Cook County Property Tax Assessments

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Abstract

This study provides evidence that how property tax assessments are disproportionately higher in South and West Suburbs of Cook County, predominately affecting neighborhoods with majority black and Hispanic residents. Over the last fifty years, Cook County property tax assessments have been a point of contention, as skewed assessments both over and under value properties across the county. In recent years, this study finds, over-assessment has been found to affect properties in South and West villages far more frequently than North and Northwest villages. The same areas that see the highest assessment ratios (assessed value/market value) tend to be the areas with the lowest median income, and are predominately black and Hispanic. This study looks at a combination of variables that should affect the assessment ratio- like age of the property, building square footage, density of foreclosures in surrounding areas, and land square footage- and factors that might indicate residual bias, including demographic and socio-economic data. In doing this, the study suggests why the Cook County assessor may be over assessing South and West suburbs over North and Northwest suburbs, and contributes to a larger effort to mend such inequalities within the county.

Introduction and Motivation

The motivation behind this paper is to draw attention to property tax inequality within Cook County suburbs. Although many homeowners may recognize tri-annual property tax assessment increases for their own properties, few are likely aware of the systemic, regional inequalities associated with increased assessments. In recent years, more attention has been drawn to the lack of uniformity among assessment ratios by the *Chicago Tribune* and *Pro-Publica*. However, even with these exposés, little has been done to fix skewed property tax assessments in Cook County. Though the lack of uniformity is a very relevant issue, another important issue when looking at property tax assessments is the racial composition of areas seeing the highest assessments ratios. Historically, Cook County has been known for redlining, or financially discriminating against particular groups due to race or socio-economic status, particularly in terms of one's ability to purchase property. Though redlining was officially deemed illegal in the mid-1960's through the Fair Housing Act, racial and socio-economic disparities can still be seen on the Southern regions of Cook County through structural issues, like a consistent lack of uniformity within housing assessments.

In showing the deep interconnectedness of race and region within Chicago, a modern iteration of economic and racial segregation, we see that through the overassessment of South and West suburbs comes the overassessment of Cook County's minority populations. The intention of this project is to analyze the intersecting factors associated with high property tax assessments, including factors that *should* affect the assessment value of residential properties, like building square footage, land square footage, age, year of sale, and area, as well as other factors that might impact the assessment ratio, including racial composition, density of distressed sales, and property tax delinquencies in the areas surrounding a property. By incorporating a combination of physical characteristics, market trends, and bias driven factors, the models will test which factors have a greater impact on assessment ratios. The goal of this project is to give insight into the assessment process, providing estimates of the assessment inequalities across Cook County.

We hypothesize that housing in South and West suburbs is disproportionately affected by high assessment ratios. Through several models, we expect to find certain areas of South suburbs to see high assessment ratios relative to the ideal assessment ratio of 1/1, and to see demographic data that suggests the same areas with high assessment ratios have large minority populations within the sample.

Literature Review

Property taxes in Cook County, high assessment ratios in particular, have been a subject of dispute pre-dating the 2008 housing crisis. Within the last ten years, however, Cook County has seen a greater amount of regional inequality in the assessment process. In 2017, a study published by Robert Ross, the Chief Assessment Officer for Cook County - with the assistance of University of Chicago Harris School of Public Policy faculty Christopher Berry *and Chicago Tribune* reporter Jason Grotto- exposed the regressive nature of property taxes in Cook County. His study used information from over 1.5 million residential properties to analyze effective tax rates for properties across Cook County, revealing not only that properties of greater market value had a smaller effective tax rate, but found that even after the appeals process, higher value properties saw greater assessment decreases than properties of lower market value. (Ross, 2017)

The inequity noted in Ross' paper was quickly followed by an expose' written by *Chicago Tribune* reporter Jason Grotto that showed the institutional inequalities taking place within the assessment process. The report was published as multi-part series entitled "The Tax Divide," that reiterated the findings of Robert Ross' study, and more acutely challenged the lack of transparency in the assessment process. The study revealed that the city's poorest neighborhoods, predominately composed of black and Latino residents, were disproportionately experiencing high assessment ratios in comparison to richer, whiter areas in the city. (Grotto, "The Tax Divide", 2017) Jason Grotto's other work through Pro-Publica (in partnership with the Chicago Tribune), "How the Cook County Assessor Failed Tax Payers" released in December of 2017, addressed Cook County Assessor Joe Berrios' failure to re-assess homes every three years as the tri-annual assessment process requires, in addition to other administrative missteps related to the perpetual underassessment of some of Chicago's most valuable commercial properties. The article claims that the systemic underassessment of commercial properties leads to a void in the tax-base that only increases in residential properties could fill. (Grotto, How the Cook County Assessor Failed Taxpayers, 2017) Following these articles, Joe Barrios was not reelected for Cook County assessor in 2017.

Despite the "Tax Divide" causing Cook County tax payers to re-examine the system by which they abide, the series neglected to address where explicit improvements could be made. Time and time again, the Cook County Assessor's Office has made announcements of changes to the assessment process, but stark differences in assessment ratios- and subsequently effective tax rates- persist. The need to re-evaluate the inequities within the Cook County assessment process should compel researchers- and eventually assessors- to look at the entire story behind a property's value, examining all geographic, social, economic, and physical aspects of a property that affect its overall value, including the significant impact surrounding properties have on the value of a parcel.

Although Cook County serves as a prime example of a flawed assessment process, unequal assessments are not unique to this area. Detroit, Michigan stands as another region plagued with significant divergence in assessment ratios between high and low-value properties. Bernadette Autuahene's "Stategraft" published in the *Southern California Law Review* explores inequalities in Detroit's assessment process, and how properties of lower market value are assessed far above market value, breaking a Michigan state constitutional provision deeming that a property tax assessment cannot exceed fifty-percent above the property's true market value.

Autuahene suggests that high assessments have caused property tax foreclosures, economic and social insecurity, and tend to be racially discriminatory. (Autuahene, 2018) Autuahene later did another study with Christopher Berry, that further explored the relationship between property tax foreclosures and high assessment values. Autuahene and Berry found that high assessment values were, as stated above, associated with parcels of a lower market value, but also discovered that 10% of properties that experienced property tax foreclosure were assessed unconstitutionally. (Berry & Atuahene, 2017)

"Neighborhood Foreclosures and Property Tax Burden" by Seth B. Payton published in the *Journal of Urban Affairs* studies the effect of high foreclosure densities on assessment values in Merion County, Indiana. The study finds that a higher concentration of foreclosures affects the real market value of surrounding properties. Peyton suggests that accounting for high concentrations of foreclosures within the assessment process may mitigate the difference between real market value and high total assessment values. (Payton, 2016)

The above studies all make similar claims about the types of inequalities that exist in the property tax assessment process, including the ways in which areas with predominately minority residents and areas of the lowest socio-economic status tend to be taxed disproportionately higher than other residents. Within this data, many of these areas also have higher densities of distressed housing, which if unaccounted for, could cause disproportionately high assessment values according to Seth Payton's study. Though recent exposés have sought to draw attention to property tax inequalities in Cook County, this study intends to identify the key factors that drive assessment ratios upward.

Empirical Model

Each of these models uses a sample of sales within Cook County suburbs over the course of ten quarters, ranging in date from January of 2015 to October of 2018. Since the hypothesis aims to shed light on regional assessment inequalities across Cook County, the primary dependent variable within our regression, or the "Y" is the assessment ratio, or the assessed value over the most recent sales price. The primary independent variable is the village fixed effect, which shows how particular areas in the city see higher or lower assessment ratios relative to the reference village "0", or Des Plaines, IL, which has an average assessment ratio closest to 1/1. Other predicting factors within our regression, include the sales price, date of sale, whether the property was “distressed” or a foreclosure or short sale, age of the property, land square footage, building square footage, and delinquency for the first regression. This regression includes only physical characteristics and sales characteristics, showing the factors the assessor should theoretically take into consideration when valuing a property. The equation for the first model goes as follows:

$$\text{Assessment Ratio} = \beta_o + \beta_1 \cdot \text{i.village} + \beta_2 \cdot \log(\text{salesprice}) + \beta_3 \cdot \text{i.date} + \beta_4 \cdot \text{i.sfs}$$
$$+ \beta_5 \cdot \text{age} + \beta_6 \cdot \text{build} + \beta_7 \cdot \text{land} + \beta_8 \cdot \text{deli} + \mu$$

Since the first model only isolates variables that should be included in the assessment, the second model seeks to include variables that would be driven in part by assessor bias. This regression makes percent white the primary independent variable while keeping the assessment ratio as the dependent variable. Since race and income bracket are paired with particular villages, to remove collinearity within the dataset, regional and local data was omitted from the regression. Although this does widen the scope, this provides a way to better identify how a high percent white affects assessment. The equation for the second model goes as follows:

$$\text{Assessment Ratio} = \beta_o + \beta_1 \cdot \text{demo} + \beta_2 \cdot \log(\text{salesprice}) + \beta_3 \cdot \text{i.date} + \beta_4 \cdot \text{i.sfs}$$
$$+ \beta_5 \cdot \text{age} + \beta_6 \cdot \text{build} + \beta_7 \cdot \text{land} + \beta_8 \cdot \text{deli} + \beta_9 \cdot \text{i.cash} + \mu$$

The third and final model focuses on the effect of sales price on the assessment ratio by making the log of sales price the primary independent variable. In doing this, the effects of sales price on assessment ratios can be isolated from village fixed effects, distinguishing if lower housing prices are the primary driver of high assessment values- which could be due to more drastic shifts in the assessment ratio from a smaller denominator, or bias on the part of the assessor. The equation for this final regression goes as follow:

$$\text{Assessment Ratio} = \beta_o + \beta_1 \cdot \log(\text{salesprice}) + \beta_2 \cdot \text{i.date} + \beta_3 \cdot \text{i.sfs} + \beta_4 \cdot \text{age} + \beta_5 \cdot \text{build}$$
$$+ \beta_6 \cdot \text{land} + \beta_7 \cdot \text{deli} + \beta_8 \cdot \text{i.cash} + \mu$$

The combination of these three regression will give some insight into which variables were most indicative of assessed value for the observations within our sample, and will hopefully point out the ways in which improvements can be made in the future to mitigate biases that drive the assessed value of a property up or down.[1]

Acquiring and Cleaning the Data

The data for this project was acquired through many sources in an effort to find all the necessary variables to compose our regression. To begin, housing sale data was acquired for the years 2015 through 2018 for all Cook County suburbs through the MLS Property Data Portal. This data was downloaded by village, and provided the PIN, or property index number, sales price, date of sale, and whether the property was a standard, foreclosure, or short sale. This data was re-formatted from a PDF to an Excel spreadsheet. After this, township level data was downloaded from the Cook County Assessor's web page to find building square footage, land square footage, the age of the property, and the last assessment value given to the property (which included any adjustments from the appeals process). After this data was accumulated, the PIN numbers were matched with delinquency data from the Cook County Treasurer's office. Finally, demographic data, like race, was acquired by US Census data on a village level. Post cleaning (process discussed below), observations with extremely low values were searched on the Cook County Recorder of Deeds website to insure all sales were arm's length transactions, or a transaction where the buyer and seller have no relationship and are acting in their own self-interest. Finally, the assessment ratio variable was developed by dividing the assessed value by the sales price.

Since Cook County assessment ratios vary so drastically from village to village, removing outliers from the full dataset would have likely removed valuable observations from each particular township. To prevent unnecessarily removing data from the dataset, the data was cleaned on a village level, and all assessment ratios and sales prices were divided into standard sales, short sales, and foreclosures. The mean and standard error were calculated for all standard sales within a particular township, and all outliers outside three standard errors were removed. The same process was performed for all short sales and foreclosures within that particular township. The process was divided into these three categories to account for differences in housing prices- and subsequently- assessment ratios, between distressed and non-distressed sales.

[1] Appendix 1: Data Summary

Since foreclosures and short sales tend to have housing prices lower than typical market value, and high assessment ratios relative to that township, it is important to look at distressed sales separately in an effort to preserve observations that would ordinarily be deemed outliers. The process was repeated for every village within the dataset.

The ages of homes, the square footage of the building, and the square footage of the land were cleaned by calculating the mean and standard error of each category within the full dataset, and then removing all outliers that fell outside three standard errors of the mean. Since these variables appeared to be observationally consistent throughout most of the data, regardless of village, the data was cleaned according to these observed patterns (or lack thereof). The cleaning process resulted in the loss of around 1,000 observations, leaving us with approximately 55,000 observations for each model.

Assessment and Region

The "region" predictor divides our data into two key test categories, North and Northwest and South and West. The division of these two categories is broken down into two other subcategories, Township and Village, both formal municipal boundaries determined by the Illinois State Government. Although the primary independent variable within the regression is region, sub-categories are used to better identify the areas in each region that are seeing the highest and lowest assessment ratios.

Although the regression could have placed the spotlight on a number of factors, including racial composition, median income, or distressed housing predictors, region was chosen because it serves as a structural way of looking at how properties in a particular area are assessed relative to other areas. In looking at raw assessment data, it is clear that regional differences in assessment exist in Cook County; the question then becomes, *but why?* Region was chosen as the primary independent variable because it captures the *but why*'s within our regression by allowing certain characteristics like average housing size, racial demographics, and median income to be associated with a particular location. Thus, region allows village and township level effects to be estimated and compared to better identify why lack of uniformity may exist across Cook County property tax assessments.[2]

[2] Appendix 2: Assessment Ratio by Village

Sales Price

The sales price variable was included to see if lower value homes have higher assessment ratios. Since the assessment ratio is composed of the assessed value over the sales price, it would be reasonable to assume there is a greater amount of volatility in the assessment ratio for lower value housing since the denominator is smaller. Thus, it is very likely that lower value houses see higher assessment ratios.[3] Each village varies significantly in terms of sales prices, which is due to a number of factors including the percentage of distressed sales, the environmental/ locational features that may add or subtract from the property's value, or the physical characteristics of a property that are often common within a particular area of the city. These factors, as well as the method by which the data was cleaned on a village level, have caused the range in sales price within a particular village to be fairly narrow, but the variation within the full dataset to remain quite large.

Age and Property Square Footage

Age and property square footage both describe physical aspects of a home outside of region. Although there are a number of factors, both observed and unobserved, age, building, and land square footage are said to largely contribute to a property's assessed value.

In the preliminary stages of the project, it became clear that many observed predictors did not behave as expected, adding a new dimension to the project. Both age and land square footage showed very little observed relationship the assessment ratio, but were included due to their supposed connection with both sales price and assessment value. However, building square footage showed a strong positive connection with the assessment ratio. Knowing that building square footage may make up a greater portion of the assessment value, relative to other physical characteristics, is important in evaluating how assessments are determined by the assessor.

Quarter and Year

The quarter and year predictor was included to account for the time variable within the dataset. Since the data follows housing sales from January of 2015 until July of 2018, is

[3] Appendix 3: Average Sales price by village

important to account for the ways the date of sale may impact the market value of the property, and subsequently, the assessment ratio.

An important factor to consider when analyzing the “date” predictor, is the seasonal cyclicality of the housing market. Houses tend to sell most commonly in spring and summer versus fall and winter, which perhaps could change certain aspects of the data, like sales price. The other factor that should be considered when analyzing the ways in which date interacts with other predictors in the regression, is considering the decline in foreclosures over time. As time has moved away from the Great Recession, foreclosures have declined in Cook County. Since foreclosures tend to have higher assessment ratios, the changes in the coefficients of the varying dates would be less significant with the addition of the foreclosure predictor.

Distressed Sales

The predictor “sfs” or standard, foreclosures, and short sales was included in the regression to account for the differences in assessment ratio between distressed and non-distressed sales. Since foreclosures and short sales tend to sell for lower than typical market value, the assessment ratios tend to be skewed upward as a result. If areas have a particularly high number of distressed sales, it may appear that assessment ratios are bias upward. By including the “sfs” predictor, the inflation in the assessment ratio caused by distressed sales can be accounted for within the regression.

The other reason why the “sfs” variable was added, was to observe whether or not standard sales in areas with high densities of distressed sales continued to have high assessment values even after adjusting for this factor. To give an example, a homeowner was looking to purchase a home, and was choosing between two neighborhoods, one with a high number of foreclosures and another with little to no foreclosures. Since areas of economic growth tend to have fewer foreclosures, the buyer would be more likely to choose the house of the same price in the area with a lower density of foreclosures. Thus, the market value is more likely to go down with a higher density of foreclosures in the surrounding area, thereby it would be reasonable to suspect the assessor accounts for such factors. To better understand if the assessor takes such factors into account, the “sfs” factor was included to observe changes in coefficients with the addition of the distressed predictor, and to monitor if areas who saw significant changes with the addition of this variable still experienced high assessment ratios relative to other areas. [4]

Property Tax Delinquency

The "deli," or property tax delinquency predictor, was included to test if areas where residents experienced high assessment ratios are the same areas that see a high number of property tax delinquencies. Though it impossible to deem whether one has caused the other through this regression, it is important to note the ways in which property tax delinquency interacts with the assessment ratio. One scenario could be that because delinquency indicates a subtraction from the tax base, the government might attempt to make up for this gap by over-assessment. Another scenario could be that as assessment values increase, it becomes more difficult for property owners to pay their taxes. For these reasons, it is important to observe the role of delinquency within areas of high assessment ratios.

Race and Assessment Ratios

In December of 2017, Brighton Park Neighborhood Council (BPNC) and Logan Square Neighborhood Association (LSNA) filed a law suit against Cook County Assessor Joseph Berrios, claiming Berrios systematically over-assessed property owners in majority Hispanic and African American neighborhoods within Cook County. The case claimed Berrios to be in violation of the Illinois Civil Rights Act, the Equal Protection Clauses of the Illinois and United States Constitutions, the Uniformity Clause of the Illinois Constitution, and the federal Fair Housing Act through property tax schemes that are neither accurate nor uniform. The lawsuit claims majority Black and Hispanic neighborhoods are two times more likely to be over-assessed by twenty percent or more than minority white neighborhoods.

Although the issue of race may seem one step removed from the regional differences in assessment values in North and Northwest suburbs versus South and West Suburbs, the demographic data within this sample suggests that a village located in a South suburb is on average composed of 67.5% minority residents versus only 47.2% minority residents on average in a village located in the North and Northwest suburbs.[5] Since the demographic data used within this dataset is determined on a village-level, it is important to note that not all predominately

[4] Appendix 4: Percent Foreclosure of All Total Sales By Village
[5] Appendix 6: Percent White by Village

minority villages are located in South and West suburbs in the same way that not all predominately white villages are located in North and Northwest suburbs. This is to say that "percent white" and "region" are not collinear. If the claim presented in the BPNC/LSNA vs. Berrios lawsuit, that the Cook County Assessor's Office under Joseph Berrios is racially biased is correct, this would suggest that South and West Cook County suburbs would see disproportionately high assessments due in part to a greater population of non-white residents. Although it is difficult to say whether such biases are implicit or explicit, regardless, including potential racial biases may contribute to a better understanding of the regional differences seen in suburban assessment ratios across the county.

The graphs published in the BPNC/LSNA vs. Berrios lawsuit have been included to further iterate why the race predictor was included in the regression.[6] The graphics from both this study and the lawsuit have been placed next to one another to analyze similarities and differences. The graph used by the BPNC/LSNA vs. Berrios case shows high assessment ratios for areas with a low percentage of white residents, and a gradual decline as percent white increases, displaying underassessment for areas with predominately white residents. Unlike the graph utilized by the BPNC/LSNA vs. Berrios case, the graph created with the dataset used in this study shows even higher assessment ratios for majority non-white areas, peaking at 11.6% over market value for areas within a 0-10% white population. Then, the graph drops significantly for majority-white areas with populations over 50% white, showing assessments at least 4.5% under market value. The other graphic included shows the percentage of white, Hispanic, and black areas that have been over-assessed by 20%. Although the data used in this study sorts only by minority and non-minority percentages, the two bar graphs show a common theme of over assessment in areas where minority populations outnumber the white population.

Un-Observed Factors

Although the predictors included in the regression certainly contribute to a better understanding of assessment inequalities across the county, it is important to consider the number of unobserved variables that could contribute to changes in assessment.

[6] Appendix 5: BPNC/LSNA vs. Berrios graphs & Graphs Comparable

The first- and perhaps most important- unobserved variable would be assessor bias. Since all housing assessments should be determined by an assessor, one could suppose each assessor has biases that steer the assessed value of the home in one direction or another. Such factors could be physical characteristics, like preferring houses with tile floors and electric stoves over hardwood floors and gas stoves. Other biases might be less physical, including how the assessor views the demographics of the surrounding neighborhood, including race and socio-economic make-up. Even if data supports that the assessor might prefer white neighborhoods over black, or electric stoves over gas, it is impossible to avoid imposing these biases onto our regression, since it is impossible to enter the brain of the assessor. For this reason, assessors' perspectives should be considered an omitted variable.

Physical characteristics of a house are another key variable that go unaccounted for within these regressions. Although the data does include building square footage, land square footage, and age, other factors like the number of rooms and bathrooms, recent updates, luxury features like fireplaces and lighting fixtures, etc. are not quantified. These factors can easily build upon each other, making houses that look identical from the outside worth far more because of the internal features. Thus, physical characteristics that go unaccounted for should be acknowledged, as they may starkly change a property's assessed value.

Neighborhood level characteristics are yet another factor that impact assessment, but there is no real way of quantifying neighborhood factors into the assessment ratio. Factors that might make up a neighborhood's characteristics are ethnic and racial makeup, crime rates, nearby parks, proximate public transportation, cleanliness, government provided services, friendliness of neighbors, etc. When thinking about the number of factors that make one neighborhood more palatable over another, it may be difficult to quantify these factors to make up an assessed value. Thus, it is nearly impossible to reflect the desirability of a neighborhood within these regressions. Subsequently, unexplained differences in assessment could certainly be attributed in part to these neighborhood-level characteristics. Thus, it is important to consider how this omitted variable effects the results.

Single Predictor Regression Analysis

Assessment Ratio and Villages

During the initial regression the independent variable, “i.village,” and the dependent variable, assessment ratio, were included to see the isolated effects of village on assessment ratio. The “village” variable was broken into village fixed effects in an effort to see the relationship between assessment and location on a smaller scale. Since Des Plaines’ mean assessment ratio is 99.88%, the closest assessment ratio to 100%, it was chosen to be the “0” village, or dropped village, within the dataset. This further means that values listed within the regression are relative to Des Plaines.

Upon running our regression, Blue Island (.46), Burnham (.58), Calumet City (.71), Calumet Park (.91), Chicago Heights (.85) Country Club Hills (.31), Dixmoor (.87), Dolton (.92), Glenwood (.43), Harvey (2.24), Hazel Crest (.48), Markham (.83), McCook (.63), Park Forest (1.02), Phoenix (1.08), Posen (.34), Richton Park (.4385), Riverdale (1.45), Robbins (.71), Sauk Village (1.47), and South Chicago Heights (.68) were all found to have coefficients positively correlated with assessment value. Each of the listed villages are located in the South and West suburbs of Cook County, indicating that within the sample, South and West Villages are seeing higher assessment ratios than northern villages, sometimes by over 100%. Of the above villages, Riverdale, Sauk Village, Park Forest, Hazel Crest and Harvey all have coefficients higher than 1. The standard error of Riverdale (.0348), Sauk Village (.0313), Park Forest (.0243), Hazel Crest (.0276), and Harvey (.0310)- the villages with the highest coefficients- are relatively close to zero, indicating that the samples sizes for these particular villages are fairly large, and the majority of properties within these villages had coefficients close to the village mean. The relatively low confidence intervals within this regression indicate a small spread in observations, likely due to the village-level cleaning process.

The four most negative coefficients within this regression were Rosemont, (-.26), Park Ridge, (-.14), Norwood (-.1915), and Norridge (-.1197), all of which are North or Northwest villages. Although none of these can be viewed as large changes in assessment, the location should be noted. However, of these four townships, Rosemont (.2597) and Norwood (.0976) have high standard errors, displaying the small number of observations from these two villages and indicating a wide variance among these observations. Thus, Rosemont and Norwood may not be the best examples of low assessments. However, both Park Ridge (.0227) and Norridge (.0275) have small standard errors, showing a larger sample size and many observations within

.02 to .03 percentage points from the mean of each of the villages. The confidence intervals for Park Ridge (-.183, -.0939) and Norridge (-.174, -.066) indicating that 95% of observations lie within a small range, showing a conglomeration of coefficients surrounding the village mean.

The r-squared for this initial regression was .3009, showing a relatively strong relationship between assessment ratio and village, particularly since all other predictors have been excluded from this regression.

+ Sale Price Predictor

The second regression performed included both village and assessment ratio, as well as the sales price predictor. The “salesprice” beta was transformed to better fit a non-linear relationship between assessment ratio and sales price. Since houses of smaller sales prices had many of the highest observed assessment ratios, a new variable was generated, “salesprice1”, that corrected for the skewedness of the data by finding log of the sales price. Log was chosen, as it fits a nonlinear least squares line to the relationship between “ar” and “salesprice”, and compensates for the trend in the relationship between “ar” decreasing at a decreasing rate as sales price increases. In full, this transformation, through the generation of “salesprice1”, allowed sales price to take on a more linear quality and to more accurately represent the sample. It should be noted that since the assessment ratio is created by placing the assessment value over the sales price, the houses with the smallest sales prices see the biggest changes in assessment ratio when assessment values increase or decrease. As a result of this, the variance in assessment ratio for properties with lower sales price may be greater due to how changes in assessment value may drastically impact the assessment ratio. Thus, the new value “salesprice1” should correct for some of this variation in lower-value homes. The adjusted change in the r-squared from running the regression with the variable “salesprice” and running the regression with the adjusted beta “salesprice1” is the difference in r-squared from the untransformed sales price (.34) to the transformed sales price (.63).

The coefficient for sales price is -.8608, meaning the relationship between sales price and assessment ratio is quite strong, representing a negative correlation between sales price and assessment ratio. In short, lower value houses see higher assessment ratios within this sample. The standard error of “salesprice1” in this regression is close to zero (.004), indicating a large sample size. The 95% confidence interval (-.8684, -.8531) is very narrow, indicating that the majority of observations within the sample have similar coefficients to the mean.

Looking at the effects of “salesprice1” on individual villages, it is important to keep in mind that because “salesprice1” has a negative coefficient, houses selling for less than Des Plaines average sales price of $158,000 will see a decrease in coefficient. All of the South and West villages who had strongly positive coefficients in the first regression saw decreases in coefficients across the board. The villages with the highest coefficients in the initial regression, including Riverdale (1.44 decrease), Sauk Village (1.63 decrease), Park Forest (1.02 decrease), Hazel Crest (2.104 decrease), and Harvey (1.05 decrease), saw a decrease of one point or more in their coefficient. This, alone, indicates that these five villages have relatively low value homes relative to Des Plaines within our sample, and subsequently, see higher assessment ratios as a result.

+ Date Predictor

The third regression performed included assessment ratio, village, and sales price data with the addition of data regarding the date of sale. The “date” beta is sorted by quarter, where the “0” is the first quarter of 2015. Since all data is relative to the first quarter of 2015, the coefficients display a downward sloping trend in assessment ratio as time goes on. Assessment ratios in the third quarter of 2018 appear to be much closer to the assessment value; this could be for a number of reasons. This could simply mean that assessments in Cook County have generally become more accurate over time, which would show signs of promise for the future. However, this is more likely to be attributed to a decrease in foreclosures over the course of the fourteen quarters included in our data sample. Since foreclosures have considerably higher assessment ratios within the dataset, a decreasing trend in the number of foreclosures relative to the number of standard sales could show a decreased assessment ratio over time.

Village coefficients generally decreased with the addition of the date beta. This perhaps indicates that villages with the majority of housing sales occurring recently have more negative coefficients, or lower assessment ratios. Villages that had older sales were likely less negatively impacted, or positively impacted, by the addition of the date predictor.

The overall impact of the date predictor on the r-squared was small, increasing the r-squared from .629 to .633. This small increase revealed that the addition of the date beta didn't allow the regression to better represent the sample population.

+ Distressed Sales Predictor

The next regression included the predictor "sfs" or standard, foreclosure, and short sale. All "sfs" values were relative to the standard sale coefficient, or "0", within this group. From observation, it is clear that within the sample, foreclosures have significantly higher assessment ratios due to a small sales prices relative assessment value, due to the nature of foreclosure sales. Such is why the foreclosure coefficient has a positive- and somewhat strong- relationship with assessment value within this regression. The short sale coefficient, although still positive, showed a relatively insignificant relationship with assessment value. The standard error of both values is relatively small, indicating the coefficient is fairly accurate for each of the betas within our sample. The addition of the "sfs" predictor also allowed for a .03 increase in r-squared. Although seemingly small, "sfs" increased the r-squared far more than the "date" predictor increased the r-squared.

After performing this regression, the impact of "sfs" on the South and West villages who initially had the highest positive coefficient was surprisingly small, particularly since these areas have the highest percentages of foreclosures within our sample. However, Des Plaines has a relatively high percentage of foreclosures relative to standard and short sales, with foreclosures accounting for 21% of Des Plaines' housing market within our sample. This simply means that because all village coefficients are relative to Des Plaines, the coefficients are less likely to see significant changes since Des Plaines was likely impacted significantly. However, of the twenty-one South and West villages who saw a positive correlation with assessment in the initial regression, all twenty-one saw an increase in coefficient with the addition of the "sfs" beta. Of these villages, Harvey, Sauk Village, Riverdale, Park Forest and Hazel Crest- the villages who had the strongest coefficients in the initial regression- all saw an increase of at least .10 in their coefficients, indicating that foreclosures and high assessment ratios are particularly common in these areas. Of the North and West villages, few saw significant changes with the addition of the "sfs" predictor. Some villages within this region increased and others decreased, but none changed substantially in either direction, perhaps indicating that within the sample North and West townships are not as impacted by foreclosures.

The sales price coefficient became less significant with the addition of the “sfs” variable, likely due to the decrease in variation accounted for by foreclosures and short sales. As previously mentioned, since the houses within our sample with the lowest sales prices and highest assessment values are likely foreclosures, adding the “sfs” beta diminished the effect of sales price on the assessment ratio.

+ Age Predictor

In adding the “age” predictor in the next regression, little to no change occurred within the data. The coefficient for age states the relationship between age and assessment ratio for each additional unit increase to be negative, showing that the assessment ratio becomes increasingly negative as the size of the house increases. Despite this, no matter how old the house, age, it appears, will never have a significant impact on assessment ratio since the age range in our sample is relatively limited. However, all of the South villages who began with a significantly positive relationship with assessment ratio, including Blue Island, Burnham, Calumet City, Calumet Park, Chicago Heights, Country Club Hills, Dixmoor, Dolton, Glenwood, Harvey, Hazel Crest, Markham, McCook, Park Forest, Phoenix, Posen, Richton Park, Riverdale, Robbins, Sauk Village, and South Chicago Heights all saw minute decreases in coefficients with the addition of the age variable, and the two Northern villages, Park Ridge and Norridge, with the two most negative correlations in the beginning saw increases. This indicates that the South and West villages being observed are likely older, and seeing smaller assessments as a result, and those in the North and North West regions are newer, and seeing larger assessments as a result.

Upon running this regression, the r-squared increased by approximately .01, but such change can be seen with the addition of any variable, thus, the change is almost negligible. The small standard error and tight range of the 95% confidence interval show that the relationship between age and assessment ratio have been accurately depicted through the coefficient.

+ Build Predictor

The addition of the “build” predictor or building square footage brought the r-squared from .673 in the previous regression to .752, showing that by adding building square footage, the regression more accurately represents the population. Though the coefficient of building square footage appears small, it is by unit variable, meaning that for each additional square foot, the coefficient increases by .0003. The smallest homes in the sample are 400 square feet, meaning the smallest coefficient for a single building could potentially be .12 and the largest could be 1.27. Thus, the relationship between building square footage and assessment ratio is by no means small. The standard error associated with build is also quite small, indicating that the mean correlation listed would be similar to the coefficients of the majority of individual observations; this is further iterated by the small standard error.

A factor to consider when looking at the impact of the "build" predictor on village coefficients, is that all coefficients are relative to Des Plaines, who has a relatively small building square footage of 1247 square feet on average. Of the South and West villages being followed throughout the regressions, all decreased between the ranges of .03 and .60 with the addition of the "build" variable. This indicates that houses within these villages are smaller, and thus see lower assessment ratios relative to buildings with a higher square footage within the assessment. Of the two North and West Townships, Norridge saw a very slight positive increase in coefficient, and Park Ridge saw an even smaller decrease in coefficient. Standard errors decreased for villages quite a lot in some cases, showing that adding the "build" predictor into the regression brought the coefficient even closer to the sample average.

The reason the addition of the "build" beta significantly affected almost every predictor within the regression, is because every observation within the regression is impacted by building square footage to some extent; most every parcel has a slightly smaller or larger building square footage and certain areas tend to have houses of similar sizes, providing a lot of variance when comparing one village to another, and subsequently showed significant increases or decreases in the coefficient of many villages. With the same idea in mind, other predictors like sale price, date, "sfs", and age were all impacted by the addition of build. The coefficient of age became closer to zero, as well, indicating that age was bias downward before building square footage was added. This suggests that the "build" variable captures some of the negative age effects, showing that older houses are likely smaller houses, and this combination sees low assessment ratios. The relationship that is perhaps most important in this regression, however, is that between "salesprice1" and "build." With the addition of the "build" variable to the regression, "salesprice1" sees an even greater negative correlation, shifting from -.766 to -1.085. This shows that perhaps "salesprice1" was bias upward with the omission of building square footage. This is important, as it shows that unlike the relationship between "age" and "build", building square footage does not capture any of the effects of sales price, and in fact, further indicates that lower value houses (regardless of building square footage) are seeing higher assessment ratios.

+ Land Predictor

The addition of the "land" beta, or land square footage, showed little to no relationship with assessment ratio. The coefficient for the land variable is incredibly close to zero, with a relatively low standard error. This, along with the negligible difference in r-squared and the little impact "land" had on other predictors shows that land square footage –within this regression – does little to predict assessment ratios.

+ Delinquency Predictor

The next regression included the "deli" or delinquency variable, showed very little increase in r-squared, but suggests some relationship between delinquency and assessment. As hypothesized, the addition of the delinquency beta brought the foreclosure dummy closer to zero, showing that within the sample, delinquency captures some of the effect of foreclosure. However, delinquency seemed to have little to no impact on the short sale dummy within the regression, counter to the initial hypotheses.

Results

Model #1[7]

After analyzing this regression variable by variable, it became clear that sales price had the largest effect (aside from village fixed effects) on the assessment ratio. However, because "salesprice1" shows an inverse effect on coefficients due to its negative relationship with the assessment ratio, in an effort to better analyze the final outcome of our data, the change in

[7] Appendix 7: Regression Model One

coefficient for “salesprice1” was inverted to show how sales price affects assessment ratios for each village.

To do this, a regression was performed omitting the “salesprice1” variable, including all other predictors, and another regression was performed including the “salesprice1” variable. The change in coefficient with the inclusion of the sales price was calculated for each village. To remove the effect of sales price from the full regression, the changes in coefficient were subtracted from the full regression. In place of that effect, the inverse change of the coefficient was added to the regression.[8] In doing this, coefficients for village-level data now represent how villages with lower-value houses experience higher assessment ratios, rather than the other way around.

The regression revealed an r-squared of .756, suggesting the sample used within the regression is fairly representative of the population. The f-stat is 308, showing the data fits a linear model.

After reversing the effects of sales price on our assessment ratio, only ten of the 36 South and West villages were not negative, and of the ten that were not negative, most were on the far West side of the city, on the border between Northwest and West. Winnetka (-.979), Wilmette (-.805), River Forest (-.764) and Evanston (-.722) saw the lowest coefficients with this change. Although these coefficients look extremely low, before the adjustment, coefficients were equally as low, suggesting this is perhaps not an effect of the adjustment but just a culmination of variables. These extremely low coefficients simply mean that in spite of accounting for distressed housing, age, building and land square footage, these areas still saw far lower assessment ratios than Des Plaines.

The adjustment also suggested that only thirteen of seventy-four Southern villages saw negative coefficients, suggesting that 82% of South and West villages experienced overassessment relative to Des Plaines. Accounting for distressed sales, sales price, building square footage, land square footage, and the age of the home, Harvey (3.87), Sauk Village (3.13)

[8] Appendix 8: Adjusted Village Coefficients Model 1

Riverdale (3.00), Phoenix (2.711), and Park Forest (2.44) all show the highest coefficients within the regression, suggesting the highest assessment ratios within the sample.[9]

This model suggests that areas within South and West villages within our sample clearly see significantly higher assessment ratios than villages in North and Northwest regions. Harvey, Riverdale, Sauk Village, Phoenix, and Dixmoor saw the largest assessments within Cook County, even after accounting for distressed housing and the negative relationships between building square footage and assessment. North and Northwest villages like Winnetka, South Barrington, Glencoe, and Inverness all saw the lowest coefficients, indicating their assessment ratios fell far below that of Des Plains. This is further iterated in the general pattern in the data that expressed North and Northwest villages saw much lower assessment ratios than South and West villages within our sample.

Model #2[10]

Model two uses percent white as the primary independent variable, and assessment ratio as the primary dependent variable to analyze the effect of a one percent increase of percent white on the assessment. The correlation between "ar" and "demo" or assessment ratio and percent white within our dataset, shows a -.354 correlation coefficient, showing a statistically significant negative relationship between the two variables.[11]

When performing the full regression, including assessment ratio, percent white, distressed housing, age, building square footage, land square footage, delinquency and income bracket, the coefficient for the "demo" predictor (.005) appears to have a positive relationship with assessment ratio and a very low t-stat. This is contradictory to the correlation coefficient between assessment ratio and percent white shown above.

To better analyze why the "demo" coefficient appears to have a negative relationship with assessment ratio, each predictor was added one at a time to better decipher the effects on the regression. In doing this, it was discovered that the "salesprice1" beta shifted the coefficient of percent white from negative to positive. Before the "salesprice1" predictor was included in the regression, the t-stat associated with percent white was -46.80, with a coefficient of .004,

[9] Appendix 9: Map of Regression Results
[10] Appendix 10: Model 2 Regression
[11] Appendix 11: Percent White to Assessment Ratio

expressing a .004 percent decrease in assessment with each additional increase in percent white. The f-stat for this regression was 501.95, suggesting a linear model is more compatible with the data. However, after adding the “salesprice1” predictor, the t-stat for percent white shifted to 55.05, with a coefficient of .005, where the sales price predictor had a t-stat of -87.44 and a coefficient of -.744. The f-stat became 885.9, further supporting a linear regression. This shift is due to the very strong correlation between “salesprice1” and “demo", with a correlation coefficient of .68. Due to the overlapping effects of sales price and racial demographics, showing that areas with large minority populations have lower sales prices, the addition of “salesprice1” to the regression compensated for downward bias in the “demo” predictor.

Although this model did not explicitly explain the relationship between demographic data and assessment ratios, the model did reveal the tight knit relationship between sales prices and demographic data, which could perhaps show why areas with high percentages of minority residents see some of the highest assessment ratios in the county.

Model 3[12]

Since the sales price predictor was shown to have a strong effect on both assessment ratio and demographic data, the final model looks at the “salesprice1” predictor as the primary independent variable and “ar” as the dependent variable. This regression excludes both regional variables and percent white to exclude regional and demographic fixed effects.

The first regression performed only included the assessed value and “salesprice1”, displaying an adjusted r-squared of .46, indicating that sales price alone is a fairly solid predictor of the assessment ratio within our sample. The t-stat for “salesprice1” in this initial regression was -220.49, with a coefficient of -.510, showing a very strong negative relationship between assessed value and sales price. The f-stat for this regression was 8,904, supporting a linear relationship between the adjusted sales price and assessment. This negative relationship explains that as the sales price of a home increases, the assessment ratio decreases.

With the addition of the other predictors, including date, distressed housing, age, building square footage, land square footage, delinquency, and income bracket, the r-squared increased to .65, showing the regression is a fairly good estimate of the population. The t-stat for sales price

[12] Appendix 12: Model 3 Regression

became less negative at -84.83, but the coefficient for sales price became increasingly negative (-.66). The f-stat decreased with the addition of other predictors to 870, still corresponding to a linear model. This shows that other variables did absorbs some of the effects of sales price as they were added to the regression, however, the omission of these variables caused sales price to be bias upward.

This model show how significant of an impact sales price plays on assessment ratio within our sample, showing that perhaps sales price is the biggest determinate of a skewed assessment in either direction.

Conclusion and Recommendations for Further Studies

After testing all three models, certain relationships emerged that showed why certain areas may be seeing the highest assessment ratios. The first model displayed the relationship between assessment ratios and localities in an effort to identify where the highest assessment ratios were occurring in Cook County. The model showed particular areas in South and West Cook County, like Harvey, Sauk Village, Riverdale, Phoenix, Park Forest, and Dixmoor, saw extraordinarily high assessment ratios relative to Des Plaines, even after accounting for sales price, age of property, date of sale, building square footage, land square footage, distressed housing, and delinquency, affirming the hypothesis that certain areas in Cook County see disproportionately higher assessment ratios.

Model two served to determine a clear relationship between percent white and the assessment ratio. However, what was found was a strongly correlated relationship between sales price and percent white, suggesting that the lowest value housing is in areas with the smallest percent white. This relationship blurs the line between clear bias against areas with predominately black and Hispanic residents and the volatility in assessment ratio for low value housing due to a small denominator (since the assessment ratio is made up of the assessed value over the market value). Thus, it is difficult to determine if any sort of intentionality is occurring in the over-assessment of predominately black and Hispanic areas, however, this model did affirm that non-white areas experience the highest assessment ratios.

The final model focused entirely on the relationship between sales price and assessment ratio by removing regional and village level fixed effects and demographic data. In doing this, the regression showed a very strong negative correlation between sales price and assessment ratio, suggesting the lower the value of a house, the higher the assessment ratio. In large, this model serves to show a regressive tax, where the highest value homes receive the largest tax breaks, even after accounting for distressed sales. This is perhaps the biggest finding within our results, as it shows without question, how within our sample that those experiencing the highest taxes are those who likely have the lowest incomes.

Although this data only represents the sample, it showed strong differences in assessment ratios across the city. The internal validity of this study is believed to be quite strong. Having a large sample of properties and assessments from across the city, no missing variables, and strong evidence from other studies showing similar findings, the internal validity of these models should be fairly representative of the sample.

The external validity of the sample is strong within the context of Cook County. The large sample size and evidence from other studies also suggest that our models are consistent with other information about Cook County property tax assessments. This goes without saying, there exist many unobserved variables that effect this regression, however, these same unobserved variables exist outside of this regression in unexplained differences between housing assessments and the market value of a home. Thus, the regression is equally as representative of the lack of information that exists within the current Cook County assessment process. Although this study may fairly well represent Cook County, it would be difficult to argue external validity beyond Cook County. Since high assessment ratios seem to be unique to certain regions in the United States, it may be difficult to argue that assessment inequalities would exist in any area in the US or internationally, particular since many rules and regulations change on a regional level. Thus, the external validity for these models is weak outside of Cook County.

In the future, it would be interesting to further untie the relationship between sales price and demographic data. Since there is a clear amount of overlap between these two variables, looking at the demographic data on a household level may allow more variation in sales price and assessment. Some of this strong correlation could very well be due to the data cleaning process on a village level within our dataset. Perhaps another factor that could be helpful in future studies would be to account for the work of each individual assessor. Since properties across Cook County are assessed by different individuals, isolating these assessors may provide insights into each of their biases.

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Appendix 1

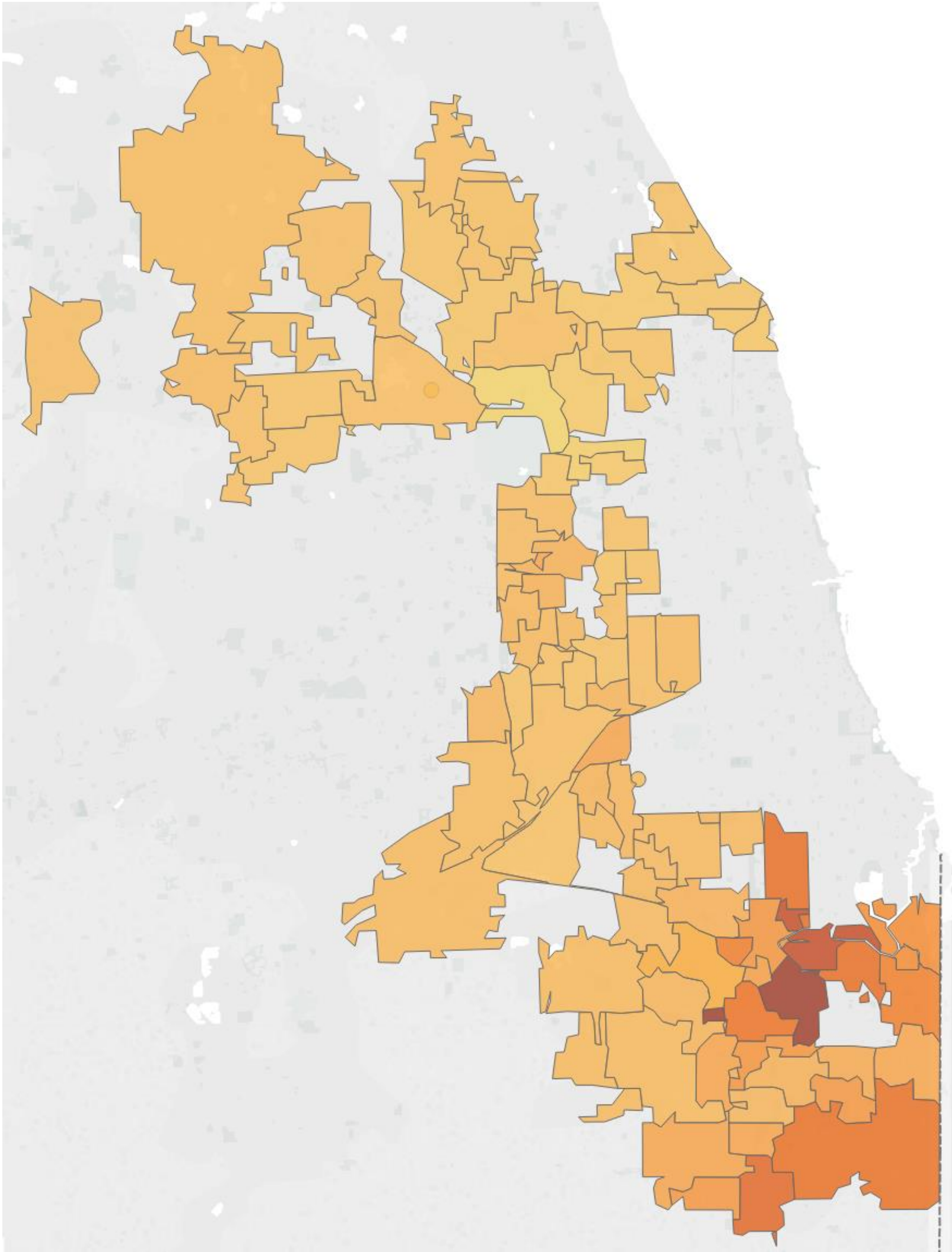
```
. sum i.village salesprice1 i.date i.sfs ar age build land deli demo i.cash
```

Variable	Obs	Mean	Std. Dev.	Min	Max
village					
1	55,301	.0238875	.1526999	0	1
2	55,301	.0073055	.0851601	0	1
3	55,301	.0002712	.0164674	0	1
4	55,301	.0147375	.1205014	0	1
5	55,301	.004358	.0658715	0	1
6	55,301	.0170883	.1296017	0	1
7	55,301	.0083543	.09102	0	1
8	55,301	.0061663	.0782837	0	1
9	55,301	.0063109	.0791909	0	1
10	55,301	.0173415	.1305413	0	1
11	55,301	.0099817	.0994097	0	1
12	55,301	.0022784	.047679	0	1
13	55,301	.0018264	.0426974	0	1
14	55,301	.0170883	.1296017	0	1
15	55,301	.0043218	.0655988	0	1
16	55,301	.0171064	.129669	0	1
17	55,301	.0044303	.0664135	0	1
18	55,301	.0171064	.129669	0	1
19	55,301	.0083181	.0908244	0	1
20	55,301	.0024231	.0491658	0	1
21	55,301	.0048824	.0697038	0	1
22	55,301	.0107774	.1032542	0	1
23	55,301	.0008318	.0288294	0	1
24	55,301	.017468	.1310085	0	1
25	55,301	.0007776	.0278742	0	1
26	55,301	.0121155	.1094027	0	1
27	55,301	.0141408	.1180724	0	1
28	55,301	.0058408	.0762021	0	1
29	55,301	.0147918	.1207197	0	1
30	55,301	.0157321	.1244382	0	1
31	55,301	.0170702	.1295343	0	1
32	55,301	.0066726	.0814136	0	1
33	55,301	.006546	.0806428	0	1
34	55,301	.0145567	.1197709	0	1
35	55,301	.0073236	.0852646	0	1
36	55,301	.0084628	.0916041	0	1
37	55,301	.0074863	.0861997	0	1
38	55,301	.0118804	.108349	0	1
39	55,301	.0070523	.0836822	0	1
40	55,301	.0043037	.065462	0	1
41	55,301	.0098732	.0988733	0	1
42	55,301	.0010488	.0323686	0	1
43	55,301	.0060939	.0778261	0	1
44	55,301	.0023146	.0480551	0	1
45	55,301	.0001808	.0134462	0	1
46	55,301	.0063471	.0794161	0	1
47	55,301	.0000542	.0073652	0	1
48	55,301	.0143035	.1187401	0	1
49	55,301	.0012839	.0358086	0	1

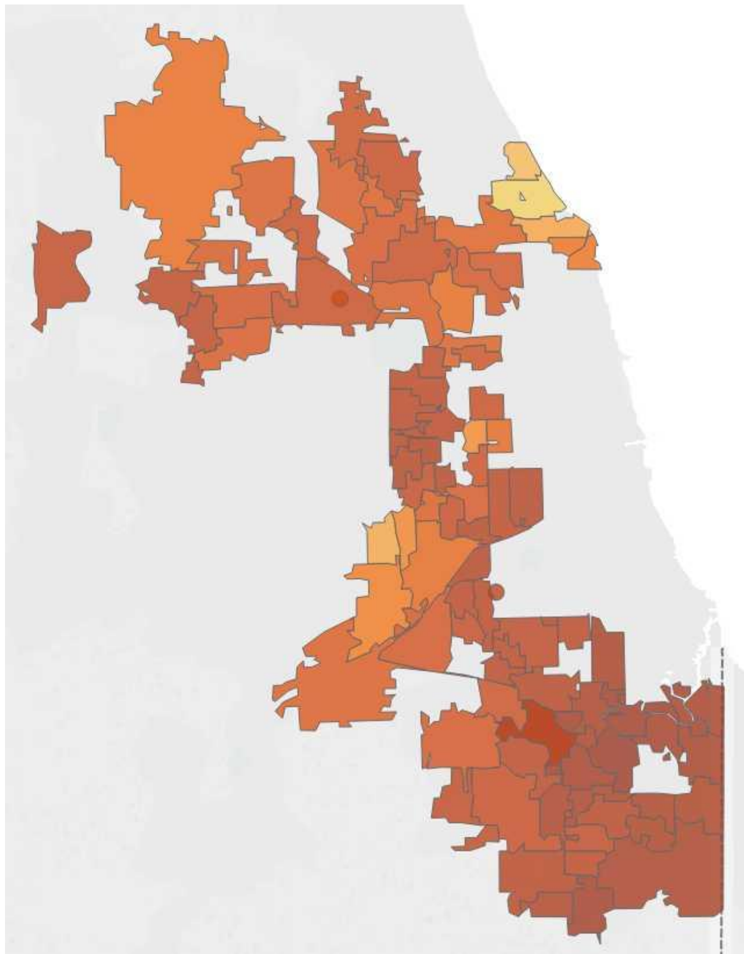
50	55,301	.0031283	.0558445	0	1
51	55,301	.0035442	.0594285	0	1
52	55,301	.0160757	.1257677	0	1
53	55,301	.0096743	.0978821	0	1
54	55,301	.0227844	.1492169	0	1
55	55,301	.0132367	.1142877	0	1
56	55,301	.0049005	.0698321	0	1
57	55,301	.0066364	.0811941	0	1
58	55,301	.0084266	.0914098	0	1
59	55,301	.015714	.1243678	0	1
60	55,301	.0001085	.0104157	0	1
61	55,301	.0114826	.1065409	0	1
62	55,301	.0014466	.0380074	0	1
63	55,301	.0124048	.1106851	0	1
64	55,301	.0060035	.0772501	0	1
65	55,301	.031645	.1750547	0	1
66	55,301	.0108859	.1037669	0	1
67	55,301	.0099998	.0994988	0	1
68	55,301	.0051717	.071729	0	1
69	55,301	.0011573	.0339998	0	1
70	55,301	.0076129	.0869199	0	1
71	55,301	.0005244	.022894	0	1
72	55,301	.01745	.1309418	0	1
73	55,301	.0172872	.1303406	0	1
74	55,301	.0169798	.1291967	0	1
75	55,301	.0054429	.0735759	0	1
76	55,301	.0048281	.0693174	0	1
77	55,301	.0166724	.1280419	0	1
78	55,301	.0171787	.1299381	0	1
79	55,301	.00481	.0691881	0	1
80	55,301	.015063	.1218047	0	1
81	55,301	.0198731	.1395653	0	1
82	55,301	.0005967	.0244211	0	1
83	55,301	.0035081	.0591255	0	1
84	55,301	.0064194	.0798644	0	1

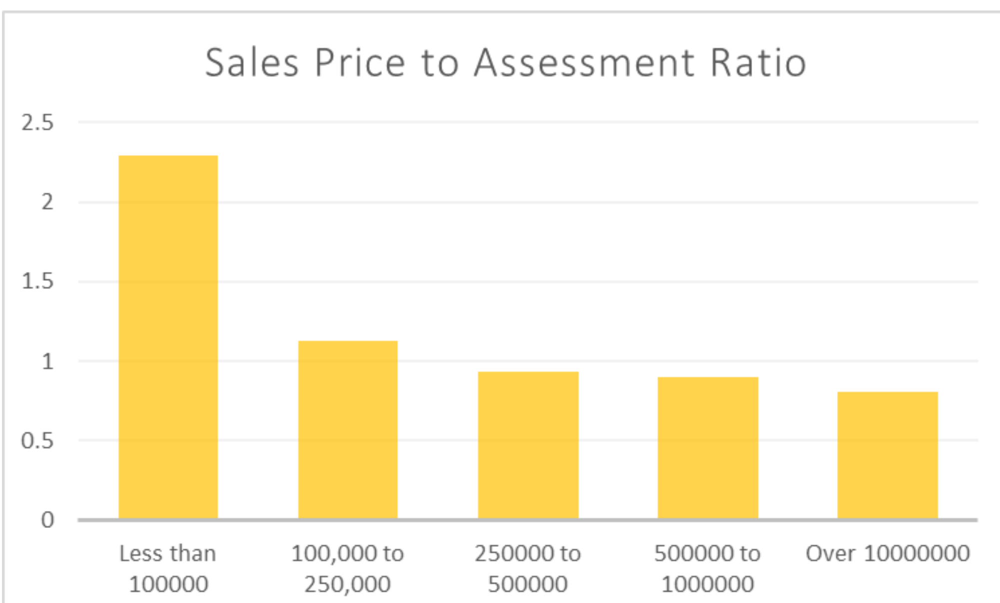
85	55,301	.0096562	.0977915	0	1
86	55,301	.0079745	.0889443	0	1
87	55,301	.0051717	.071729	0	1
88	55,301	.0077575	.0877354	0	1
89	55,301	.0008861	.0297538	0	1
90	55,301	.0130558	.1135148	0	1
91	55,301	.001537	.0391753	0	1
92	55,301	.0000723	.0085046	0	1
93	55,301	.0068353	.0823937	0	1
94	55,301	.0171425	.1298036	0	1
95	55,301	.0047196	.0685378	0	1
96	55,301	.0015551	.0394048	0	1
97	55,301	.0029475	.0542114	0	1
98	55,301	.0054429	.0735759	0	1
99	55,301	.0010307	.0320886	0	1
100	55,301	.0173234	.1304745	0	1
101	55,301	.0034357	.058515	0	1
102	55,301	.0021699	.0465325	0	1
103	55,301	.02707	.162289	0	1
104	55,301	.0173234	.1304745	0	1
105	55,301	.0116815	.1074489	0	1
106	55,301	.0110486	.1045311	0	1
107	55,301	.0034177	.0583613	0	1
108	55,301	.0160395	.1256285	0	1
109	55,301	.0121878	.1097247	0	1
110	55,301	.0050813	.0711024	0	1
salesprice1	55,301	12.20238	.8299931	8.306472	15.12384
date					
1	55,301	.0903058	.2866219	0	1
2	55,301	.0906132	.2870608	0	1
3	55,301	.0679192	.2516095	0	1
4	55,301	.0496013	.2171217	0	1
5	55,301	.0862191	.2806898	0	1
6	55,301	.0856223	.2798081	0	1
7	55,301	.0601074	.2376879	0	1
8	55,301	.0520605	.2221512	0	1
9	55,301	.0868158	.2815675	0	1
10	55,301	.0679011	.2515784	0	1
11	55,301	.0518435	.2217131	0	1
12	55,301	.0402163	.1964679	0	1
13	55,301	.0622593	.241628	0	1
14	55,301	.0542486	.2265096	0	1
sfs					
1	55,301	.166525	.3725546	0	1
2	55,301	.036455	.1874212	0	1
ar	55,301	1.146754	.6194205	.0869086	10.9377
age	55,301	58.09311	22.92696	1	129
build	55,301	1606.188	694.236	400	4238
land	55,301	8609.617	5602.195	935	61899
deli	55,301	.0408673	.1979844	0	1
demo	55,301	54.81693	27.32479	3	96.8
cash					
1	55,301	.2170666	.4122521	0	1
2	55,301	.1445724	.3516724	0	1
3	55,301	.2395978	.4268419	0	1
4	55,301	.1638488	.3701416	0	1

Appendix 2: Map of Assessment Ratio by Village (Red = Highest)

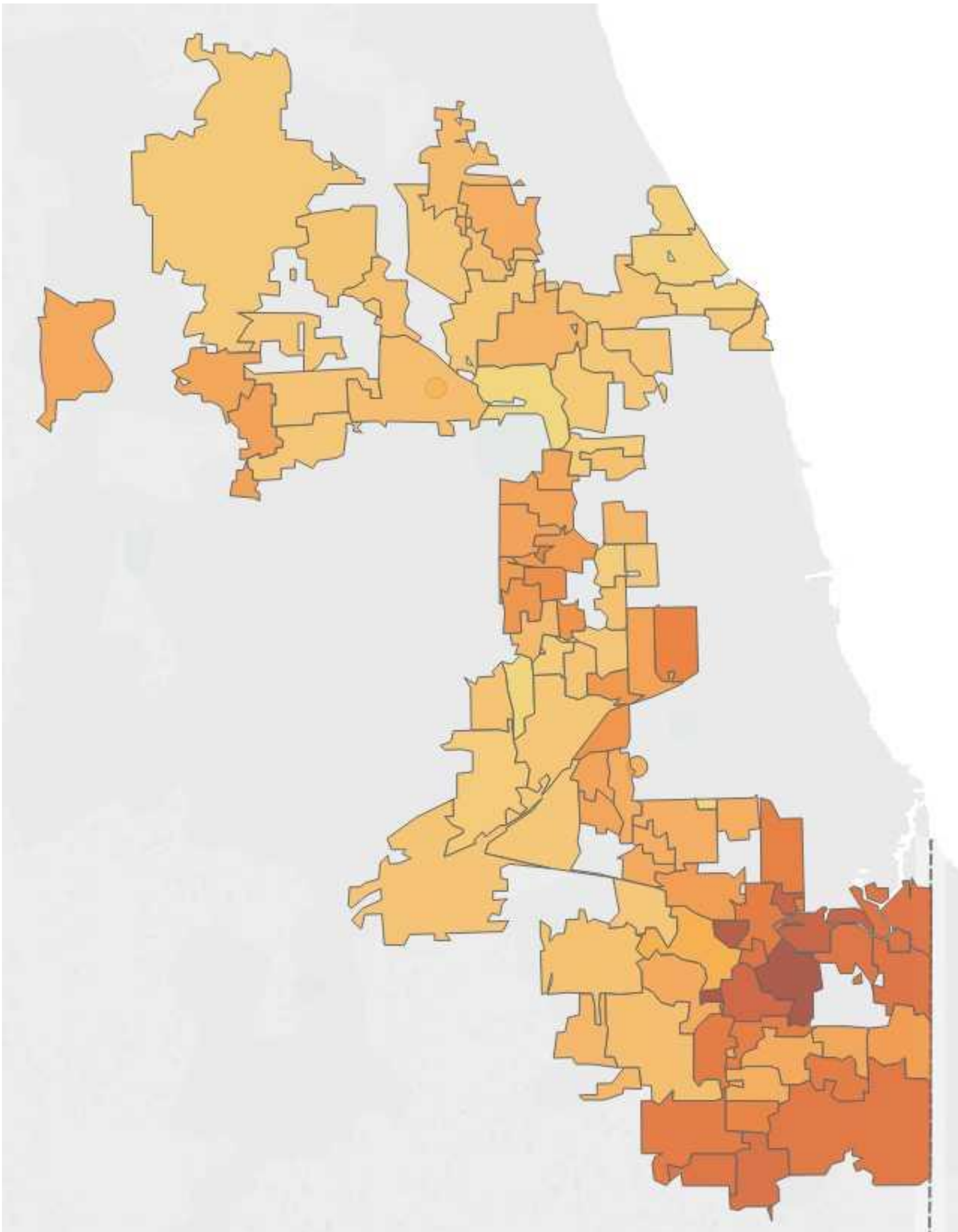


Appendix 3: Average Sales Price By Village (Red = Lowest Sales Price)

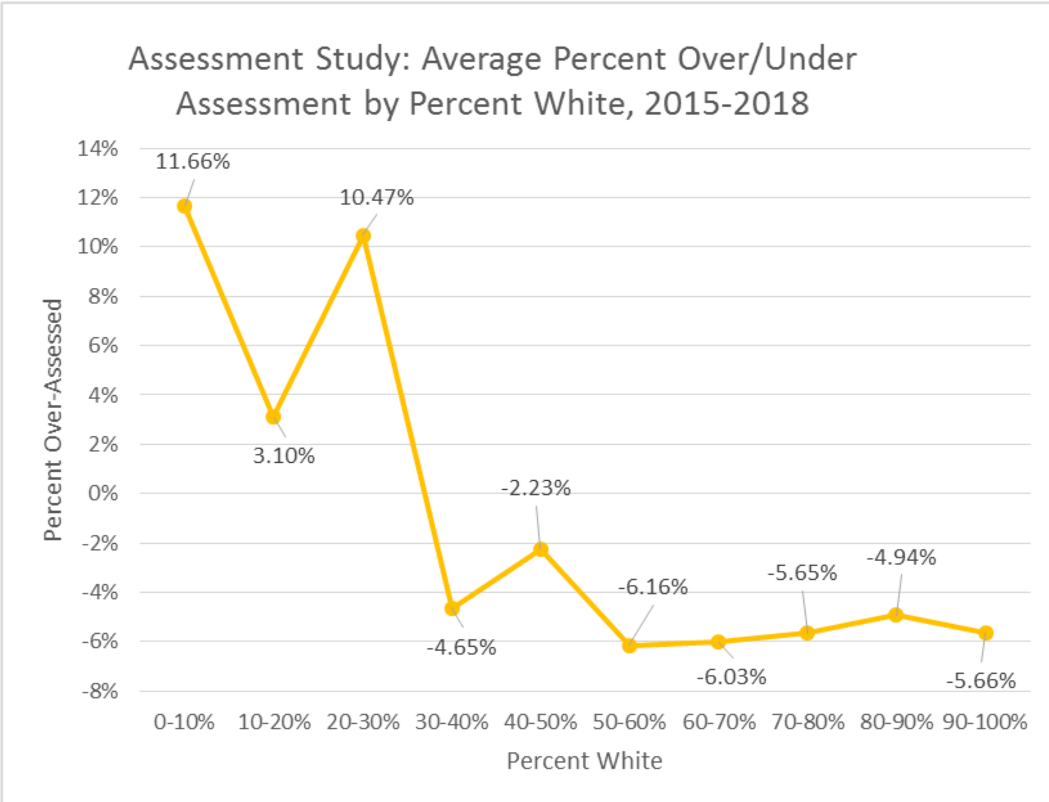


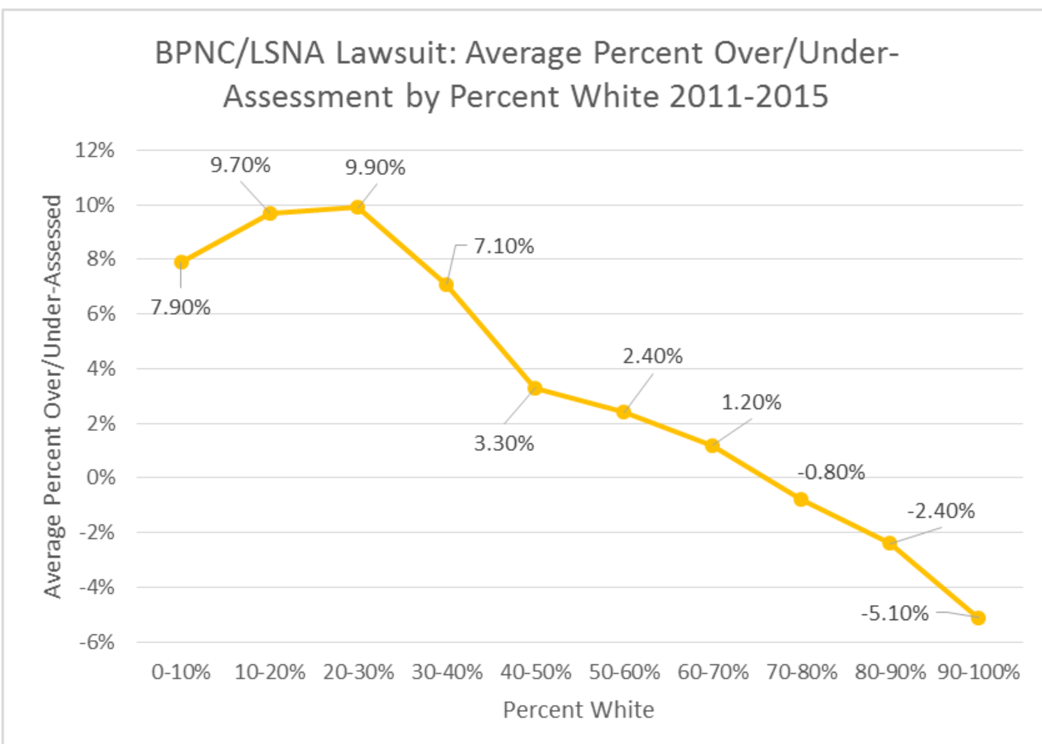


Appendix 4: Percent Foreclosures of Total Sales by Village

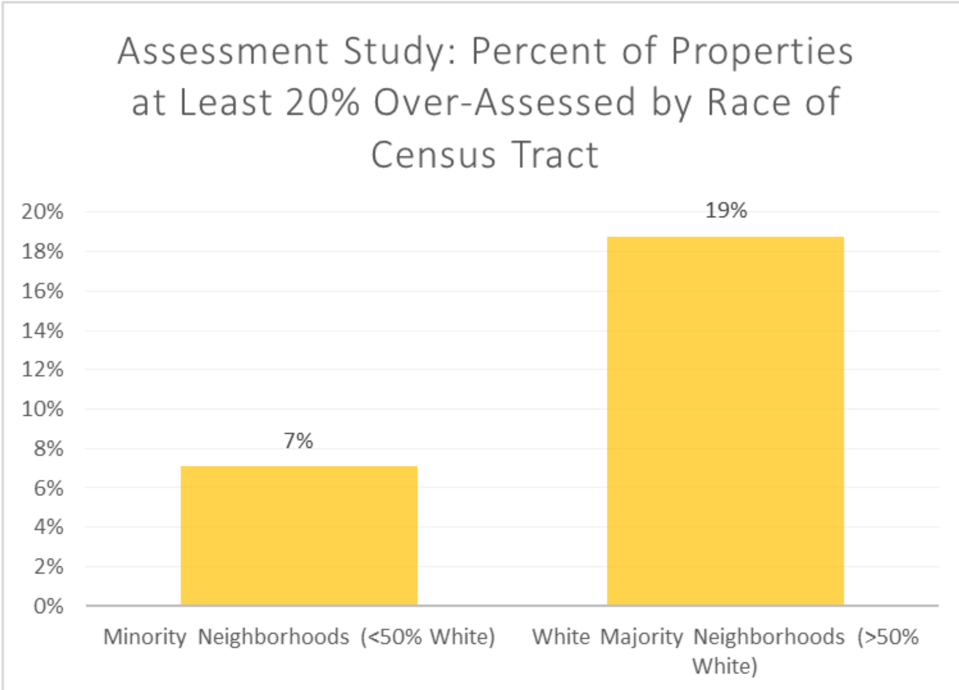


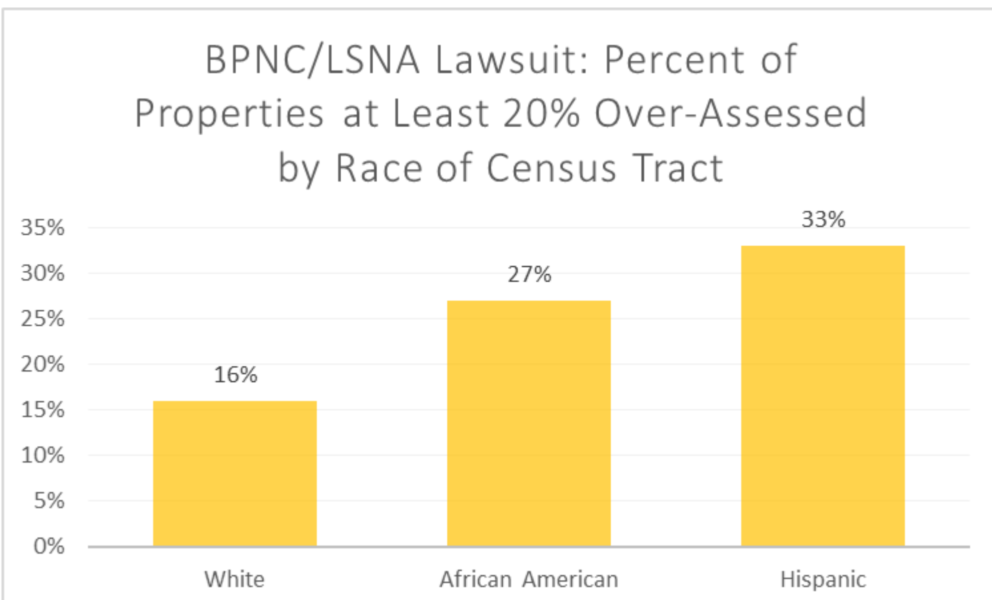
Appendix 5: Graph Comparison Berrios Lawsuit versus This Study



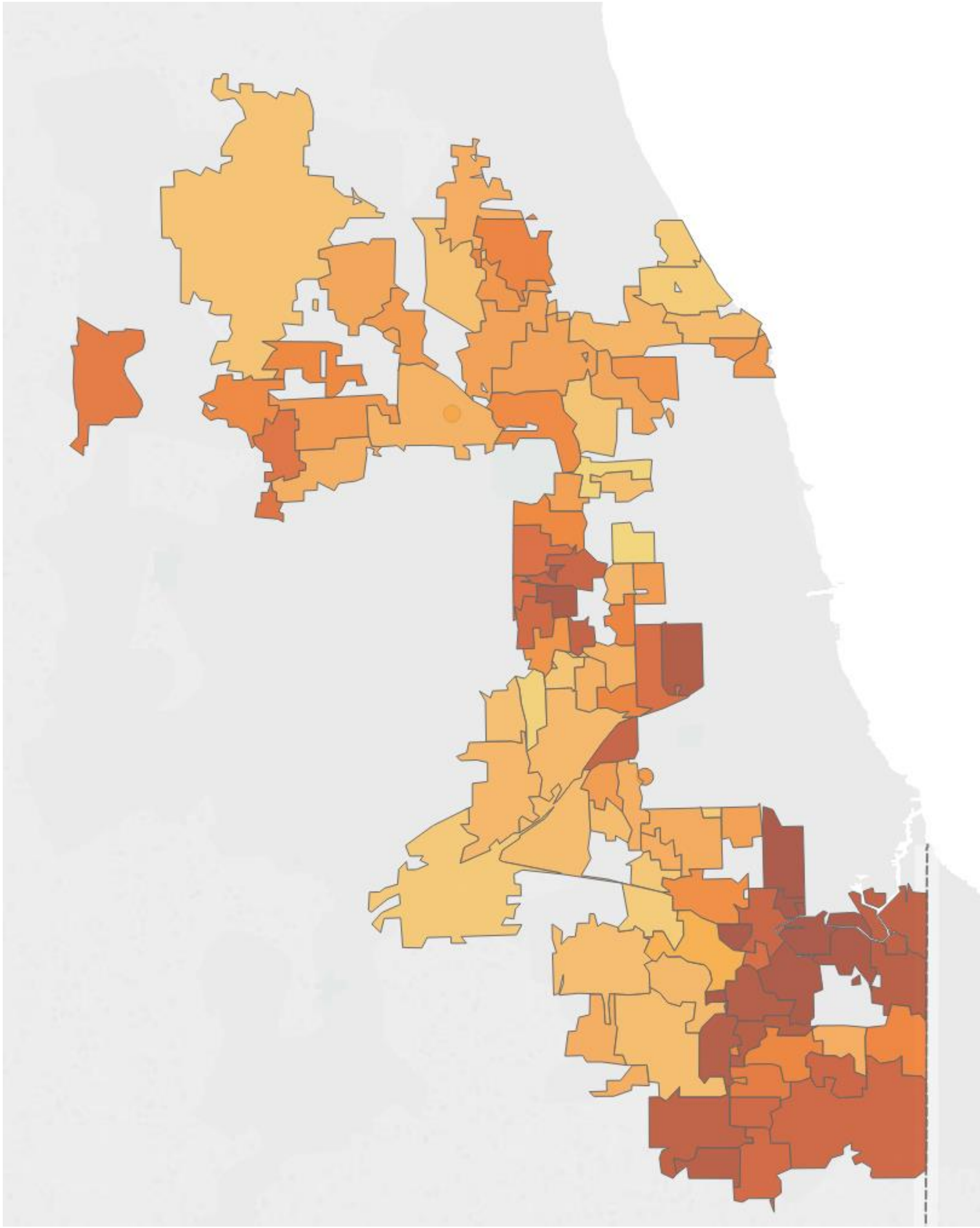


Appendix 5 Continued: Graph Comparison Berrios Lawsuit versus This Study





Appendix 6: Map of Racial Demographics (Red = Smaller Percent White)



Appendix 7: Model 1 Regression

VARIABLES	(1) ar
1.village	0.202***
	(0.00729)
2.village	0.309***
	(0.0138)
3.village	-0.290***
	(0.0426)
4.village	-0.522***
	(0.0113)
5.village	-0.349***
	(0.0125)
6.village	-0.213***
	(0.00952)
7.village	-0.614***
	(0.0239)
8.village	-0.279***
	(0.0110)
9.village	-0.435***
	(0.0143)
10.village	0.0315***
	(0.00935)
11.village	0.0772***
	(0.00785)
12.village	-0.913***
	(0.0412)
13.village	0.288***
	(0.0245)
14.village	-0.811***
	(0.0204)
15.village	-0.475***
	(0.0386)
16.village	-0.607***
	(0.0223)
17.village	-0.346***
	(0.0120)
18.village	-0.515***
	(0.0113)
19.village	-0.790***
	(0.0159)
20.village	0.0913***
	(0.0227)
21.village	-0.327***
	(0.0140)
22.village	-0.334***
	(0.0101)
23.village	-1.262***
	(0.122)
24.village	-0.744***
	(0.0225)
25.village	-0.943***
	(0.0656)
26.village	-0.392***

	(0.00848)
27.village	-0.0159**
	(0.00673)
28.village	0.0723***
	(0.00858)
29.village	0.0312***
	(0.00758)
30.village	0.527***
	(0.0150)
31.village	-0.338***
	(0.0108)
32.village	-0.521***
	(0.0134)
33.village	0.165***
	(0.0125)
34.village	-0.195***
	(0.00899)
35.village	0.793***
	(0.0166)
36.village	0.286***
	(0.0112)
37.village	-0.586***
	(0.0160)
38.village	-0.270***
	(0.00840)
39.village	-0.538***
	(0.0684)
40.village	0.0860***
	(0.0117)
41.village	-0.859***
	(0.0211)
42.village	-0.147***
	(0.0176)
43.village	-0.368***
	(0.0156)
44.village	0.744***
	(0.0264)
45.village	-0.0642
	(0.0963)
46.village	-0.124***
	(0.0126)
47.village	-0.270*
	(0.142)
48.village	-0.500***
	(0.0116)
49.village	0.326***
	(0.0204)
50.village	0.0197
	(0.0167)
51.village	-0.277***
	(0.0196)
52.village	0.462***
	(0.0121)
53.village	0.342***
	(0.0125)
54.village	-0.707***

	(0.0136)
55.village	-0.0232***
	(0.00882)
56.village	-0.549***
	(0.0150)
57.village	-0.384***
	(0.0149)
58.village	-0.927***
	(0.0321)
59.village	-0.651***
	(0.0124)
60.village	0.0776
	(0.0973)
61.village	-0.282***
	(0.00996)
62.village	-0.536***
	(0.0192)
63.village	-0.456***
	(0.0123)
64.village	0.223***
	(0.00913)
65.village	0.148***
	(0.00628)
66.village	0.205***
	(0.00811)
67.village	0.134***
	(0.00793)
68.village	0.001000
	(0.00958)
69.village	0.473***
	(0.0207)
70.village	-0.355***
	(0.00966)
71.village	0.235***
	(0.0255)
72.village	-0.306***
	(0.00860)
73.village	-0.274***
	(0.0103)
74.village	0.516***
	(0.0111)
75.village	-0.588***
	(0.0168)
76.village	-0.153***
	(0.0113)
77.village	-0.0867***
	(0.00759)
78.village	0.0775***
	(0.00737)
79.village	-0.0860***
	(0.0105)
80.village	-0.835***
	(0.0243)
81.village	0.347***
	(0.00865)
82.village	-1.329***

	(0.0982)
83.village	-0.750***
	(0.0270)
84.village	0.0396***
	(0.0111)
85.village	-0.672***
	(0.0174)
86.village	0.633***
	(0.0125)
87.village	-0.715***
	(0.0499)
88.village	0.314***
	(0.0122)
89.village	-1.345***
	(0.0932)
90.village	-0.0263***
	(0.00743)
91.village	-0.0324*
	(0.0170)
92.village	0.262***
	(0.0881)
93.village	-0.627***
	(0.0417)
94.village	0.00593
	(0.00717)
95.village	-0.205***
	(0.0142)
96.village	0.184***
	(0.0334)
97.village	-0.608***
	(0.0351)
98.village	-0.355***
	(0.0162)
99.village	-0.551***
	(0.0407)
100.village	-0.297***
	(0.00744)
101.village	-0.286***
	(0.0192)
102.village	-0.814***
	(0.0255)
103.village	-0.160***
	(0.00742)
104.village	-0.0267***
	(0.00773)
105.village	0.607***
	(0.0114)
106.village	-0.126***
	(0.00861)
107.village	-0.0344
	(0.0221)
108.village	0.789***
	(0.0134)
109.village	0.938***
	(0.0141)
110.village	-0.367***

	(0.0132)
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	(0.0109)
1.date	-0.00610
	(0.00863)
2.date	-0.00706
	(0.00892)
3.date	-0.00550
	(0.00901)
4.date	-0.0212**
	(0.00987)
5.date	-0.0142*
	(0.00843)
6.date	-0.0199**
	(0.00843)
7.date	-0.0216**
	(0.00967)
8.date	-0.0425***
	(0.00970)
9.date	-0.0301***
	(0.00820)
10.date	-0.0408***
	(0.00859)
11.date	-0.0495***
	(0.00916)
12.date	-0.0637***
	(0.00953)
13.date	-0.0376***
	(0.00888)
14.date	-0.0420***
	(0.00864)
1.sfs	0.153***
	(0.00567)
2.sfs	0.00626
	(0.00806)
age	-0.00172***
	(0.000101)
build	0.000372***
	(4.69e-06)
land	7.91e-06***
	(3.46e-07)
deli	0.113***
	(0.0136)
Constant	13.89***
	(0.131)
Observations	55,301
R-squared	0.756

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 8: Adjusted Coefficients for Model 1 from Greatest to Least

Region	Village Name	village #	Original	Coefficient with Salesprice 1	Difference	Inverse Change in Coefficient	W/SP- Change in Coefficient	Final Adjusted
S	Harvey	39	1.670533	-0.53779	-2.2083216	2.2083216	1.670533	3.8788546
S	Sauk Village	93	1.252831	-0.62686	-1.8796901	1.8796901	1.252831	3.1325211
S	Riverdale	87	1.144644	-0.7154	-1.8600446	1.8600446	1.144644	3.0046886
S	Phoenix	82	0.690922	-1.32949	-2.020411	2.020411	0.690922	2.711333
S	Park Forest	80	0.802845	-0.8355	-1.6383401	1.6383401	0.802845	2.4411848
S	Dixmoor	23	0.520126	-1.26224	-1.782363	1.782363	0.520126	2.302489
S	Robbins	89	0.446225	-1.3447	-1.7909281	1.7909281	0.446225	2.2371532
S	Dolton	24	0.733881	-0.74361	-1.4774931	1.4774931	0.733881	2.2113738
S	Markham	58	0.598467	-0.92709	-1.5255559	1.5255559	0.598467	2.1240224
S	Calumet Park	15	0.777511	-0.47479	-1.2522994	1.2522994	0.777511	2.0298106
S	Chicago Heights	16	0.682598	-0.60721	-1.2898101	1.2898101	0.682598	1.9724078
S	Calumet City	14	0.530403	-0.81103	-1.3414373	1.3414373	0.530403	1.87184
S	South Chicago Heights	97	0.596571	-0.60778	-1.2043514	1.2043514	0.596571	1.8009219
S	Burnham	12	0.412056	-0.91333	-1.3253894	1.3253894	0.412056	1.7374451
S	East Hazel Crest	25	0.328191	-0.94259	-1.2707805	1.2707805	0.328191	1.598971
S	Hazel Crest	41	0.347692	-0.85926	-1.2069506	1.2069506	0.347692	1.554643
S	Richton Park	85	0.323539	-0.67236	-0.9958954	0.9958954	0.323539	1.3194341
S	Thornton	102	0.232906	-0.81381	-1.0467149	1.0467149	0.232906	1.2796208
S	McCook	60	0.667843	0.07756	-0.5902838	0.5902838	0.667843	1.2581271
S	Glenwood	37	0.320766	-0.58573	-0.9064919	0.9064919	0.320766	1.2272575
S	Posen	83	0.222071	-0.75031	-0.9723825	0.9723825	0.222071	1.1944538
S	Blue Island	7	0.283296	-0.6144	-0.8976915	0.8976915	0.283296	1.1809878
S	Lansing	54	0.232821	-0.7073	-0.9401237	0.9401237	0.232821	1.1729446
S	Country Club Hills	19	0.189136	-0.79049	-0.9796288	0.9796288	0.189136	1.1687648
S	Matteson	59	0.181935	-0.65106	-0.8329936	0.8329936	0.181935	1.0149281
S	Lynwood	56	0.221103	-0.5489	-0.7700039	0.7700039	0.221103	0.9911069
S	Hometown	47	0.343943	-0.27009	-0.6140292	0.6140292	0.343943	0.9579725
S	Midlothian	63	0.230826	-0.45569	-0.68652	0.68652	0.230826	0.9173463

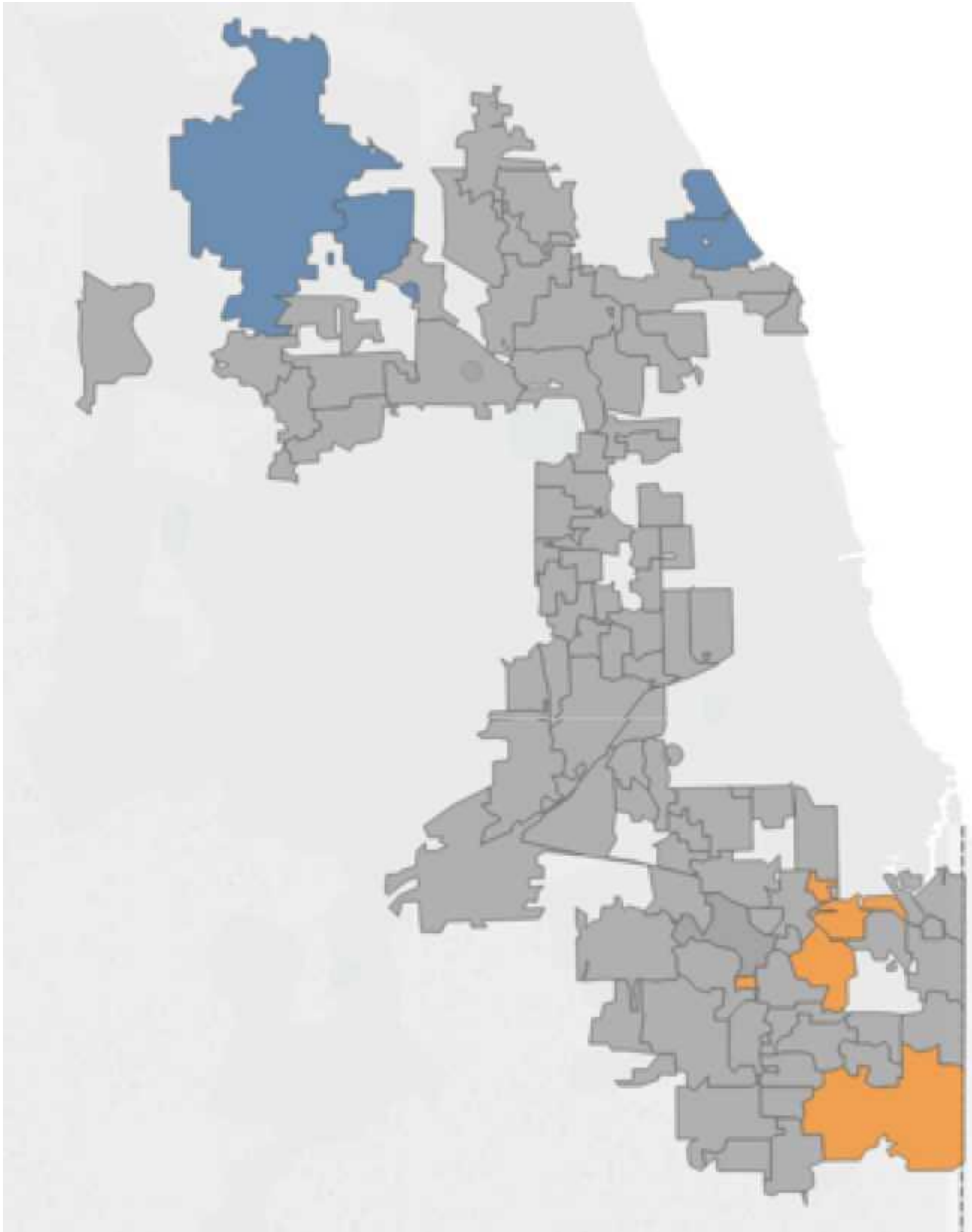
S	Olympia Fields	75	0.142839	-0.5883	-0.7311383	0.7311383	0.142839	0.8739768
S	Stone Park	99	0.153035	-0.55099	-0.7040221	0.7040221	0.153035	0.8570571
S	Homewood	48	0.137602	-0.50041	-0.6380162	0.6380162	0.137602	0.7756183
S	Merrionette Park	62	0.118743	-0.53551	-0.65425	0.65425	0.118743	0.7729933
S	Summit	101	0.218658	-0.28566	-0.5043155	0.5043155	0.218658	0.722973
S	Flossmoor	32	0.061373	-0.5206	-0.581968	0.581968	0.061373	0.6433405
S	Alsip	22	0.148238	-0.3345	-0.482737	0.482737	0.148238	0.6309751
S	Bellwood	4	0.051514	-0.52232	-0.5738299	0.5738299	0.051514	0.6253434
S	Crestwood	21	0.128403	-0.32729	-0.4556909	0.4556909	0.128403	0.5840941
S	Worth	110	0.093825	-0.36729	-0.4611187	0.4611187	0.093825	0.5549438
S	Oak Forest	72	0.123137	-0.3062	-0.4293365	0.4293365	0.123137	0.5524732
S	Justice	51	0.124234	-0.27661	-0.4008416	0.4008416	0.124234	0.5250755
S	Bridgeview	8	0.118292	-0.27906	-0.3973487	0.3973487	0.118292	0.5156406
S	Orland Hills	76	0.168939	-0.1532	-0.3221428	0.3221428	0.168939	0.4910819
N	Elgin	26	0.049164	-0.39196	-0.4411193	0.4411193	0.049164	0.490283
S	Chicago Ridge	17	0.061938	-0.3461	-0.408034	0.408034	0.061938	0.4699722
S	Tinley Park	103	0.149984	-0.15979	-0.3097782	0.3097782	0.149984	0.4597622
S	Hodgkins	45	0.191746	-0.06425	-0.2559923	0.2559923	0.191746	0.4477387
S	Evergreen Park	31	0.054239	-0.33822	-0.392463	0.392463	0.054239	0.4467024
N	Melrose Park	61	0.079924	-0.28211	-0.3620339	0.3620339	0.079924	0.4419577
S	Lyons	57	0.02296	-0.38364	-0.4065977	0.4065977	0.02296	0.4295572
S	Broadview	9	-0.00852	-0.43545	-0.426933	0.426933	-0.008521	0.4184124
S	Hillside	43	0.024731	-0.36758	-0.3923118	0.3923118	0.024731	0.417043
N	Streamwood	100	0.058942	-0.29665	-0.3555951	0.3555951	0.058942	0.4145366
S	Palos Heights	79	0.150515	-0.08599	-0.2365082	0.2365082	0.150515	0.387023
N	Northlake	70	0.004397	-0.35499	-0.3593818	0.3593818	0.004397	0.3637786
S	Oak Lawn	73	0.043656	-0.2741	-0.3177513	0.3177513	0.043656	0.3614072
N	Hoffman Estates	46	0.116152	-0.12403	-0.2401779	0.2401779	0.116152	0.3563302
S	Berkeley	5	-0.00766	-0.34894	-0.3412738	0.3412738	-0.007663	0.3336113
S	Orland Park	77	0.119873	-0.08667	-0.2065416	0.2065416	0.119873	0.326415
S	Hickory Hills	42	0.077271	-0.14671	-0.2239771	0.2239771	0.077271	0.3012481
S	Cicero	18	-0.10958	-0.51522	-0.4056441	0.4056441	-0.10958	0.2960638
S	Lemont	55	0.133918	-0.02319	-0.1571042	0.1571042	0.133918	0.2910218

S	Stickney	98	-0.03572	-0.35528	-0.319556	0.319556	-0.03572	0.2838359
N	Hanover Park	38	0.002347	-0.26964	-0.2719861	0.2719861	0.002347	0.2743331
S	Bedford Park	3	-0.01821	-0.29012	-0.2719114	0.2719114	-0.01821	0.2537012
S	Westchester	104	0.100209	-0.02668	-0.1268849	0.1268849	0.100209	0.2270939
N	Franklin Park	34	0.014819	-0.19531	-0.210132	0.210132	0.014819	0.2249511
N	Rolling Meadows	90	0.09032	-0.02626	-0.1165758	0.1165758	0.09032	0.2068955
S	Willow Springs	107	0.07899	-0.03443	-0.1134161	0.1134161	0.07899	0.192406
N	Wheeling	106	0.029885	-0.12571	-0.1555995	0.1555995	0.029885	0.1854843
N	Roselle	91	0.068778	-0.03242	-0.1011998	0.1011998	0.068778	0.1699781
N	Elk Grove	27	0.069271	-0.01593	-0.0852011	0.0852011	0.069271	0.1544718
S	North Riverside	68	0.055858	0.001	-0.0548577	0.0548577	0.055858	0.1107152
N	Buffalo Grove	11	0.078031	0.077214	-0.0008172	0.0008172	0.078031	0.078848
N	Schiller Park	95	-0.07178	-0.20463	-0.1328519	0.1328519	-0.071779	0.0610734
N	Elk Grove Village	28	0.05836	0.072343	0.0139831	-0.0139831	0.05836	0.0443765
S	Countryside	20	0.062819	0.091318	0.0284988	-0.0284988	0.062819	0.0343206
S	Indian Head Park	49	0.179889	0.32571	0.145821	-0.145821	0.179889	0.0340682
N	Schaumburg	94	0.016629	0.005929	-0.0107007	0.0107007	0.016629	0.02733
N	Palatine	78	0.051287	0.07747	0.0261823	-0.0261823	0.051287	0.025105
S	Berwyn	6	-0.09709	-0.21348	-0.1163964	0.1163964	-0.097088	0.0193085
S	Brookfield	10	0.006954	0.031494	0.0245396	-0.0245396	0.006954	-0.0175857
N	Prospect Heights	84	0.007625	0.039618	0.0319926	-0.0319926	0.007625	-0.0243676
N	Inverness	50	-0.00621	0.01971	0.0259208	-0.0259208	-0.006211	-0.0321314
N	South Barrington	96	0.070301	0.184238	0.1139372	-0.1139372	0.070301	-0.0436367
N	Elmwood	29	-0.01951	0.031236	0.0507505	-0.0507505	-0.019514	-0.0702648
N	Mount Prospect	65	0.0187	0.147646	0.1289468	-0.1289468	0.0187	-0.1102472
S	Burr Ridge	13	0.086982	0.288124	0.2011418	-0.2011418	0.086982	-0.1141601
N	Barrington	2	0.09463	0.309478	0.214848	-0.214848	0.09463	-0.1202181
N	Niles	66	0.037851	0.205289	0.1674379	-0.1674379	0.037851	-0.129587
N	Harwood Heights	40	-0.0223	0.085971	0.1082666	-0.1082666	-0.022295	-0.1305618
N	Morton Grove	64	0.04572	0.223058	0.1773388	-0.1773388	0.04572	-0.1316193
S	Forest Park	33	0.006445	0.164967	0.1585223	-0.1585223	0.006445	-0.1520777

N	Arlington Heights	1	0.015596	0.20152	0.1859238	-0.1859238	0.015596	-0.1703279
N	Norridge	67	-0.01956	0.133542	0.1530988	-0.1530988	-0.019557	-0.1726561
S	LaGrange Park	53	0.058737	0.342339	0.2836023	-0.2836023	0.058737	-0.2248657
N	Glenview	36	-0.02298	0.28579	0.3087741	-0.3087741	-0.022984	-0.3317585
N	Norwood Park	71	-0.07006	0.234854	0.3049165	-0.3049165	-0.070063	-0.3749791
S	Riverside	88	-0.03215	0.314289	0.3464418	-0.3464418	-0.032153	-0.3785946
S	La Grange	52	0.02903	0.462378	0.433348	-0.433348	0.02903	-0.4043181
S	Hinsdale	44	0.163763	0.744045	0.5802827	-0.5802827	0.163763	-0.41652
N	Rosemont	92	-0.08092	0.261671	0.3425941	-0.3425941	-0.080923	-0.4235169
S	Western Springs	105	0.077387	0.607345	0.5299577	-0.5299577	0.077387	-0.4525707
N	Park Ridge	81	-0.057	0.347283	0.4042869	-0.4042869	-0.057004	-0.4612906
N	Northfield	69	-0.00993	0.473035	0.4829697	-0.4829697	-0.009935	-0.4929043
S	Oak Park	74	-0.09185	0.515611	0.6074616	-0.6074616	-0.091851	-0.6993125
N	Glencoe	35	0.040949	0.792636	0.7516869	-0.7516869	0.040949	-0.7107375
N	Evanston	30	-0.0974	0.527094	0.6244925	-0.6244925	-0.097398	-0.7218906
S	River Forest	86	-0.06588	0.633204	0.6990847	-0.6990847	-0.065881	-0.7649654
N	Wilmette	108	-0.00839	0.788837	0.7972272	-0.7972272	-0.00839	-0.8056171
N	Winnetka	109	-0.02096	0.93764	0.9586027	-0.9586027	-0.020963	-0.9795659

Appendix 9: Map of Regression Results

(Blue = Low Assessment Ratio, Orange = High Assessment Ratio)



Appendix 10: Model 2 Regression

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	(9.26e-05)
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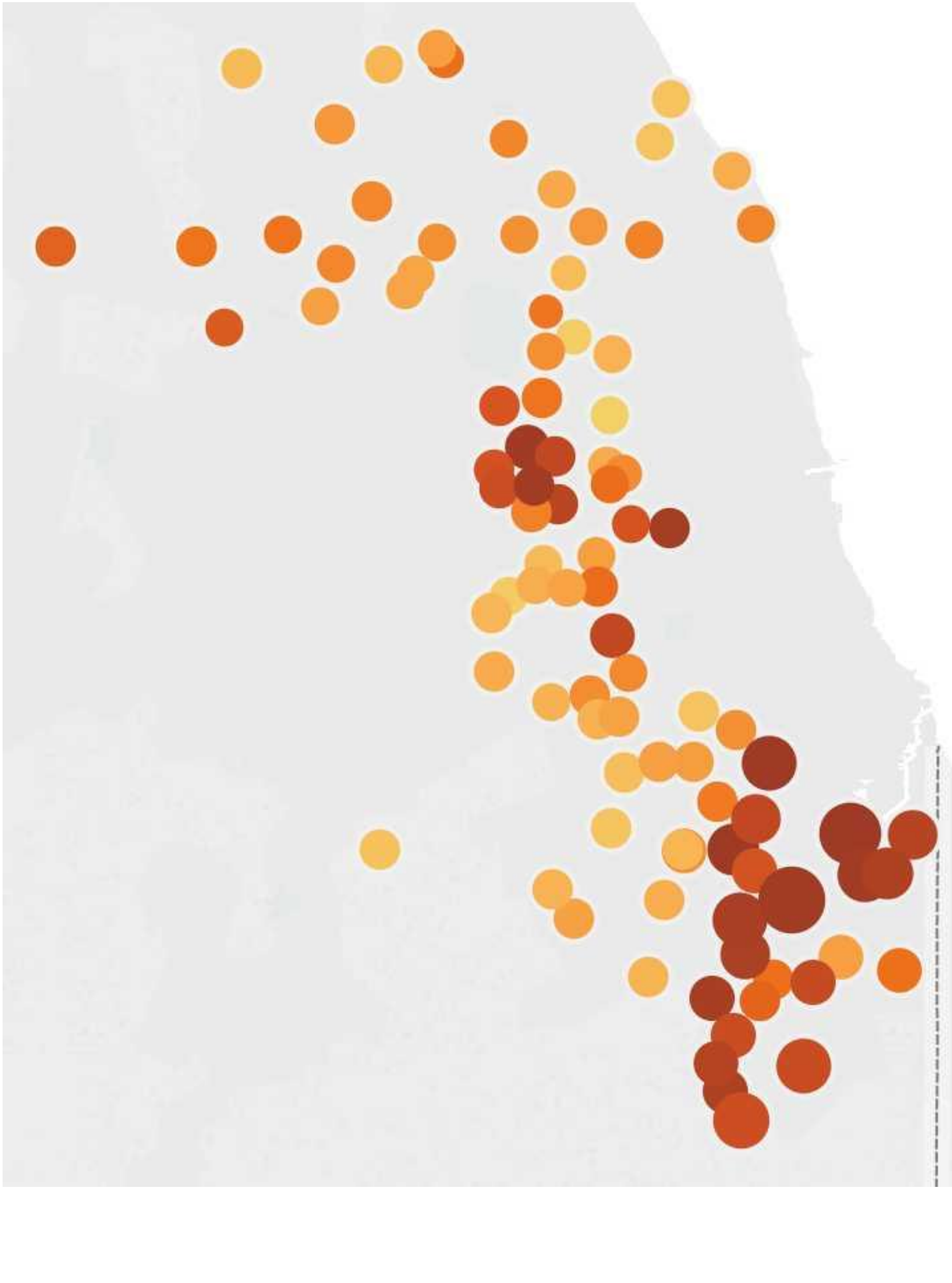
	(0.0103)
2.date	-0.0297***
	(0.0105)
3.date	-0.0317***
	(0.0107)
4.date	-0.0439***
	(0.0118)
5.date	-0.0465***
	(0.0101)
6.date	-0.0592***
	(0.00991)
7.date	-0.0639***
	(0.0114)
8.date	-0.0822***
	(0.0114)
9.date	-0.0800***
	(0.00972)
10.date	-0.102***
	(0.0101)
11.date	-0.117***
	(0.0109)
12.date	-0.130***
	(0.0111)
13.date	-0.112***
	(0.0104)
14.date	-0.121***
	(0.0102)
1.sfs	0.297***
	(0.00570)
age	0.00192***
	(9.15e-05)
build	0.000326***
	(4.94e-06)
land	2.27e-06***
	(2.92e-07)
deli	0.222***
	(0.0161)

1.cash	-0.124***
	(0.00364)
2.cash	-0.136***
	(0.00408)
3.cash	-0.224***
	(0.00495)
4.cash	-0.148***
	(0.00747)
Constant	9.318***
	(0.0952)
Observations	53,285
R-squared	0.673

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 11: Percent White to Assessment Ratio

(Larger Circle= High Assessment Ratio, Red = Low Percent White)



Appendix 12: Model 3 Regression

VARIABLES	(1) ar
salesprice1	-0.654***
	(0.00785)
1.date	-0.0180*
	(0.0105)
2.date	-0.0317***
	(0.0108)
3.date	-0.0328***
	(0.0109)
4.date	-0.0488***
	(0.0121)
5.date	-0.0506***
	(0.0103)
6.date	-0.0655***
	(0.0101)
7.date	-0.0690***
	(0.0117)
8.date	-0.0924***
	(0.0118)
9.date	-0.0898***
	(0.00999)
10.date	-0.112***
	(0.0104)
11.date	-0.127***
	(0.0113)
12.date	-0.140***
	(0.0115)
13.date	-0.117***
	(0.0107)
14.date	-0.129***
	(0.0106)
1.sfs	0.310***
	(0.00585)
age	0.00199***
	(9.41e-05)
build	0.000299***
	(4.80e-06)
land	2.84e-06***
	(2.96e-07)
deli	0.238***
	(0.0167)
1.cash	-0.131***
	(0.00377)

2.cash	-0.194***
	(0.00433)
3.cash	-0.301***
	(0.00571)
4.cash	-0.311***
	(0.00813)
Constant	8.693***
	(0.0911)
Observations	53,285
R-squared	0.652

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Fine.