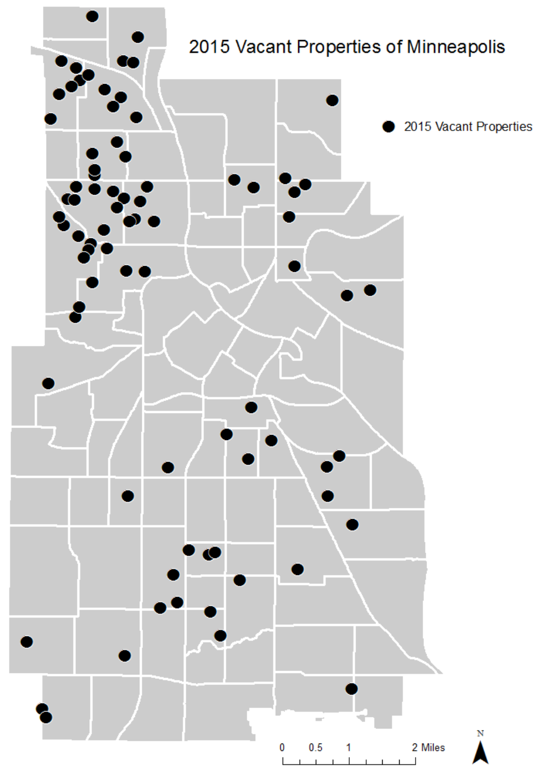

Figure 2. The distribution of vacant properties in 2015 compared to the 87 Neighborhoods of Minneapolis, Minnesota.

The categories of years according to the spreadsheet titled "Minneapolis List of Vacant Land and Condemned Properties" from the Minneapolis Department of Regulatory Services included: VBR (date entered into the vacant building registry), CVBR (not specified), CONB (Date the building was condemned for being boarded), CON1 (Date Condemned for lack of maintenance), DIRORD (Date Director's Order to Demolish was sent), and RA (Date Restoration Agreement was signed). The category used to assign year attributes was VBR, which was the date the property was entered into the vacant building registry. In some cases, the VBR attribute was empty or not specified, so CONB, CON1, or DIRORD was used respectively, as an alternative value for VBR.

The vacant property data was geocoded utilizing the Hennepin County Geocoder. This geocoding was conducted in ArcGIS Desktop by adding Hennepin County Rest Services (Hennepin County, 2016) as a server connection. 2010 Census Block data was acquired from the Hennepin County GIS Open Data (2010) website.

More attributes were desired than the ones provided from Hennepin County, such as income and other demographics, so data from the American Community Survey (ACS) for the year 2010, obtained through the Minnesota Geospatial Commons (2017), was added. Once these census datasets were brought into a .dbf table format and joined, the Dissolve tool was utilized to aggregate the data into the 87 neighborhood boundaries. Dissolve is a tool that "aggregates features based on specific criteria" (Esri, 2017a). The sum statistics field was used on all the categories of the census data from the ACS to get the total for each neighborhood. The ACS data was then utilized for analysis.

There were 10,747 reported property sales for the City of Minneapolis. The data for the property sales was obtained from the City of Minneapolis Open Data website in the form of a shapefile. There were two attributes with price values in the property sales shapefile: gross sales and adjusted sales. The gross sale price was chosen to conduct analysis for this research.

The gross property sales for 2015 were exported into an Excel document, and the average gross sale price was calculated per neighborhood. The average gross property sale values will be referred to as property values throughout this research. The distribution of the average property sale prices for 2015 is displayed in Figure 3. The Excel table was then converted back to a table in ArcMap and joined to the neighborhood shapefile. This data was then joined with all the ACS data, as well as the crime and vacant property data, into one layer to perform tests.

The police incidents of 2015 are displayed in Figure 4. The original data was acquired from City of Minneapolis Open Data (2016). Each crime incident was assigned a neighborhood value, and the Dissolve Tool was utilized to calculate a sum of crimes/police incidents per neighborhood. A crime incident can be described as any type of crime, but this study only used the single reported incidence of a crime, regardless of the type.

There were 23 incidents without a neighborhood assigned to them in the original dataset before geocoding. The 23

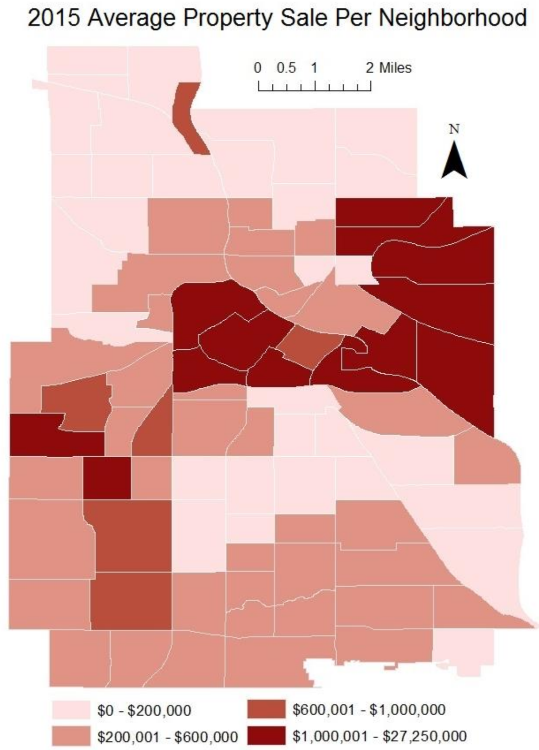

Figure 3. The average gross property sale price in 2015 for the 87 neighborhoods of Minneapolis, Minnesota.

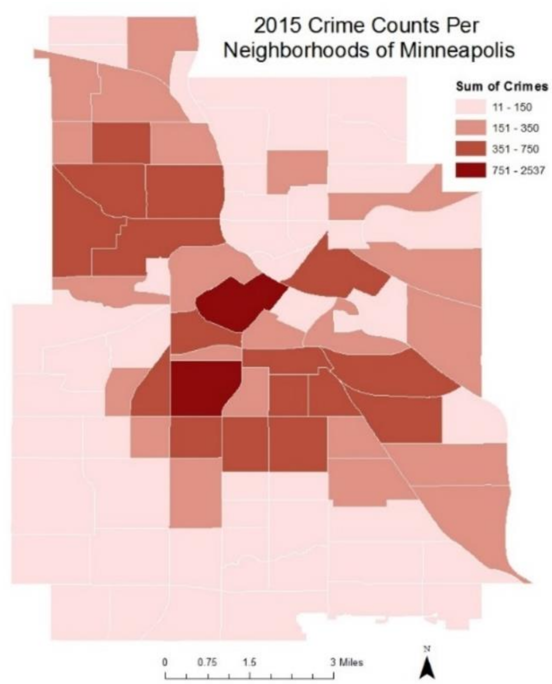

Figure 4. The number of police incidents in 2015 for the 87 neighborhoods of Minneapolis, Minnesota.

incidents were on or near the Minneapolis border and not included in the analysis. It was speculated that the Minneapolis police were called to these incidents and afterwards the reports were included in the Minneapolis Police database. The police incidents data will also be referred to as "crime" throughout this study.

Summary Statistics

Various descriptive statistics were calculated regarding vacant properties, crime, and property values for the 87 neighborhoods of Minneapolis. Table 1 displays the mean, sum, minimum value, maximum value, and range for the year 2015. The statistics were calculated using the Summary Statistics tool in ArcGIS Desktop 10.4.1 (Esri, 2017a).

Table 1. The summary statistics for the variables of the 87 Neighborhoods of Minneapolis, Minnesota.

Statistic Summary	Crime	Property Values	Vacant Properties
Mean	229.5	1,362,895.7	0.93
Sum	19,972	118,571,927	81
Min	9	0	0
Max	2532	27,250,000	7
Range	2523	27,250,000	7

Graphs representing the distribution of the data in relation to the other variables are shown in Appendix A.

Ordinary Least Square Regression

To investigate the original research question, Ordinary Least Squares (OLS) was utilized to analyze the correlation between crime/police incidents, vacant properties, and property values for the year 2015 in the City of Minneapolis. OLS is "a common statistical method used to generate predictions or to model a dependent variable in terms of its relationships to a set of explanatory variables on a global level" (Esri, 2017a).

In the research of Eckerson (2013), OLS analysis was utilized to examine the correlation between tree cover canopy and crime in the City of Minneapolis. Other factors included population, income, education, and age of the Minneapolis residents. Eckerson (2013) concluded some correlation was evident in the relationships after analyzing the regression results.

In this study, the first set of correlations analyzed included vacant properties and crime in the City of Minneapolis. As previously mentioned in the data section, the crime was organized per the 87 neighborhoods of Minneapolis, and the number of crimes were used for statistical analysis.

The goal of running OLS is to find a properly specified model which passes all six statistical checks (Esri, 2017b). The six statistical checks are (Esri, 2017b):

1. Are the explanatory variables helping your model? *If the value is zero for the coefficients, or very close to zero, this indicates that the value is not helping your model. Statistically significant, as shown by an asterisk next to the model, is beneficial to the model.*
2. Are the relationships what you expected? *If there is no asterisk next to the Koenker test, use probability over the robust probability. Closer to 0 is more desirable.*
3. Are any of the explanatory variables redundant? *If the VIF value is below 7.5, it passes this check.*
4. Is the model biased? *If the Jarque-Bera statistic is significant, this indicates the model is biased and is likely missing key explanatory*

variables. An unbiased model would be normally distributed on a bell-shaped curve (graph).

5. Do you have all key variables*? By running Spatial Autocorrelation, you can check if the residuals are clustered, which indicates bias.*
6. How well are you explaining your dependent variable?

Using these six statistical checks, OLS analysis was performed on the variables.

OLS: Vacant Properties and Crime

For the first test of OLS, the number of vacant properties was the dependent variable and crime was the independent variable. Figure 5 displays the map results of the variables crime and vacant properties. The areas in dark red depict areas where the actual values are higher than where the model predicted. On the contrary, the light blue to dark blue values indicate where the actual values are lower than the model predicted. As clustering is evident in the map, this indicates it is missing some key explanatory variables. (Esri, 2017a).

The values for the variables vacant properties and crime were analyzed and the results are as follows. The Adjusted R Square value was 0.003, the Akaike's Information Criterion (AIC) value was 335.42, and the Koenker Statistic Test was significant with the value of 13.22 with 1 degrees of freedom. The Jarque-Bera Statistic was 89.33, and was significant with a p-value of 0.000000, which indicated that the model is biased, and further testing is recommended. The coefficient values were positive, which indicated a positive relationship, meaning when the value of one variable increases, so does the value of the other.

A properly specified model must pass all six checks. This model, which used vacant properties as the dependent variable and crime values as the independent variable, did not pass and is therefore not properly specified.

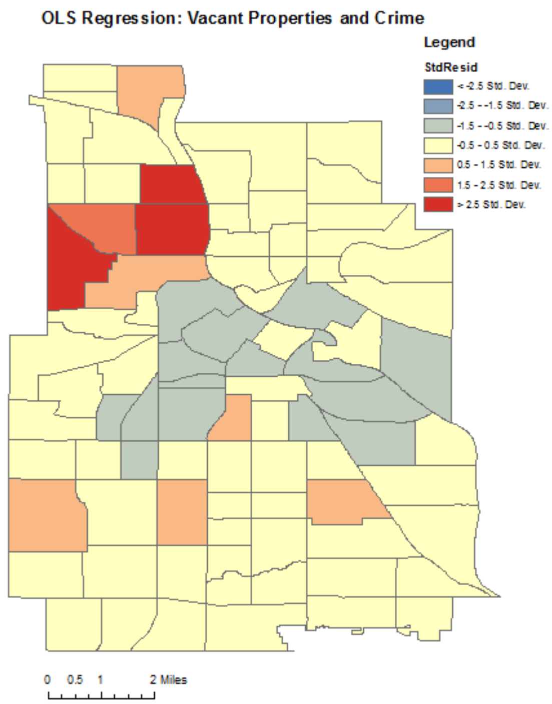

Figure 5. The map of residuals resulting from the OLS regression analysis of vacant properties and crime.

OLS: Vacant Properties and Property Values

The second test was to run OLS with vacant properties as the dependent variable and property values as the independent variable. Figure 6 displays the results of the residuals. Like the previous test (Figure 5), the residuals were clustered and indicated missing key explanatory variables. The relationship was expected to be inverse; when the vacant properties increased, the property values decreased. The Akaike's Information Criterion value was 337.31, which was higher than the previously conducted model. This indicated that this model is not as good a fit as the previous.

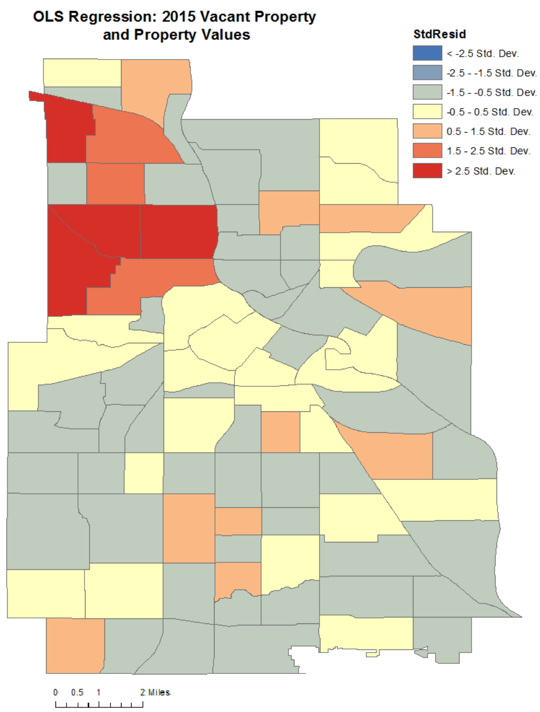

Figure 6. The map of residuals resulting from the OLS regression analysis of vacant properties and property values.

The Jarque-Bera statistic is significant with a value of 113.99. This significance indicated a biased model, and therefore automatically assumes that all key explanatory variables were not identified or included.

Overall, this model did not pass all the six statistical checks, and therefore was not a properly specified model.

OLS: Vacant Properties, Crime, and Property Values

The next test was to include a second independent variable in the OLS test. The variable added was property values. The vacant properties variable was the dependent variable, and the independent variables were crime and property values. Figure 7 depicts the resulting map of residuals from the OLS Regression analysis for the variables property value means per neighborhood, crimes per neighborhood, and vacant properties per neighborhood. Figure 7 also concluded that the residuals of over and under predictions were clustered and therefore indicative of missing explanatory values.

The Adjusted R Square value was 0.28, which indicates that roughly 30% of the variation in the number of vacant properties can be explained by the independent variables. The Akaike's Information Criterion (AIC) was 1096.18, which was a larger value than the test between the two variables crime and vacant properties. This implied that this model with three variables was less of a good fit than the model with two.

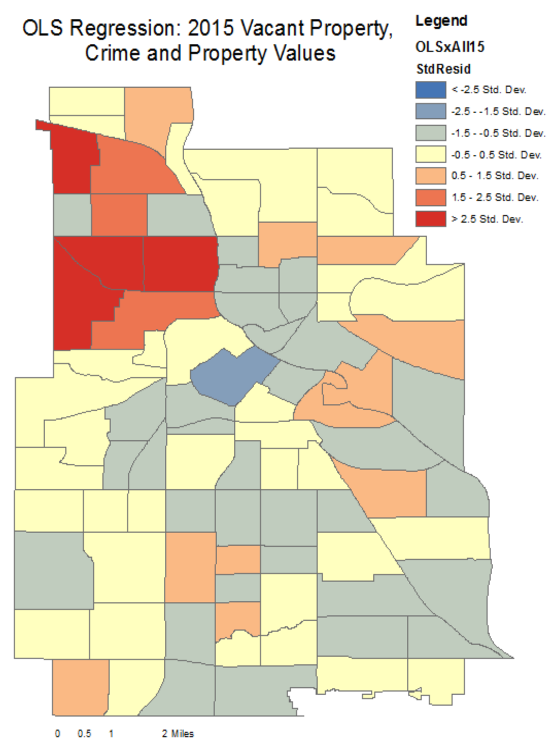

Figure 7. The map of residuals resulting from the OLS regression analysis of vacant properties, crime values and property values.

The Koenker Statistic Test value of 0.000727 with 6 degrees of freedom was not significant. The Jarque-Bera Statistic was significant (0.000000). A significant Jarque-Bera statistic indicated that another test would be beneficial. The recommended test was Spatial Autocorrelation.

Spatial Autocorrelation

The OLS results recommended that Spatial Autocorrelation be conducted for all three previous models. Spatial Autocorrelation (Global Moran's I) evaluates "feature locations and feature values simultaneously … it evaluates whether the pattern expressed is clustered, dispersed, or random" (Esri, 2017a).

The residuals of the "all three variables test" (vacant properties, crime, and property values) were chosen as the input to run the Moran's Spatial Autocorrelation test. The Global Moran's I summary is as shown in Table 2 (Esri, 2017a). Figure 8 displays the Global Moran's summary distribution image (Esri, 2017a).

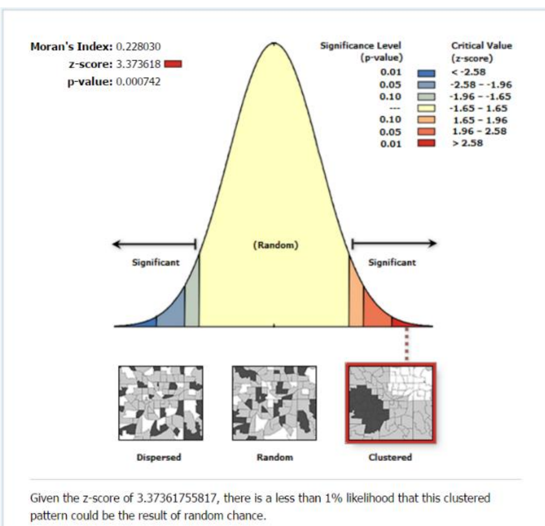

Figure 8. Global Moran's summary (Esri, 2017a).

The Spatial Autocorrelation test concluded that the clustered pattern has a likelihood of less than 1% that it is due to random chance. This suggests there are underlying explanations and further variables to investigate within the dataset.

Table 2. Global Moran's I summary.

Moran's Index	0.23
Expected Index	-0.012
Variance	0.005
z-score	3.37
p-value	0.01

Exploratory Regression

Exploratory Regression explores the relationships between the dependent and independent variables. The regression equation is shown below (Esri, 2017b).

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n + \varepsilon$$

The y variable represents the dependent variable. The Beta (β) values represent the coefficients. The explanatory variables are represented by X and they explore the influence or effect on the dependent variable. The ε represents the residuals. Residuals are the difference between the predicted and observed, or actual, values (Esri, 2017b).

Since there were no passing models from the OLS results, the data for the Exploratory Regression tests was acquired from the American Community Survey for the year 2015 as published by the Metropolitan Council (Metropolitan Council, 2017). The data was combined with the previous layers acquired from the City of Minneapolis Department of Regulatory Services (2016) and the City of Minneapolis Open Data website (2016) using the Dissolve tool.

The Minneapolis neighborhood field was used to aggregate the attributes. A statistical function within the Dissolve tool was utilized to produce a sum of each attribute category for the ACS data, which excluded the property values, which were calculated by means. Fields aggregated to create the new layer are described in Appendix B.

The Exploratory Regression Tool

was conducted, and no models passed. The variables that comprised the top five values of the Summary of Variables Significance for all the model variations tested are shown in Table 3.

Table 3. Summary of variable significance: percent of models where variable was significant (%Sig), percent with a negative relationship (%Neg), and percent with a positive relationship (%Pos).

Variable	%Sig	%Neg	%Pos
PPHSF	99.85	0.00	100.0
Val100_124	89.53	0.00	100.0
MedHomeVal	85.52	99.94	0.06
PPHMF5	80.17	3.33	96.67
PPH234	78.96	1.15	98.85

The definitions of the top five variables are as follows (Metropolitan Council, 2017):

PPHSF - average household size in single family housing.
Val100_124 - homeowners valuing their home in the range of $100,000 to $124,000.
PPHMF5 - average household size in larger buildings.
PPH234 - average household size in duplexes and 3 to 4-unit buildings.
MEDHOMEVAL – median home value of ownership housing.

Although no models passed, the results provided insight towards future variables to explore.

Geographically Weighted Regression

Considering that the OLS and Exploratory Regression tests did not produce a properly specified model, the Geographically Weighted Regression (GWR) tool was not utilized for this study. Eckerson (2013) conducted a study on the relationship between tree canopy and crime in the City of Minneapolis. He used regression analysis in the form of spatial statistics, OLS, and GWR to evaluate the findings. According to Eckerson (2013), GWR was an excellent method to further analyze and compare the explanatory variables regarding a regression model. However, GWR was not necessary in this study as no properly specified model from the OLS results was identified.

Pearson's Correlation

Considering that the OLS and Exploratory Regression tests did not produce a properly specified model or indicate correlation, Pearson's Correlation statistical test was conducted between the three main variables (vacant properties, property values, and crime) as confirmation. This statistic tests for linear relationships between two sets of values, in the form of X and Y values (Zar, 2010). The result is r, where values of 1 or -1 indicate a very strong or perfect linear relationship, otherwise known as the coefficient of correlation (Zar, 2010). R^2 is simply the squared value of r. It is often better at explaining how correlation can be explained by certain relationships between variables.

The equation for Pearson's Correlation Statistic is as follows (Zar, 2010):

$$r = \frac{\sum XY - \frac{\sum X \sum Y}{n}}{\sqrt{\left(\sum X^2 - \frac{(\sum X)^2}{n}\right)\left(\sum Y^2 - \frac{(\sum X)^2}{n}\right)}}$$

Where n equals the sample size, X is the variable for the X values, and Y is the variable for the Y values.

Vacant properties were used as the dependent variable (X) for the first two correlation tests. The variables of the first test included vacant properties (X) and crime (Y). The value of r was 0.2036. This indicated that there was a positive correlation. Although it was not necessarily significant, it was an indication of strength between the variables. The coefficient of determination, the value of R^2, was 0.0415, which matched the OLS R^2 result (0.041470). This suggested that each test had predictably similar results. This means that only 4% of the variation in vacant properties could be explained by crime.

The variables for the second test included vacant properties (X) and property values (Y). The value of r was -0.143. This indicated a negative correlation, although a very weak one. The coefficient of determination R^2 was 0.0204, which again matched the OLS R^2 result (0.020448). This suggested that each test had predictably similar results. This means that only 2% of the variation in vacant properties could be explained by property values.

The variables for the third test included crime (X) and property values (Y). The value of r was 0.1684. This indicated a positive correlation, although a very weak one. The coefficient of determination R^2 was 0.0284. This means that only 2% of vacant properties could be explained by both variables, crime and property values.

Since none of the original variables studied had much of a correlation, the results of the Exploratory Regression variables were tested. The top five variables from the ACS data with the highest correlations were analyzed with the Pearson's Correlation. These five values are: PPHSF, Val100_124, PPHMF5, PPH234, and MEDHOMEVAL.

Table 4 displays the values from the top five significant variables from the Exploratory Regression test. The X Value for the values in Table 4 was vacant properties. The significance of the P Value was set to 0.05.

Table 4. Correlation results for vacant properties and individual ACS variables: r, R^2, and P Values.

Y value	r	R^2	P Value
PPHSF	0.0181	0.0003	0.867844
Val100_124	0.4992	0.2492	0.00001
PPHMF5	0.4535	0.2057	0.00001
PPH234	0.534	0.2852	0.00001
MEDHOME VAL	-0.3754	0.1409	0.0000345

The values from the Pearson's correlation tests indicated slight correlation. The variable which indicated the highest correlation is PPH234 (average household size in duplexes and 3 to 4-unit buildings). The two second highest variables were Val100_124 (Home owners valuing their home in the range of $100,000 to $124,000) and PPHMF5 (average household size in larger buildings).

The R^2 value, or coefficient of determination, for the highest variable PPH234 was 28%. This means that 28% of the variation in vacant properties can be explained by PPH234, which was average household size in duplexes and 3 to 4-unit buildings.

Discussion

Results Discussion

OLS was used to identify if there were any passing models. There were none discovered. A Spatial Autocorrelation analysis was performed as suggested by the results of the OLS tests. The spatial autocorrelation model residuals proved to have clustered, or biased, results. This means that there were probably clustered areas of vacant properties, and therefore skewed or insignificant results. Since there was nothing significant that came from

OLS or Spatial Autocorrelation, the next step was to use Exploratory Regression. There were no significant values from the original independent variables, so more were added from the ACS to see if correlation existed with vacant properties. The quest for influential factors on vacant properties was not over. Variables added from the ACS are displayed in Appendix B. The top five resulting variables from the Exploratory Regression were used for further statistical testing. There was no significance to choosing the top five variables to report besides having more options to explore. The values from the Pearson's Correlation statistic that best explained the location of vacant properties was PPH234, or "average household size in duplexes and 3 to 4-unit buildings" (Metropolitan Council, 2017). PPH234 could explain 28% of the variation in vacant properties. More research between these variables would be beneficial.

Limitations of the Research

The limitations of this research included the preconceived notions of the author regarding their views and definitions of crime, blight, and low property values. Other limitations included low numbers of explicitly parallel studies, therefore limiting the ability to compare results.

The author presumed that crime would be higher in areas with lower income. This was disproved, as the downtown areas of Minneapolis had the most crime, but not the lowest income. This is similar to the findings of Ihlanfeldt and Mayock (2010), where the actual amounts of crime versus the reported amounts of crime that occurred in Miami-Dade County varies. Findings included that the wealthier an area is, the more likely it is to attract criminals and therefore crime. The payoffs are argued to be more lucrative in a wealthier neighborhood; therefore, it was found that the crime may be slightly higher in those specific areas (Ihlanfeldt and Mayock, 2010).

Other limitations included the data collection and reporting of crime. There are different types of crimes, but this study only used the reported incidence of a crime. Ihlanfeldt and Mayock (2010) found evidence violent crime is more characteristic of neighborhoods with property devaluation. "Neighborhoods with a violent crime problem are also those with a property crime problem" (Ihlanfeldt and Mayock). Ihlanfeldt and Mayock went on to state using a smaller offensive crime as an indicator of decreased property values and overall crime is incorrect, as their studies showed more correlation with violent crime.

Future Research

Suggestions for future research would be to conduct a more in-depth investigation regarding the correlation between variables from the ACS data and vacant properties. Variables to include would be population, age, income, and other demographic information as suggested by other authors and scholarly research. Another suggestion would include calculating the mean of some of the ACS variables with the Dissolve tool, instead of sum, which was used for this study. Summing average values could skew the results if there are different numbers of census areas per neighborhood. It would also be beneficial to include a longer time increment, instead of only one year, as this study only focused on the year 2015. Perhaps if the past ten to twenty years were analyzed, new insights would result.

Ihlanfeldt and Mayock (2010) found that the two main forms of crime that showed any statistically significant effect on housing values were aggravated assault and robbery. Future variables could include different categories of crime as suggested by Ihlanfeldt and Mayock, (2010). Further exploration of the relationships could provide areas to invest more research.

This study could be utilized as a starting place to identify areas of the city which need attention regarding housing stock revitalization.

Suggestions regarding further research surrounding topics of property values and vacant properties include a potential proximity analysis. A proximity analysis surrounding vacant properties would explore potential effects on the surrounding properties and neighborhood. It would be interesting to see if the surrounding properties were devalued after the vacant property became vacant. Field research in the form of observations and interviews regarding neighborhood perceptions could also conducted, such as the studies conducted by Whelan (2015).

Another suggestion includes isolating areas of Minneapolis that have either different geographic boundaries or properties, or areas that have higher concentrations of poverty or crime. Once the smaller boundaries in Minneapolis are set, it would be recommended to compare the results to other areas in Minneapolis.

Conclusions

The purpose of this study was to analyze the correlation between vacant properties and crime in the City of Minneapolis. This was completed with OLS, Spatial Autocorrelation, Exploratory Regression, and Pearson's Correlation statistical tools. A third explanatory variable of property values was added to clarify the relationships that exist between the original two variables of crime and vacant properties. Data from the ACS was added to explore other possibilities of correlation.

A significant model was hoped for, but none of the variable variations with OLS met all the requirements to pass the statistical checks that produce a properly specified model. Tests with Pearson's Correlation suggested slight linear correlation with a few variables from the ACS data but nothing strong enough to make definite conclusions. Overall, further research would be necessary to isolate and identify strong contributing factors to vacant properties in Minneapolis, MN.

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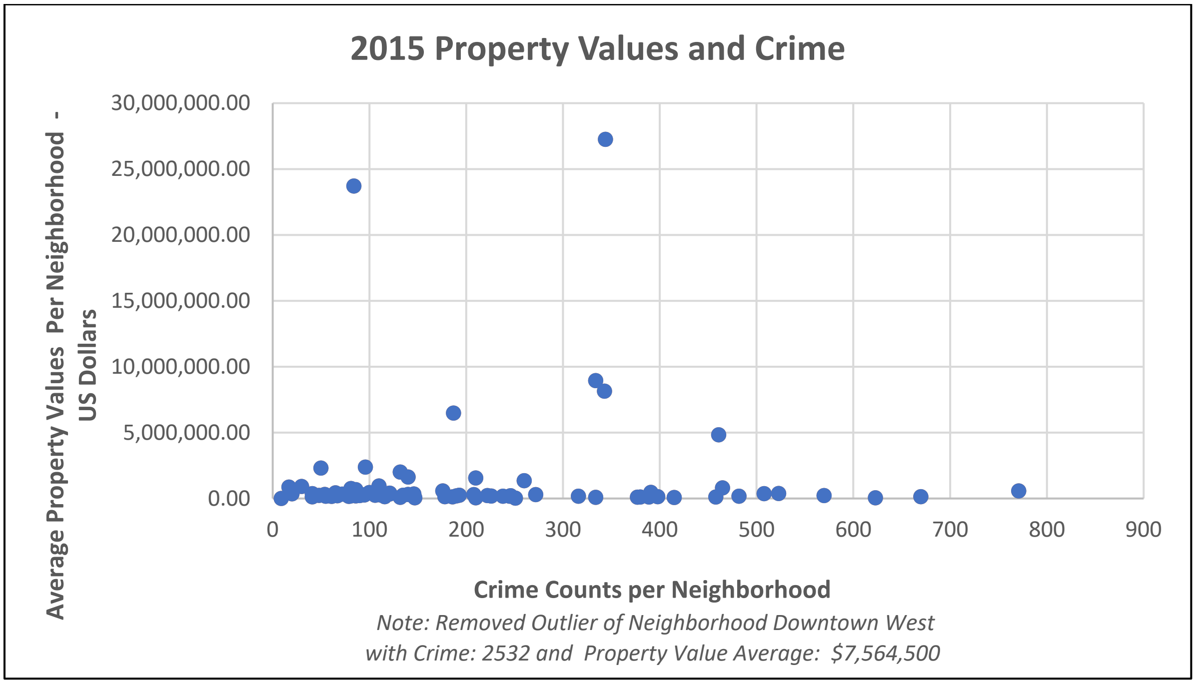
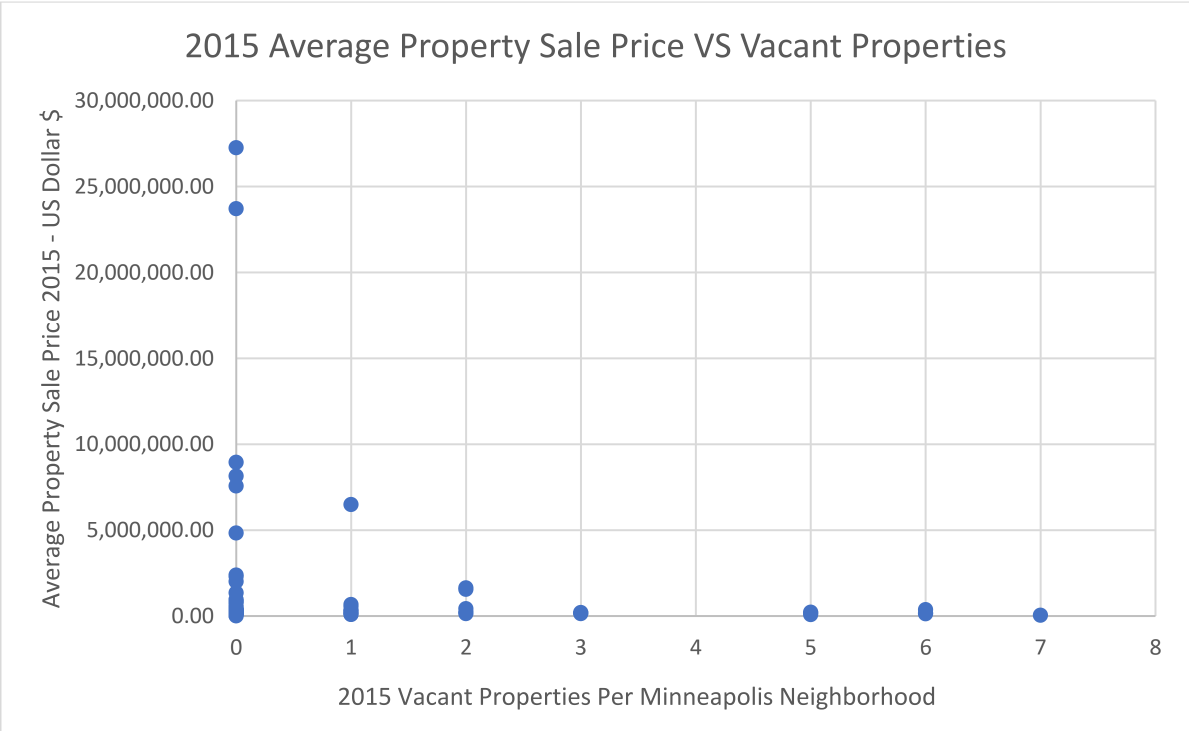
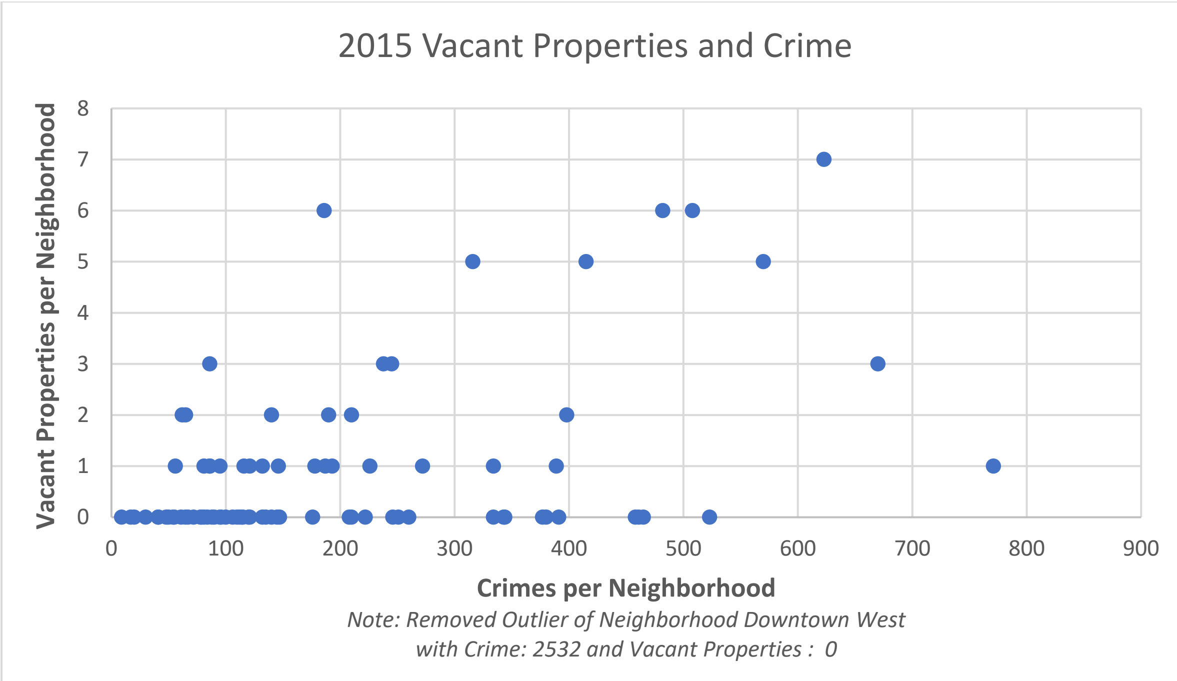
Appendix A. Graphs displaying the relationships between property values, crime, and vacant properties.



Graph representing property values and crime.



Graph representing average property sales and vacant properties.



Graph representing vacant properties and crime.

Appendix B. ACS Attribute Descriptions.

Name	Description
AGE18_39	Population in this range.
AGE40_64	Population in this range.
AGE65UP	Population age 65 +.
AGEUNDER18	Population under 18.
ASSOCIATE	Adult population that completed 2-year degree.
BACHELORS	Adult population that completed bachelor’s degree.
F_15_19	Females in this age range.
F_20_24	Females in this age range.
F_25_29	Females in this age range.
GRADPROF	Adult population that completed post-bac graduate or professional degree.
HIGHSCHOOL	Adult population that completed high school.
LESSHS	Adult population that did not complete high school.
LIVEDALONE	Households with 1 person.
M_15_19	Males in this age range.
M_20_24	Males in this age range.
M_25_29	Males in this age range.
MEDHOMEVAL	Median home value of ownership housing.
NONFAMILY	Other households that are not families and with more than 1 person.
OWNEROCC	Owner households or owner-occupied units.
POP_OVR18	Population age 18 +.
POP_TOTAL	Total population.
POP1_AMIND	Population that identifies as American Indian only and non-Hispanic.
POP1_ASN	Population that identifies as Asian/Asian-American only and non-Hispanic.
POP1_BLK	Population that identifies as black only and non-Hispanic.
POP1_HAWPA	Hawaiian Pacific population.
POP1_OTHR	Population of one race, Some other race alone.
POP1_WHT	Population that identifies as white only and non-Hispanic.
POPOVER25	Adult population (25 and over) used as a denominator in % calculations.
PPH234	Average household size in duplexes and 3 to 4-unit buildings.
PPHMF5	Average household size in larger buildings.
PPHSF	Average household size in single family housing.
RENTEROCC	Renter households or renter-occupied units.
SOMECOLLEG	Adult population that attended some college.
TOT_OCCHU	Housing units occupied.
TOT_VACHU	Total vacant housing units.
UNMARRKIDS	Family households with children and headed by a single person or unmarried.
Val100_124	Homeowners valuing their home in the range of $100,000 to $124,000.