Assessment Inequity in a Declining Housing Market: The Case of Detroit

Timothy R. Hodge[1]
Mark Skidmore[2]
Gary Sands[3]
Daniel McMillen[4]

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Abstract

In this paper we examine the degree to which assessment practices in the City of Detroit have created substantial inequities in property tax payments among residential properties. Two key contributions of this paper include: 1) we examine the inequities created by assessment practices in a collapsed real-estate market, and 2) we use quantile regression techniques to determine how assessment practices have altered assessment distributions within and across property value groups. Results show that current practices have created a wide range of property tax payments across properties with similar value (horizontal inequity), and similar tax payments for properties of differing values (vertical inequity).

[1] Department of Agricultural, Food, and Resource Economics, 125 Cook Hall, East Lansing, MI 48824; hodgetim@msu.edu.
[2] Department of Agricultural, Food, and Resource Economics and Department of Economics, 91 Agriculture Hall, East Lansing, MI 48824; mskidmor@msu.edu.
[3] Urban Planning Program, Wayne State University, 1051 Hartsough Street, Plymouth, MI 48170-2143; gary.sands@wayne.edu.
[4] Department of Economics, IGPA and Department of Economics (MC 037), University of Illinois, 1007 W. Nevada St., Urbana, IL 61801; mcmillen@illinois.edu.

I. INTRODUCTION

Michigan law requires property to be assessed uniformly at 50 percent of true cash value (Michigan Taxpayer's Guide, 2011).[5] In practice, however, the assessment ratio – assessed value divided by the sales price – often varies considerably from this standard, exhibiting a regressive relationship: high-priced properties have lower ratios than low-priced properties within the same jurisdiction. Concerns regarding assessment practices have been the topic of a growing list of empirical research, including: 1) methods of measuring inequity; 2) the underlying determinants of inequity; 3) the degree of horizontal and vertical inequity resulting from assessment practices; and 4) the economic beneficiaries of assessment inequity. However, little is known about the degree to which assessment practices have generated unequal tax payments during a period of significant disequilibrium such as the one created by the recent housing crisis. To examine this issue, data has been collected from one city hit particularly hard by the housing crisis—Detroit. Michigan.

It is no secret that Detroit property values have dropped significantly over the last five years. This fact is partially reflected in that residential property assessments have dropped 46 percent between 2007 and 2012 (MacDonald, 2013). Despite the large decline in assessed values, evidence recently reported in the media suggests that assessors are not following the market closelyenough and concerns over assessment accuracy and equity are being raised.[6] For example, houses that sold for $2,300 are being valued by the city at $42,000, more than 18 times

[5] True cash value is also referred to as the market value or the properties "usual selling price" (Michigan Taxpayer's Guide (2011)).
[6] A number of articles in The Detroit News were recently devoted to these concerns. The following link provides a series of articles on Detroit property taxes and assessment practices: http://www.detroitnews.com/article/99999999/METRO/130221002andtemplate=THEMEandtheme=METRO-DETROIT-TAXES

their selling price (MacDonald, 2013).[7] Anecdotal evidence suggests that properties that did not sell during the housing crisis are also significantly over-assessed.[8]

One hypothesis for the observed level of assessment inaccuracy in Detroit is that assessors have attempted to avoid the near complete erosion of the tax base.[9] From city data on sales prices and assessed values, if assessments were 50 percent of market value as reflected in actual sales prices, tax revenue from just those residential properties that sold in 2009 would drop from $18.4 million to less than $4.2 million. This represents a decrease in average property taxes from $2,100 to $480.[10] Assuming this estimated decrease is indicative of all residential properties (not just those that sold), the pressure to keep assessments artificially high is understandable. In addition to the decline in property values, problems generating property tax revenue in Detroit are exacerbated by the continued exodus of residents as well as an exceptionally high property tax delinquency rate.[11] A second possible reason for the observed level of assessment inaccuracy in Detroit is that limited resources and staffing have hindered the ability of assessors to make the proper adjustments to assessed values. Recently, budget cuts have decreased the assessment division's staff from 90 employees in the late 1990s to 36 in

[7] Other examples of over-assessment include: houses selling for $12,500 are valued at $62,000 and properties less than $100 are valued at nearly $46,000 by the City.

[8] Bill McCarthy, a Detroit resident, lived in his home since 1985 and had his $38,594 assessment decreased to $8,500; however, this decrease came only after appealing to the Michigan Tax Tribunal when the Detroit Board of Review refused to change the assessment. This changed his annual tax bill from $3,000 to $800 (MacDonald, 2013).

[9] DeCesare and Ruddock (1998) state that assessed values may contain errors caused by political decisions to intentionally override market values.

[10] This estimate was calculated using the sample of properties used in this study (i.e. residential properties sold in 2009). Current tax revenues are calculated by multiplying the State Equalized Value (SEV) by the millage rate each property is subject to, whereas estimated tax revenues are calculated by multiplying half the property's sale price by the millage rate.

[11] The 2010 Census estimates a population of 713,777, which is down from 951,270 in 2000 and 1.85 million at its peak in 1950 (U.S. Census). Regarding tax delinquency, about 47 percent of property owners did not pay their 2011 tax bills – leaving nearly $246.5 million in uncollected taxes and fees (MacDonald, 2013).

2012. As stated by Detroit's Chief Assessor, Linda Bade, these "...workers do their best under tough conditions" (MacDonald, 2013). A third, and final possible explanation for the observed level of assessment inaccuracy is the subjectivity of the valuation process (DeCesare and Ruddock, 1998). That is, assessors may be assessing properties using standard procedures; however, because the valuations are based on limited comparables, the results are not truly representative of market conditions.[12]

The purpose of this paper is to thoroughly examine assessment regressivity in an eroded housing market by conducting a thorough evaluation of assessment practices in Detroit. This study makes two key contributions to the existing literature: 1) we examine the effect of assessment practices on vertical and horizontal inequities in a collapsed real-estate market; and 2) we use quantile regression techniques to assess inequity. Standard regression analysis has been the traditional tool for measuring vertical and horizontal inequities resulting from assessment practices; however, standard regressions are not well suited to evaluate inequity because of their reliance on central tendencies. As we discuss in detail later, the quantile regression technique reveals how assessment practices affect the entire distribution of assessment ratios, making this approach ideal for examining equity issues. The quantile regression approach also reveals the sources of the average effect observed in standard regression analysis – whether the effect is the result of a location shift (i.e. a change in the mean value), a scale shift (i.e. a change in the variance), or both. Understanding the degree of the inequities may provide an additional incentive to conduct a formal reassessment of properties to create a more coherent and

[12] As anecdotal evidence of handpicking optimal sales in Detroit, the most recent sales study undertaken by the assessment division included only 684 sales (or 5.6 percent) of the city's 12,118 home sales from October 2011, to September 2012. This is a much lower percentage than other cities surrounding Detroit: Hazel Park, Pontiac, and Ferndale had assessments based on 15, 16.5, and 30 percent of sales, respectively (MacDonald, 2013).

equitable property tax.[13]

In the next section, we provide a brief description of assessment practices in Detroit. In Section 3, we review earlier research regarding assessment practices and the effect of those practices on horizontal and vertical equity. The empirical strategy for measuring vertical and horizontal equity across Detroit is discussed in Section 4. The data and estimation results are presented in Sections 5 and 6, respectively. Finally, we provide a discussion of the implications of assessment practices on property tax payments in Section 7 and offer concluding remarks in Section 8.

2. ASSESSMENT PRACTICES IN DETROIT

All taxable properties in the City of Detroit are assessed on an annual basis by the City's assessment division. To accomplish this task, city assessors are responsible for two basic functions: 1) they must inventory all property within the City;[14] and 2) equitably value all taxable property in accordance with Michigan's General Property Tax Law.[15] Assessors calculate property values by inspecting new construction, analyzing recent sales of comparable properties, and observing neighborhood advantages and disadvantages that may affect market

[13] Assessment practices in Detroit are currently under review by a private firm hired by the State Tax Commission. This evaluation will determine whether assessment practices are within State guidelines and whether a citywide reassessment will be undertaken. For details, see: http://www.detroitnews.com/article/20130409/POLITICS02/304090341/1022/POLITICS/Michigan-s-tax-board-investigate-whether-Detroit-overtaxing-property-owners.

[14] Assessors inventory properties by: identifying and tracking property by tax descriptions and parcel numbers, changing tax descriptions if properties are split by being re-platted or sold, and analyzing property improvements/losses.

[15] According to Michigan law, property must be assessed uniformly at 50 percent of true cash value. True cash value is also referred to as the properties "usual selling price" in an open market, with the sale being an arm's length transaction (Michigan Taxpayer's Guide, 2011).

value. Assessors are required to establish the market value of each property in the jurisdiction as of December 31 the previous year (a.k.a. Tax Day).

After Tax Day, additional steps are taken to monitor the accuracy of the municipality's assessed values and to insure that assessments are both equitable and at the appropriate level. By March each year, the City assessor must complete an assessment roll and submit a copy of the property's assessment to each property owner, as well as submit the assessment roll to be examined and approved by the March Board of Review. That is, the assessor must provide the true cash value (i.e. fair market value), assessed value (i.e. 50% true cash value), and taxable value of each property in the jurisdiction. At this time, property owners disagreeing with the valuation outlined by the assessor may file a petition to the Board of Review. Finally, upon the Board's approval of the assessment roll, the assessor delivers the roll to Wayne County Equalization and the Michigan State Tax Commission.[16] If property owners remain dissatisfied with assessment rulings by the Board of Review, they may file an appeal to the Michigan Tax Tribunal.[17]

3. LITERATURE ON ASSESSMENT INEQUITY

Early empirical research on assessment inequity focused on specifying the functional form to measure vertical inequity (Paglin and Fogarty, 1972; Cheng, 1974; IAAO, 1978; Kochin and Parks, 1982; Bell, 1984; Sunderman et al., 1990; Clapp, 1990), the functional form to measure horizontal equity (Berry and Bednarz, 1975; Goolsby, 1997; Allen and Dare, 2002), and

[16] The assessment roll is to be delivered to County Equalization either ten days after the board of review approves the roll or the Wednesday following the first Monday in April, whichever date occurs first.

[17] The Michigan Tax Tribunal handled 12,500 residential cases last year alone, of which 3,015 were from Detroit (McDonald, 2013).

the determinants of assessment inequity (Haurin, 1988; Birch, Sunderman and Hamilton, 1990; Borland, 1990; Benson and Schwartz, 1997; DeCesare and Ruddock, 1998; Smith, Sunderman, and Birch, 2003; Cornia and Slade, 2005; Cornia and Slade, 2006; McMillen and Weber, 2008; Ross, 2011; Ross, 2012; McMillen, 2013).[18] Recently, researchers have shifted their attention to a more thorough examination of assessment inequity by analyzing the distribution of assessment ratios. Given that this latter line of research is most relevant to the present research, we provide a more detailed review of these articles.[19]

McMillen and Weber (2008) examine assessment ratios in Chicago to determine if more sales in a census tract improve assessment uniformity (i.e. horizontal equity). While their analysis has important implications regarding determinants of assessment equity, the method they implement is of particular interest for this study. Rather than follow traditional regression approaches, McMillen and Weber use a multinomial logit model to examine assessment equity. With this approach, the distribution of assessment ratios and uniformity of assessments are evaluated by determining whether assessment ratios for particular properties are more (or less) likely to exist in the top or bottom of the distribution as the number of sales in the neighborhood increase. In addition, McMillen and Weber examine vertical inequity by testing whether or not higher sales prices increase the probability that assessment ratios are in the bottom of the distribution (i.e. regressivity). They conclude that high and low assessment ratios are more likely to occur in areas with fewer comparable sales; however, they are not able to support the idea that thin markets are responsible for more regressive distributions.

[18] Additional research has examined how the results of various vertical and horizontal specifications may differ (Sunderman et al., 1990; Sirmans, Diskin, and Friday, 1995; Benson and Schwartz, 1997; DeCesare and Ruddock, 1998; Smith, 2000; Cornia and Slade, 2005).
[19] For a review of papers examining horizontal and vertical inequity from assessment practices prior to 2008, see Sirmans, Gatzlaff, and Macpherson (2008).

McMillen (2011) also examines assessment ratios in Chicago, highlighting that traditional regression analysis is unable to fully evaluate the degree of variability in assessment ratios at different sales prices. He clearly makes the point that traditional regression analysis does not directly measure variability, and therefore is not well suited for analyzing assessment regressivity (or progressivity). McMillen then offers quantile regression analysis as an approach that enables one to examine how the full distribution of assessment ratios varies by sales price. Using quantile regression analysis to analyze assessment data from the City of Chicago, McMillen observes high variability in the assessment ratio at low sales prices, whereas both the variability and average assessment ratio decrease as the sales price increases. In other words, most of the regressivity is concentrated at low sales prices where the variance is high – a result that standard regression analysis would not reveal. In contrast, McMillen also examines assessment ratios for DuPage County, showing high ratios with low variance at low sales prices, but decreasing ratios and increasing variance the higher sales prices.

McMillen (2013) again examines assessment ratios in the City of Chicago, this time focusing on the effect of appeals on assessment ratios. This work is also of particular relevance to the current study as he examines the full distribution of assessement ratios using quantile regression techniques rather than focus on central tendencies. McMillen observes that while traditional methods indicate declining assessment ratios with increases in sales price, quantile regressions reveal that, "...the most pronounced degree of regressivity occurs at very low sales prices." That is, the variation of assessment ratios is much greater for low sales prices, and this, "...suggests that much of the apparent regressivity in assessments is attributable to the number of extremely high assessment ratios at low sales prices."

4. METHODS

4.1 Assessment Ratio and Equity

An assessment ratio is defined as the assessed value divided by the market value. While market values are essentially unobservable and associated with ideal conditions (Clapp, 1990), sales prices have traditionally been used as a proxy for market values since they are observable and readily available (McMillen and Weber, 2008). Furthermore, using the sales price in place of market value is acceptable in this study given the nature of Michigan assessment practices; assessments for the current year are to be completed by December 31 of the previous year, using sale price data from the previous year. To further ensure that sales prices are an appropriate proxy for market values, we restrict our examination of 2010 assessment ratios using data for properties sold in the previous year.

Concerning assessment equity, DeCesare and Ruddock (1998) provide the following definition: "The degree to which assessment bears a consistent relationship to market value for all properties at the assessment date." Perfect equity is exhibited when the ratio is constant regardless of the property value (Paglin and Fogarty, 1972).

4.2 Vertical Equity

Vertical inequity results when there are systematic differences in assessment ratios between properties of different values. These differences are considered regressive (progressive) when high-value (low-value) properties are assessed at lower rates relative to low-value (high-value) properties (DeCesare and Ruddock, 1998). As previously highlighted, traditional assessment equity research contains numerous specifications for detecting vertical inequity; Table 1 provides a summary of the various tests used by researchers to measure vertical inequity:

<Table 1: Tests for Vertical Inequity in Property Tax Assessments>

An important issue in the literature is the validity of models that examine equity using just two variables. As noted by DeCesare and Ruddock (1998), a simple bivariate model may result in omitted variable bias because assessments are likely influenced by other variables.[20] In the regression results presented later, we present the results from both the traditional bivariate models and multivariate models including property and location characteristics.

4.3 Horizontal Equity

Horizontal inequity is defined as the systematic difference in assessment ratios between properties that are similar in value and characteristics. In addition to the increasing awareness of assessor bias in favor of higher-valued properties, there is an expectation that assessors may consistently under- or over-assess properties with certain characteristics. Horizontal inequity in assessment practices has historically been concerned with these ‘other variables’. DeCesare and Ruddock (1998) recommend including a range of explanatory variables in vertical equity models. Most assessment ratio studies examine horizontal equity using the following model:

[1] $$SEV / P = \alpha_0 + \alpha_i X + u$$ (Berry and Bednarz, 1975)

where X is a vector of property and location characteristics. The null hypothesis to test horizontal equity is H_0: $\alpha_i = 0$. Consider the following example: if X represents a geographic location and the coefficient is positive and statistically significant, then the assessment ratio is higher for properties in that location compared to similar properties in other areas (Cornia and Slade, 2005). To properly measure horizontal equity, we must: 1) include sales price in X from equation [1] above (Goolsby, 1997; McMillen and Weber, 2008); 2) split the data into subsamples based on sales price (Cornia and Slade, 2005); and 3) split the data into subsamples based on assessed values (Allen and Dare, 2002).

[20] McMillen and Weber (2008) also suggest that the inclusion of additional variables is also relevant for measuring vertical equity.

An alternative method for measuring horizontal inequity was introduced by Allen and Dare (2002):

[2] $$\left|(SEV/P)_i - (\overline{SEV/P})\right| = \gamma_0 + \gamma_i X + \nu$$ (Allen and Dare, 2002)

where $(\overline{SEV/P})$ is the mean assessment ratio in the jurisdiction and X is a vector of property and location characteristics. The null hypothesis to test horizontal equity is $H_0: \gamma_i = 0$ and a rejection of the null hypothesis indicates there is horizontal inequity within the sample. A negative (positive) and statistically significant coefficient indicates decreasing (increasing) assessment error with an increase in the independent variable. For example, a positive coefficient for age indicates that older properties face increased assessment error as assessing older properties is a more difficult task (Allen and Dare, 2002).

Although there is no standardized list of variables to include in *X*, the variables often cited can be separated into three groups: 1) property characteristics; 2) neighborhood characteristics; and 3) homeowner characteristics. The property characteristics included in most studies of horizontal inequity include: age, living area, and lot size. However, the list of neighborhood characteristics varies substantially. Berry and Bednarz (1975) argue that becaused there are significant variations in assessment ratios for single-family homes between neighborhoods within major cities, inclusion of neighborhood characteristics is important. To address this issue, we include a set of neighborhood indicator variables.[21] Finally, homeowner characteristics considered in previous studies and implemented in the present analysis include: an

[21] Other neighborhood variables that have been implemented in the past include: per capita income by census tract (Ross, 2011 and 2012), number of sales in the neighborhood (Allen and Dare, 2002; McMillen and Weber, 2008; Ross, 2012), unemployment rate (Ross, 2011), and the proportion of properties in the area that are commercial or industrial (Ross, 2011). However, adding these variables with neighborhood indicator variables already included adds little to the model.

indicator variable identifying in-state vs. out-of-state residents, and and indicator variable identifying whether or not the property is the property owner's primary residence.

4.4 Quantile Regression Analysis

While measuring inequity "on average" provides a good initial assessment, observing the mean effect yields a limited perspective of how assessment practices affect the location of and shape of distributions (Buchinsky, 1994). To determine how the conditional distribution of assessment ratios varies given the covariates, we implement a quantile regression model (QRM).[22] In the context of assessment ratios, the quantile regression approach provides a more complete evaluation of equity because it shows whether the assessment practices creates a progressive, regressive, or non-linear ratios across property values. Predictions from quantile regressions enable one to examine changes in the distribution of the dependent variable because QRM allows the distribution of the dependent variable to differ from the covariate's underlying density – since the coefficients differ across quantiles. As an illustration of the difference between the quantile regression and the linear regression approaches, consider an example taken from McMillen (2012). Equation [3.1] provides the standard linear regression equation:

[3.1] $$E(y \mid X) = \beta_0 + \beta_1 x_1 + ... + \beta_i x_i + u$$

Where y is the dependent variable, x_i is independent variable i, and β is the coefficient. To see the effect on the distribution of y by changing the value of the covariate x_1 from δ_0 to δ_1, consider equations [3.2] and [3.3]:

[3.2] $$E(y \mid X, x_1 = \delta_0) = \hat{\beta}_0 + \hat{\beta}_1 \delta_0 + ... + \hat{\beta}_i x_i$$

[3.3] $$E(y \mid X, x_1 = \delta_1) = \hat{\beta}_0 + \hat{\beta}_1 \delta_1 + ... + \hat{\beta}_i x_i$$

[22] Koenker and Bassett (1978) first introduced the quantile regression model.

The distribution will shift right by $\hat{\beta}_1(\delta_1 - \delta_0)$ if $\hat{\beta}_1$>0 and will shift left by $\left|\hat{\beta}_1(\delta_1 - \delta_0)\right|$ if $\hat{\beta}_1$<0 while retaining the assumed shape of the normal distribution. This is known as a location shift (Hao and Naiman, 2007). While it may be reasonable to expect a parallel shift in the distribution of *y* in many contexts, it is a limitation we do not want to impose if we are interested in understanding how the distribution of *y* may change with respect to changes in the covariates.

To better understand how QRM enables one to estimate changes in the distribution of *y* as the covariates change (i.e. allows both a location and scale shift), consider a quantile regression model similar to that of Hao and Naiman (2007) where the *p*th conditional quantile specified as follows:

$$[4.1] \quad Q^{(p)}(y \mid X) = \beta_0^{(p)} + \beta_1^{(p)} x_1 + \ldots + \beta_i^{(p)} x_i + u^{(p)} \qquad , \quad 0 < p < 1$$

Here, the *p*th conditional quantile is determined by the quantile specific parameters, $\beta_0^{(p)}$ through $\beta_i^{(p)}$, and the values of each covariate. This approach allows one to trace out the entire conditional distribution of *y* as the quantiles are increased continuously from 0 to 1 (Buchinsky, 1998). The effect of covariates on the distribution of *y* across quantiles is illustrated by equations [4.2] and [4.3]:

$$[4.2] \quad Q^{(p)}(y \mid X, x_1 = \delta_0) = \hat{\beta}_0^{(p)} + \hat{\beta}_1^{(p)} \delta_0 + \ldots + \hat{\beta}_i^{(p)} x_i \qquad , \quad 0 < p < 1$$

$$[4.3] \quad Q^{(p)}(y \mid X, x_1 = \delta_1) = \hat{\beta}_0^{(p)} + \hat{\beta}_1^{(p)} \delta_1 + \ldots + \hat{\beta}_i^{(p)} x_i \qquad , \quad 0 < p < 1$$

Since $\hat{\beta}_1^{(p)}$ varies across quantiles, the conditional quantile functions imply a full distribution of values for *y*. Restated, changes in x_1 can result in both a scale shift ($\hat{\beta}_1^{(p)}$ differs across each quantile) and a relocation of the conditional distribution of *y*. In order to estimate a similar effect using standard regression analysis, one would need to make assumptions about the distribution and correctly specify the functional form. In the context of the present study, this is a difficult task because there is no clear theoretical basis for predicting how assessments might alter the distribution of assessment ratios across property values. In addition to the advantages outlined above, Buchinsky (1998) also shows that relative to standard ordinary least squares analysis, QRM is more robust to outliers and more efficient when the error term is non-normal.

Equations 4.2 and 4.3 allow us to present a series of graphs showing the effects of discrete changes in an explanatory variable on the full distribution of values for y. To do so, we estimate quantile regressions for p = [0.02, 0.03,…, 0.98]. Equations 4.2 and 4.3 each imply 97n predicted values – one for each i=1,…,n at each of 97 values of p. Kernel density estimates of the full set of predicted values for $x_1 = \delta_0$ show the full distribution of values of y conditional on $x_1 = \delta_0$, but unconditional with respect to the other variables. Kernel density functions can then be estimated for any other target value of x_1 to show how changes in this variable affect the overall distribution of y.

By using quantile regression techniques, the analysis presented in this paper offers a clear evaluation of: 1) the extent of assessment regressivity (i.e. vertical inequity); 2) the variation in assessments within property value groups (i.e. horizontal inequity); and 3) the distributional effect of property, location, and homeowner characteristics on horizontal equity.

5. DATA

The City of Detroit's Assessment Division provided parcel-level information for this research. Relevant information provided for each parcel in the City includes: 2010 assessed values (SEV), last sale date, last sale price, property characteristics, and homeowner characteristics. The full dataset includes information the 11,175 improved, single family, taxable properties that sold in 2009. Upon examining the data, three remaining issues required attention:

1) a number of properties were bundled and sold in a single transaction; 2) some properties had a sale price or assessed value equal to zero; and 3) a number of properties were owned by banks or other lending institutions. Bundled properties were excluded because the price of any single property within the bundle cannot be determined. Properties with a sale price or assessed value equal to zero were excluded because there is no known reason, other than error, for why a property would have zero value. Bank-owned properties were excluded for three reasons: 1) these likely represent "distressed" sales; 2) it is reasonable to expect that many of the bank-owned properties fall into disrepair, especially with the surge in foreclosures in recent years;[23] and 3) banks may have an incentive to overstate the value of foreclosed property.[24] Combined, these criteria eliminate 2,095 observations from the sample so that a total of 9,080 properties remain.

Finally, the International Association of Assessing Officers (IAAO, 2010) recommends trimming the sample of statistical outliers. The IAAO defines an outlier as an assessment ratio outside 1.5 multiplied by the interquartile range (IQR), where the IQR is the difference between the first and third quartiles. Furthermore, the IAAO (2010) notes that a distribution of ratios is often skewed to the right and suggests using the logarithmic transformation of assessment ratios to identify additional low and fewer high ratios as outliers. Table 2 shows the relevant statistics for trimming outliers using the logarithmic transformation. The lower bound for trimming is the first quartile minus 1.5 times the IQR and the upper bound is the third quartile plus 1.5 times the

[23] Without proper maintenance, foreclosed houses often suffer disrepair due to the weather (e.g. lack of heat in the winter) and are prone to vandalism (either by the homeowner being foreclosed on taking all they can, or intruders stealing copper piping and other metals to trade for cash).
[24] A comparison between bank-owned properties and the rest of the dataset highlights this concern. The average sales price of the 1,162 bank-owned properties is approximately $106,000 while the average sales price of the remaining properties is just $13,000. Banks' reluctance to record a loss seems to far outweigh (2) above.

IQR. The critical values for trimming are [-0.582, 4.578]. Following McMillen (2013), observations with sales prices that are below the 1st percentile or above the 99th percentile have also been eliminated. Combined, these criteria trim 430 observations (approximately 4.74%) from the sample.

<Table 2: Outlier Trimming>

In total, there are 8,650 observations in the final dataset. Summary statistics for the variables used in the analysis are presented in Table 3, and detailed definitions for these variables are provided in Appendix 1. Table 3 includes summary statistics for the full sample, as well as for five sub-groups based on the sales price.

<Table 3: Summary Statistics>[25]

From Table 3, the average assessment ratio is 11.87 but note that there are substantial differences across subsamples. Property owners with the lowest valued properties have an average assessment ratio that is much higher than the remaining groups and the assessment ratio declines as property values increase. Interestingly, the average assessment ratio for this sample is greater than one, regardless of the sales price quintile. These summary statistics provide initial evidence that that all properties are being over-assessed (on average). Observing systematic over-assessments is very rare: We found only one assessment ratio study where over-assessment was documented. In particular, Oldman and Aaron (1965) discovered properties in Boston with

[25] Although we would expect the statutory assessment ratio to equal 0.50 given the relationship between assessments and sales prices, we multiply the assessment portion of the ratio by two so the ratio may be compared with previous assessment ratio studies. Multiplying the assessed values by two leads to the expectation of assessment ratios that are equal (or close) to one.

assessment ratios greater than one; however, this result was true for only a few “questionable sales” that were not single-family properties.[26]

Two additional observations from Table 3 are worth noting: 1) despite large differences in assessment ratios across property values, property characteristics are very similar; and 2) the number of property owners claiming the property as their principal residence increases as the sales price increases.

6. RESULTS

6.1 Traditional IAAO Measures of Regressivity

Using the traditional measures of regressivity outlined by the IAAO, Detroit’s assessments are both variable and regressive by several measures. Table 4 presents the traditional statistics measuring assessment regressivity for the full sample, as well as for five sub-groups.

<Table 4: Traditional Assessment Performance Measures>

Although the mean provides an initial look at assessment regressivity, two simple techniques for evaluating assessment ratio uniformity are recommended by the IAAO. The price-related differential (PRD), a descriptive statistic, is the primary statistic recommended by the IAAO for evaluating the extent of assessment regressivity.[27] Although the statistic has a slight upward bias, IAAO standards call for the PRD to be between 0.98 and 1.03; differentials above 1.03 indicate assessment regressivity and differentials below 0.98 indicate progressivity. Examining the PRD for full-sample, the value far exceeds the IAAO’s upper limit of 1.03.

[26] "Questionable sales" are properties for which the Metropolitan Mortgage Bureau of Boston had reason to doubt the accuracy of information obtained from the Registry of Deeds.
[27] The PRD is calculated by dividing the arithmetic mean by the value-weighted mean (IAAO, 2010).

Examining the differentials calculated for each sales price quintile, all quintiles show some level of regressivity (PRD>1); however, only the first and fifth quintile (i.e. lowest and highest valued properties, respectively) exceed the upper limit defined by the IAAO.

The second measure of assessment uniformity recommended by the IAAO is the coefficient of dispersion (COD).[28] The COD is the traditional measure of assessment variability and assessments are considered uniform if the COD is between 5 and 15 for single-family residential properties (IAAO, 2010). With a value of 109.55, Detroit's COD indicates variability greatly exceeding IAAO's acceptable range (i.e. very low uniformity). Therefore, we can conclude that a traditional assessment ratio study implies both regressivity and variability of Detroit's assessment ratios that far exceed the standards set forth by the IAAO. Breaking the traditional analysis into sale price quintiles, each quintile exhibits variability exceeding IAAO standards, whereas only the lowest and highest valued properties exceed IAAO standards of regressivity.

6.2 Vertical Inequity: Traditional Statistical Analysis

A more formal IAAO-recommended procedure to measure assessment regressivity is regression analysis. Following the traditional regression methods presented above (Table 1), Table 5 presents the regression results that examine vertical inequity in Detroit. It has been recognized that most traditional models use a bivariate approach; however, as DeCesare and Ruddock (1998) note, differences in assessment levels can only be "properly identified when other attributes that influence this relationship are clearly represented in the model." Therefore, the fourth column of Table 5 presents multivariate regression results using the variables

[28] According to IAAO (2010), the COD is calculated by the following steps: 1) subtract the median from each assessment ratio, 2) take the absolute value of calculated differences, 3) sum the absolute values, 4) divide by the number of ratios, 5) divide by the median, and 6) multiply by 100.

previously discussed. The conclusions of the bivariate and multivariate models are identical; assessment regressivity is generally observed across all methods with the exception that the Kochin and Parks (1982) model indicates progressivity. Measuring progressivity using the Kochin and Parks model is a common finding in the literature since the model is biased towards progressivity (Clapp, 1990). Clapp (1990) claims to correct this bias in his model and as the results from the Clapp model show, regressivity is observed when the Kochin and Parks bias is corrected.

<Table 5: Traditional Results for Vertical Inequity>

To thoroughly examine assessment regressivity in Detroit, we must also analyze the degree of regressivity. Following McMillen (2011), we can examine the variability of assessments in Detroit using standard regression analysis by estimating the functions from the IAAO vertical equity model.[29] The estimated functions are presented in Figure 1. The straight line in the figure is the estimation from a simple linear regression, and the curved line is from a nonlinear estimation (locally weighted regression). As shown in Figure 1, both approaches indicate that assessment ratios fall as sales prices increase (i.e. regressivity exists); however, the linear models simply shows the average slope across observations while the nonlinear estimation indicates that the expected assessment ratios are extremely high at very low sales prices with the estimates appearing to become horizontal for properties greater than $30,000. Figure 2 provides a closer examination of the nonlinear regression estimates for properties worth more than $30,000; the assessment ratios continue to decrease as property values increase – properties worth more than $70,000 begin to see average assessment ratios equal to one. Furthermore,

[29] I focus on the IAAO (1978) model for the remainder of this section due to its widespread use and ease of interpretation. Most studies generally focus on the IAAO and/or the Paglin and Fogarty (1972) model, or some variant of the Paglin and Fogarty model (i.e. Cheng (1974) and Bell (1984) models).

properties worth more than $70,000 have ratios that are half the ratio of properties worth $30,000-$40,000 and substantially smaller than properties worth less than $10,000.

<Figure 1: Regression Estimates>

<Figure 2: Nonlinear Regression Estimates for Sales > $30,000>

6.3 Vertical Inequity: Quantile Regression Analysis

While the standard regression analysis undertaken thus far is useful for showing that assessment ratios in Detroit vary with sales prices (in a regressive nature), standard regressions techniques are too restrictive to accurately represent the relationship between assessment ratios and sales prices and are now helpful for highlighting the variability of assessment practices (McMillen, 2012). That is, standard regressions do not address the degree of assessment ratio variability at different sales prices (McMillen, 2011). We now turn to the quantile regression approach, which allows us to examine how the full distribution of assessment ratios varies by sales price, offering additional insight.

The standard quantile regression estimates for the vertical equity model is presented in Table 6, and the quantile regression coefficients for quantiles ranging from p = 0.02, 0.03, ..., 0.98 are presented in Appendix 2.[30] Mirroring the OLS results, the estimates presented in Table 6 imply that assessment ratios are lower for more expensive properties. Focusing on the coefficients for *Sales Price* across quantiles, the slope is much steeper at the 90% quantile than at the 10% quantile – indicating that assessment ratios are converging as property sale prices increase (i.e. the distribution's variance decreases).

<Table 6: Quantile Regression Results for Vertical Inequity>

[30] Quantile regression estimates for *Sales Price* are identical in the multivariate model. These results are highlighted in Table 8.

To more formally examine whether or not the assessment ratio's variance decreases as the price of property increases (i.e. scale shift), consider the difference between coefficient estimates across quantiles. The difference between the 10% and 90% quantiles is presented in the last column of Table 6. The difference statistically significant; that is, the distribution of assessment ratios narrows as the sales price increases.

While examining the changes in the assessment ratio's variance is relatively straightforward, the results presented in Table 6 require some additional explanation. Interpretation of the quantile regression estimates is perhaps most easily understood with graphical illustrations of how the distribution changes as an explanatory variable takes on different values. Figure 3 presents the predicted values from a nonparametric quantile regression of assessment ratios on sales prices.[31] The results suggest that assessment ratios are relatively high at all quantiles for low prices, with high variability displayed such that there is a large spread between the 10 and 90 percent quantile lines. As the sale price increases beyond $30,000, the regression lines appear horizontal and the variability disappears. A closer examination is offered in Figures 4 through 7; both the assessment ratios and their variability continue to decrease as the sales price increases. An alternative method of showing these results is to graph the estimated conditional density functions of assessment ratios. Figure 8 presents the estimated conditional density functions of assessment ratios for properties in the first, third, and fifth sales price quintiles. Assessment ratios are tightly clustered around one for high-value properties (quintile 5). However, the distribution shifts to the right and has a much greater variance as the sales price decreases. Figure 8 also highlights that the traditional results were derived from both

[31] The regressions are estimated using a tri-cube kernel weight function and a window size of 10%.

a scale and location shift. Together, Figure 3 through 8 provides a clear evaluation of degree of inequity resulting from assessment practices.

6.4 Horizontal Inequity: Traditional Statistical Analysis

Table 7 provides the traditional horizontal equity results.[32] Consider first the results of property characteristics. The coefficient on *Age* is positive and statistically significant, the coefficient on *Living Area* is negative and statistically significant (second column), and the coefficient on *Lot Size* is statistically insignificant. Interpreting these results from the first column, older houses have higher assessment ratios, all else equal. From the second column, older houses have increased assessment error while larger houses experience decreased assessment error, indicating that assessing older properties is perhaps a more difficult task and assessing larger houses is easier. These results seem plausible since it is reasonable to expect assessors have a more difficult time assessing older houses since the variation in property conditions is likely much larger relative to newer houses. Concerning the plausibility of the coefficient for living area in the second column, there is a larger number of big houses relative to small houses and this provides assessors more observations from which to make their assessment, all else equal.[33]

<Table 7: Traditional Results for Horizontal Inequity>

Consider next the effects of homeowner characteristics on horizontal equity. The coefficients on *MI Resident* and *PRE* are negative and statistically significant, indicating that those who live in Michigan (but not necessarily on the property), have lower assessment ratios

[32] Following Goolsby (1997), I also considered the log-log specification of the traditional approach and the results did not change.

[33] I examined the relative number of small versus big houses by comparing the number of properties lower than one standard deviation from the mean *Living Area* with the number of properties greater than one standard deviation.

and decreased assessment errors than non-Michigan property owners. In addition, those claiming the house as their principal residence (*PRE*) have lower assessment ratios and decreased assessment errors relative to those not living on the property. One possible explanation for these results is that while Detroit assessors seek to mitigate tax base erosion by over-assessing properties, they also seek to minimize community backlash and tax appeals. With these goals in mind, assessors may follow Michigan law more closely for those most familiar with Michigan's property tax law (i.e. Michigan residents) and value property closer to the market for those most familiar with current market conditions (i.e. Detroit residents).

Finally, consider the effects of neighborhood on assessment ratios. The coefficients on *District 3*, *District 4*, *District 5*, *District 7*, *District 8*, *District 9* and *District 10* are all negative and statistically significant.[34] These results indicate that assessment practices are not uniform across the city and similar properties in different parts of the city have lower assessment ratios, or experience decreased assessment error.

6.5 Horizontal Inequity: Quantile Regression Analysis

There are two primary approaches for examining horizontal equity. The first is a literal examination of horizontal equity as defined by Sirmans, Gatzlaff, and Macpherson (2008): "like properties having the same market values are assessed differently." Rather than strictly examining horizontal inequity by controlling for property value and estimate how various characteristics change assessment uniformity (as the previous research has done), it is useful to also examine how assessments vary for properties within the same value class while holding property characteristics constant. That is, horizontal inequity can be examined by analyzing the distribution of assessment ratios within property value groups. To do this, consider again

[34] *District 1* is the omitted category. Thus, these districts have lower assessment ratios than *District 1*, whereas *Districts 2* and *6* are not significantly different than *District 1*.

assessment ratio distributions previously highlighted in Figure 8, except now we want to focus on individual property value distributions rather than on how the different groups differ. With this approach we ahold property characteristics constant so that we can examine how similar properties with the same market value group are assessed differently. These results show that there is substantial inequity among low value properties (large variance) with some low value properties experiencing ratios close to one and others greater than thirty.

Following the more traditional approach for examining horizontal inequity, we again use quantile regression techniques to estimate the average effects derived from traditional analysis, but here we can determine whether the results are derived from a location shift (mean), scale shift (variance), or both. Quantile regression estimates for the horizontal equity model is presented in Table 8, and the quantile regression coefficients for quantiles ranging from p = 0.02, 0.03, ..., 0.98 are presented in Appendix 3. These results highlight the limitations of the traditional regression analysis since that approach does not identify the variation across quantiles. Focusing on the coefficients for *Age*, the slope is negative at the 10% quantile and positive at the 90% quantile – an indication that age affects assessment ratios across the distribution differently and that the assessment ratios are diverging as the property age increases (i.e. the distribution's variance increase).

<Table 8: Quantile Regression Results for Horizontal Inequity>

To more formally examine whether or not the assessment ratio's variance decreases as the property characteristics change (i.e. scale shift), the difference between coefficient estimates across quantiles is tested; this difference is presented in the last column of Table 8. As discussed earlier, examining the changes in the assessment ratio's variance is relatively straightforward, but the quantile regression estimates in Table 8 areperhaps most easily understood with graphical illustrations of how the distribution changes as an explanatory variable takes on different values. These results are presented in Figures 9 through 16.

The quantile regression results offer a much richer evaluation relative to traditional regression analysis. Regarding property characteristics, while the mean results for *Age* show that the assessment ratios increases for older properties, the quantile regression results demonstrate that the mean effect is the result of increased variance (i.e. scale shift greater than location shift). As shown in Figure 9, the peak of the assessment ratio distribution for older properties is to the left of the peak for newer properties, but note that the variance is also much larger for older properties. In other words, newer properties are subject to more uniform assessments (i.e. smaller variance), but the overall distribution is at a higher rate. There was no difference in the assessment ratios across house size (Column 1 of Table 7). However, the quantile regression results indicate that the variance decreases for larger properties (i.e. more uniform assessments) and this is consistent with the conclusion drawn from the Allen and Dare model (Column 2 of Table 7) **–** "decreased assessment error." Finally, as shown in Figure 11 *Lot Size* has no effect on mean assessment ratios from the traditional approach and no variance change from the quantile approach.

Recall that the traditional models show that Michigan residents and those occupying the property as their primary residence (*PRE*) have lower assessment ratios as well as a decrease in assessment errors. In the quantile regressions we see that estimated conditional density functions of assessment ratios shows (Figures 12 and 13), the mean effect is derived mainly by a scale change (i.e. decreasing variance). Last, it appears that only districts four and five experienced location shifts (i.e. mean shifts) that led to the mean effects drawn above (District 5 also undergoing a scale shift), whereas all the other effects derived above were the result of scale shifts.

7. PROPERTY TAX IMPLICATIONS

Vertical and horizontal assessment inequity has important implications for individual property tax bills that can be illustrated with a simplified example of residential tax payments in Detroit. If Detroit assessors strictly assessed properties at 50% the market value of property, a \$1,700 property would be assessed at \$850 and a \$37,000 property would be assessed at \$18,500 (Table 9). Based on these assessments and the full millage rate of residential properties in Detroit, the estimated tax bill of the \$1,700 property would be \$72 and the tax bill of the \$37,000 property would be \$1,562 – each would pay an amount proportionate to the market value of their property (4.22%).

<Table 9: Assessment Equity>

Table 10 illustrates vertical inequity by comparing assessed values and estimated tax bills using the assessment ratios highlighted in Figure 8 (i.e. assessments are regressive and more variable for lower valued properties). The estimated assessment ratios for the lowest valued properties (Quintile 1) range from 4 to 28, whereas the range for the highest valued properties is only 0.5 to 5. Although tax payments for low-value property owners will generally be lower than the tax payments for high-value property owners, the effective tax rates of low-value property owners are much higher.[35] Only a small number of high-valued properties are subject to effective tax rates greater than low-value properties.

[35] For purposes of this paper, effective tax rates equal the tax payment divided by the properties market value (i.e. sale price). Although the standard approach for measuring effective tax rates requires dividing the tax payment by the assessed value, this would simply yield the millage rate in our numerical example. Furthermore, calculating the effective tax rate as we have done here

<Table 10: Vertical and Horizontal Inequity>

In addition to the inequity between property value groups, there are also substantial inequities within property value groups. As discussed earlier, there are two approaches to measuring horizontal inequity: 1) examine tax payment differences within property value groups (Table 10), and 2) examine tax payment differences based on property characteristics (Table 11). Table 10 shows that actual tax payments vary significantly for otherwise identical homes – from $570 to $4,020 for the lowest valued properties and from $1,560 to $15,620 for the highest valued properties. In other words, a homeowner may receive a tax bill that is 7 to 10 times higher than their neighbor even if both property owners paid the same price for their property. Finally, Table 11 examines horizontal inequity based on the age of the house. Using assessment rates from Figure 9 and estimating the tax bills based on these rates, older houses have lower assessment rates, on average, but are subject to more variable rates – with some properties experiencing higher rates than newer houses.

<Table 11: Horizontal Inequity (Market Value = $13,000)>

8. CONCLUSION

This study offers an evaluation of vertical and horizontal inequity created by assessment practices during a period of disequilibrium such as the one created by the recent housing crisis. Using parcel level data from the City of Detroit, we use traditional IAAO measures, regression analysis and quantile regression techniques to assess the degree of assessment inequity across Detroit property owners. By all measures, assessment practices are vertically inequitable (i.e. regressive). The IAAO and traditional regression approaches highlight regressivity; however,

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offers a "true effective tax rate." That is, the rate the owner pays rather than what they may have expected to pay if their properties assessment had reflected the sales price.

additional insight is gained by using quantile regression analysis. Specifically, the variability of assessment ratios decreases as the price of properties increase, offering a clear illustration of how assessment practices violate vertical equity. In addition, our analysis shows how assessment practices generate significant horizontal inequity: properties of similar value and characteristics face substantial differences in assessment ratios and tax payments. Following traditional approaches, assessment ratios were shown to differ substantially across property, household, and neighborhood characteristics.

As a final note, our analysis is not equivalent to an actual appraisal study. There are a number of possible explanations for the differences between our evaluation and the actual assessments. The City's assessments are based on a much smaller number of comparable sales.[36] Our comparison is based on aggregate data, rather than the evaluation of individual properties. The City may employ one of the other accepted approaches to property valuation, such as the cost approach or income capitalization method. We also note that, as with all local jurisdictions in Michigan, the State Tax Commission provides oversight of Detroit assessments. In other words, the assessments are reviewed and approved at both the county and State level. Nevertheless, our evaluation highlights the substantial differences that exist between actual selling prices and assessed values. This analysis suggests that, at a minimum, the City is likely to continue receiving a large number of property tax assessment appeals.[37]

[36] As previously noted, the most recent sales study included only 684 sales (or 5.6 percent) of the city's 12,118 home sales from October 2011, to September 2012.
[37] Again, the Michigan Tax Tribunal handled 3,015 residential cases from Detroit last year alone.

Table 1: Tests for Vertical Inequity in Property Tax Assessments

Model	Null Hypothesis (no inequity)	Evidence of Regressivity	Source
$AV = \beta_0 + \beta_1 SP + \varepsilon$	$\beta_0 = 0$	$\beta_0 > 0$	Paglin and Fogarty (1972)
$\ln AV = \beta_0 + \beta_1 \ln SP + \varepsilon$	$\beta_1 = 1$	$\beta_1 < 1$	Cheng (1974)
$AV / SP = \beta_0 + \beta_1 SP + \varepsilon$	$\beta_1 = 0$	$\beta_1 < 0$	IAAO (1978)
$\ln SP = \beta_0 + \beta_1 \ln AV + \varepsilon$	$\beta_1 = 1$	$\beta_1 > 1$	Kochin and Parks (1982)
$AV = \beta_0 + \beta_1 SP + \beta_2 SP^2 + \varepsilon$	$\beta_0 = \beta_2 = 0$	$\beta_0 > 0, \beta_2 < 0$	Bell (1984)
$AV = \beta_{00} + \beta_{10} SP + \beta_{01} Low + \beta_{02} High + \beta_{11} LowSP + \beta_{12} HighSP + \varepsilon$	$\beta_{00} = \beta_{01} = \beta_{02} = 0$	$\beta_{00} > 0$ *	Sunderman et al. (1990)
$\ln SP = \beta_0 + \beta_1 \ln AV + \varepsilon$ $\ln AV = b_0 + b_1 Z + u$	$\beta_1 = 1$	$\beta_1 > 1$	Clapp (1990)

Notes:

AV = Assessed value
SP = Market value (measured by sales price)
Low = Indicator variable equal to one if the sale price is in the lower knot, zero otherwise
$High$ = Indicator variable equal to one if the sale price is in the upper knot, zero otherwise
Z = -1 if AV and SP rank in the bottom third of the data; +1 if AV and SP rank in the top third of the data; zero otherwise

* $\beta_{00} > 0$ indicates regressive for middle price range. Low and High measure whether the intercepts for these groups are different from the middle group

Table 2: Outlier Trimming

	log(Assessment Ratio)	Sales Price
1st Percentile	-0.750	1
25th Percentile	1.353	3,498
Median	1.988	7,500
75th Percentile	2.643	15,000
99th Percentile	10.545	93,812
Lower Bound for Trimming	-0.582	1
Upper Bound for Trimming	4.578	93,812

Table 3: Summary Statistics

Variable	Full Sample Mean	Full Sample Std. Dev.	Quintile 1 Mean	Quintile 1 Std. Dev.	Quintile 2 Mean	Quintile 2 Std. Dev.
Assessment Ratio	11.87	14.08	30.43	19.51	11.57	4.315
SEV (x2)	56,119	22,707	41,229	16,137	49,996	17,442
Sale Price	12,667	15,370	1,711	797.3	4,413	705.4
Age	6.666	1.357	6.970	1.425	6.678	1.318
Living Area	1,131	499.7	1,091	514.3	1,068	476.2
Lot Size	830.7	200.3	804.2	195.3	816.2	185.9
MI Resident	0.856	0.351	0.790	0.408	0.902	0.297
PRE	0.355	0.478	0.204	0.403	0.331	0.471
District 1	0.090	0.287	0.152	0.359	0.099	0.298
District 2	0.166	0.372	0.201	0.401	0.204	0.403
District 3	0.083	0.276	0.081	0.274	0.074	0.262
District 4	0.010	0.101	0.018	0.132	0.012	0.108
District 5	0.074	0.261	0.044	0.205	0.065	0.247
District 6	0.054	0.227	0.094	0.292	0.069	0.254
District 7	0.198	0.398	0.182	0.386	0.223	0.417
District 8	0.137	0.344	0.116	0.320	0.106	0.308
District 9	0.127	0.333	0.087	0.282	0.118	0.323
District 10	0.060	0.237	0.025	0.156	0.029	0.169
# of Obs.	8,650		1,929		1,531	

Table 3: (cont'd)

	Quintile 3		Quintile 4		Quintile 5	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Assessment Ratio	7.749	2.564	5.095	1.795	2.202	1.344
SEV (x2)	57,724	17,982	65,308	21,057	67,501	27,752
Sale Price	7,577	1,152	13,177	2,438	37,645	19,006
Age	6.586	1.269	6.475	1.316	6.588	1.385
Living Area	1,094	470.4	1,168	492.6	1,235	521.5
Lot Size	825.5	182.0	847.8	195.5	862.2	233.4
MI Resident	0.876	0.329	0.890	0.313	0.833	0.374
PRE	0.362	0.481	0.418	0.493	0.475	0.500
District 1	0.075	0.263	0.052	0.222	0.069	0.253
District 2	0.186	0.390	0.124	0.329	0.115	0.320
District 3	0.076	0.264	0.086	0.280	0.099	0.299
District 4	0.007	0.086	0.006	0.075	0.009	0.094
District 5	0.073	0.260	0.099	0.299	0.089	0.284
District 6	0.039	0.193	0.026	0.159	0.042	0.200
District 7	0.207	0.405	0.201	0.401	0.181	0.385
District 8	0.125	0.331	0.162	0.369	0.177	0.382
District 9	0.159	0.366	0.153	0.360	0.118	0.323
District 10	0.053	0.223	0.092	0.289	0.101	0.302
# of Obs.	1,748		1,770		1,672	

Table 4: Traditional Assessment Performance Measures

		Sales Price Quintile				
	Full Sample	1	2	3	4	5
Price-Related Differential (PRD)	2.679	1.263	1.021	1.017	1.028	1.228
Coefficient of Dispersion (COD)	109.555	58.951	28.904	25.473	27.393	57.881

Table 5: Traditional Results for Vertical Inequity

Model	**Regression Results**	β_0 **or** β_1 **(bivariate)**	β_0 **or** β_1 **(multivariate)**	**Conclusion**
$AV = \beta_0 + \beta_1 SP + \varepsilon$	$\beta_0 > 0$	50,603*** (282.02)	35,465*** (3,919.5)	Regressive
$\ln AV = \beta_0 + \beta_1 \ln SP + \varepsilon$	$\beta_1 < 1$	0.1739*** (0.0047)	0.1041*** (0.0040)	Regressive
$AV / SP = \beta_0 + \beta_1 SP + \varepsilon$	$\beta_1 < 0$	-0.0004*** (9.97e-06)	-0.0004*** (9.52e-06)	Regressive
$\ln SP = \beta_0 + \beta_1 \ln AV + \varepsilon$	$\beta_1 < 1$	0.9323*** (0.0234)	0.8407*** (0.0301)	Progressive
$AV = \beta_0 + \beta_1 SP + \beta_2 SP^2 + \varepsilon$	$\beta_0 > 0$	$44,597*** (361.75)	31,608*** (3,939.7)	Regressive at an accelerating rate
	$\beta_2 < 0$	- 0.00001*** (7.07e-07)	-8.35e-06*** (5.45e-07)	
$AV = \beta_{00} + \beta_{10} SP + \beta_{01} Low + \beta_{02} High$ $+ \beta_{11} LowSP + \beta_{12} HighSP + \varepsilon$	$\beta_{00} > 0$	42,850***	30,596***	Regressive
	$\beta_{01} > 0$	34,819***	28,156**	
	$\beta_{02} > 0$	66,725***	46,686***	
$\ln SP = \beta_0 + \beta_1 \ln AV + \varepsilon$ $\ln AV = b_0 + b_1 Z + u$	$\beta_1 > 1$	2.4529*** (0.0360)	3.3303*** (0.0710)	Regressive

Notes: Standard errors are in parentheses and regressions are corrected for heteroskedasticity. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 6: Quantile Regression Results for Vertical Inequity

	Quantile			
Independent Variable	10%	50%	90%	90% - 10%
Constant	5.830*** (0.074)	10.753*** (0.074)	30.622*** (0.816)	24.792*** (0.757)
Sales Price	-0.0002*** (3.70e-06)	-0.0003*** (3.71e-06)	-0.0004*** (0.00004)	-0.0002*** (0.00002)
# of Obs.	8,650			

Notes: Standard errors are in parentheses and the standard errors for the last column are from 100 bootstrap replications. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 7: Traditional Results for Horizontal Inequity

Independent Variable	Berry and Bednarz (1975)	Allen and Dare (2002)
Constant	19.2562***	9.4177***
	(1.3422)	(1.1357)
Sale Price	-0.0004***	-0.00002***
	(9.58e-06)	(5.72e-06)
Age	0.4502***	0.6944***
	(0.1429)	(0.1209)
Living Area	0.0002	-0.0011***
	(0.0004)	(0.0003)
Lot Size	-0.0007	0.0011
	(0.0009)	(0.0008)
MI Resident	-3.1483***	-2.9221***
	(0.5043)	(0.4338)
PRE	-1.9140***	-1.6447***
	(0.2496)	(0.2094)
District 2	0.6699	-0.5853
	(0.6304)	(0.5418)
District 3	-2.2243***	-1.4108**
	(0.7040)	(0.5887)
District 4	-4.6086***	-0.5618
	(1.7556)	(1.3847)
District 5	-6.6642***	-1.6848***
	(0.7249)	(0.5980)
District 6	-1.0994	-0.8787
	(0.9119)	(0.7776)
District 7	-2.0639***	-1.8861***
	(0.5752)	(0.4847)
District 8	-0.8046	-0.9845*
	(0.6191)	(0.5246)
District 9	-3.1283***	-2.6460***
	(0.6054)	(0.5101)
District 10	-4.0245***	-2.2526***
	(0.6542)	(0.5393)
# of Obs.	8,650	
R-squared	0.223	0.033

Notes: Standard errors are in parentheses and regressions are corrected for heteroskedasticity. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 8: Quantile Regression Results for Horizontal Inequity

Independent Variable	Quantile 10%	Quantile 50%	Quantile 90%	Quantile 90% - 10%
Constant	7.8570***	12.0601***	40.5374***	32.6804***
	(0.3834)	(0.6021)	(4.5188)	(3.7514)
Sales Price	-0.0002***	-0.0003***	-0.0003***	-0.0002***
	(2.77e-06)	(4.35e-06)	(0.00003)	(0.00001)
Age	-0.3647***	0.0195	1.4607***	1.8254***
	(0.0406)	(0.0638)	(0.4789)	(0.3703)
Living Area	0.0006***	0.0010***	-0.0019	-0.0024**
	(0.0001)	(0.0002)	(0.0016)	(0.0010)
Lot Size	-0.0006**	-0.0008*	-0.0022	-0.0017
	(0.0003)	(0.0005)	(0.0034)	(0.0024)
MI Resident	0.2266*	-0.8582***	-8.7964***	-9.0230***
	(0.1231)	(0.1933)	(1.4507)	(2.2038)
PRE	0.2021**	-0.2677*	-6.3468***	-6.5489***
	(0.0913)	(0.1433)	(1.0754)	(0.8231)
District 2	1.2089***	0.6439**	-1.7769	-2.9858
	(0.1706)	(0.2678)	(2.0101)	(2.0427)
District 3	0.3996**	-1.3169***	-7.0202***	-7.4198***
	(0.2015)	(0.3165)	(2.3752)	(2.4499)
District 4	-2.1746***	-3.6773***	-8.7414*	-6.5668
	(0.4441)	(0.6973)	(5.2336)	(5.8645)
District 5	-0.7646***	-4.2822***	-17.4850***	-16.7204***
	(0.2169)	(0.3406)	(2.5564)	(1.9693)
District 6	0.1358	-0.3569	-3.6313	-3.767
	(0.2433)	(0.3820)	(2.8670)	(2.9628)
District 7	0.6443***	-1.0197***	-8.8688***	-9.5131***
	(0.1663)	(0.2611)	(1.9597)	(1.7461)
District 8	0.7947***	-0.6072**	-6.4476***	-7.2422***
	(0.1784)	(0.2802)	(2.1028)	(1.9880)
District 9	0.7580***	-1.4353***	-10.9468***	-11.7048***
	(0.1805)	(0.2835)	(2.1275)	(1.9795)
District 10	0.7741***	-2.0576***	-13.0811***	-13.8552***
	(0.2220)	(0.3487)	(2.6168)	(1.9038)
# of Obs.	8,650			

Notes: Standard errors are in parentheses and the standard errors for the last column are from 100 bootstrap replications. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 9: Assessment Equity

	Quintile 1	Quintile 5
Average Market Value	$1,700	$37,000
Assessment Rate (50%)	0.50	0.50
Assessed Value	$850	$18,500
Full Millage Rate	0.08444	0.08444
Estimated Tax Bill	$72	$1,562

Table 10: Vertical and Horizontal Inequity

	Quintile 1			Quintile 5		
Average Market Value		$1,700			$37,000	
Assessment Rate	4	16	28	0.5	2	5
Assessed Value	$6,800	$27,200	$47,600	$18,500	$74,000	$185,000
Full Millage Rate		0.08444			0.08444	
Estimated Tax Bill	$574	$2,297	$4,019	$1,562	$6,249	$15,621
Effective Tax Rate	33.78%	135.10%	236.43%	4.22%	16.89%	42.22%

Table 11: Horizontal Inequity (Market Value = $13,000)

Age	**11**		**0**	
Assessment Rate	5	24	9	19
Assessed Value	$65,000	$312,000	$117,000	$247,000
Full Millage Rate	0.08444		0.08444	
Estimated Tax Bill	$5,489	$26,345	$9,879	$20,857
Effective Tax Rate	42.22%	202.66%	76.00%	160.44%

Figure 1: Regression Estimates

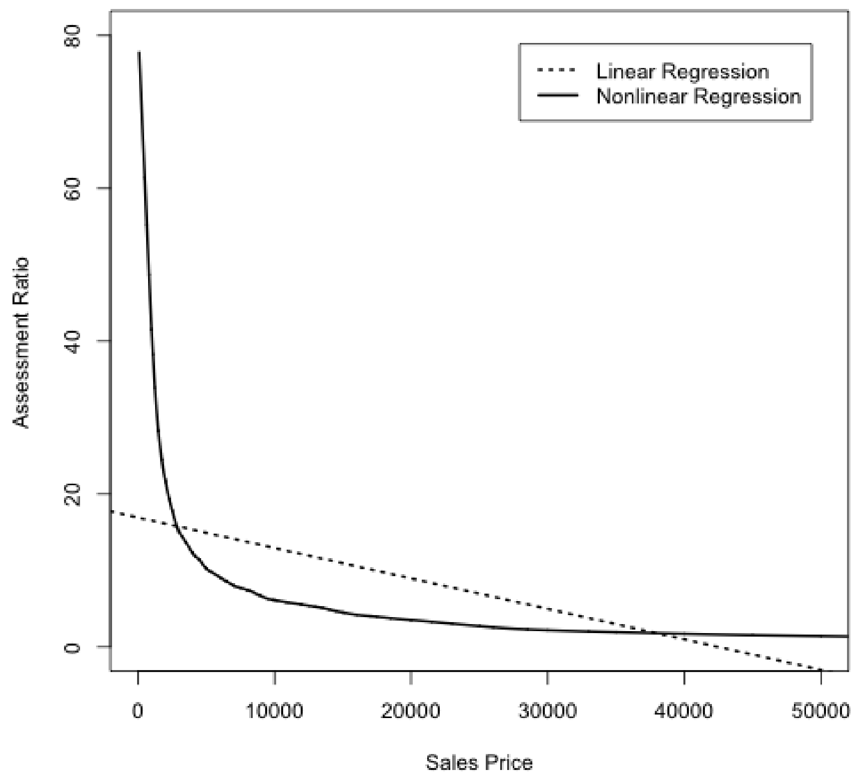


Figure 2: Nonlinear Regression Estimates for Sales > $30,000

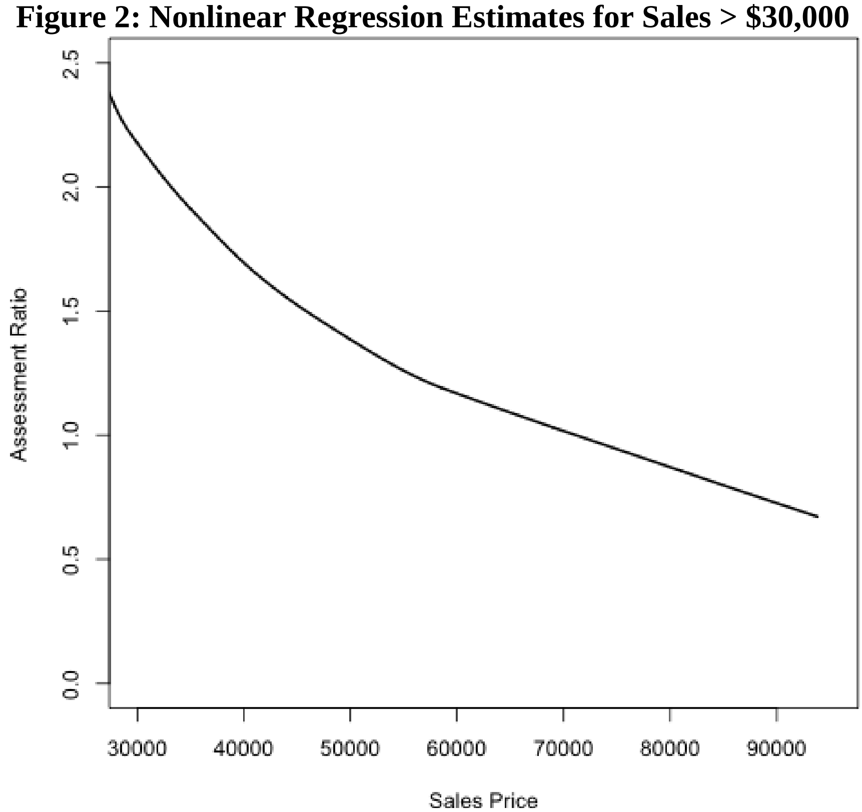


Figure 3:

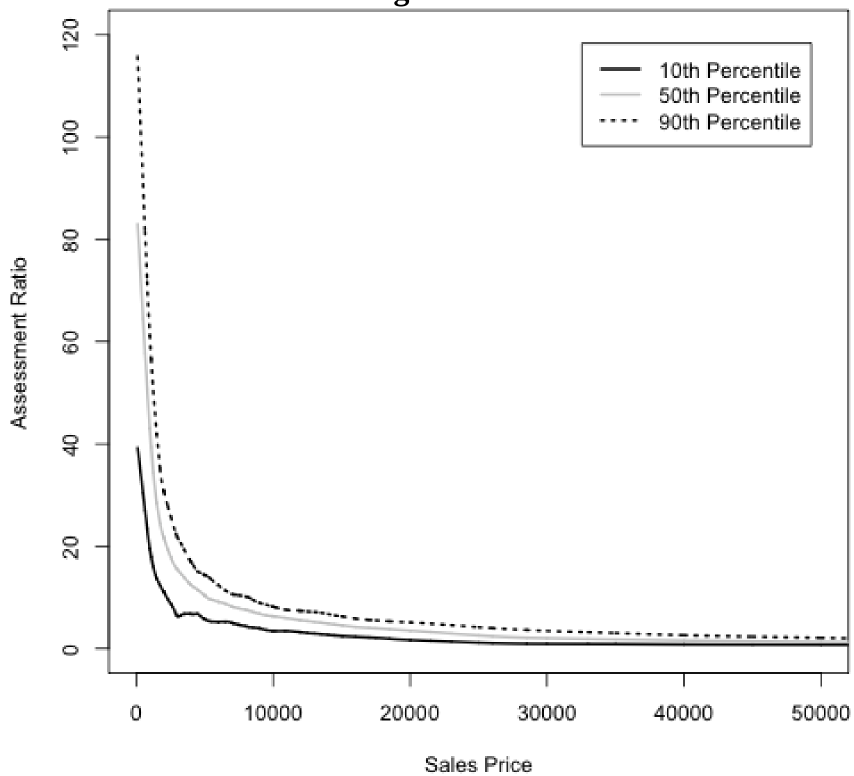

10th Percentile
50th Percentile
90th Percentile
Assessment Ratio
0
20
40
60
80
100
120
0
10000
20000
30000
40000
50000
Sales Price

Figure 4:

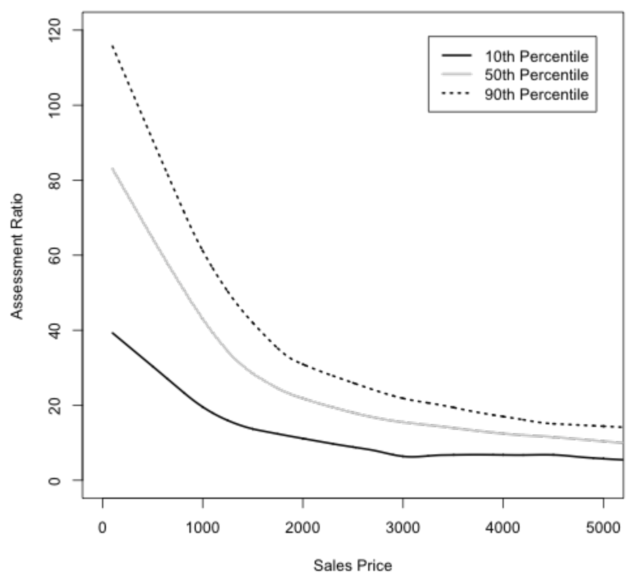


Figure 5:

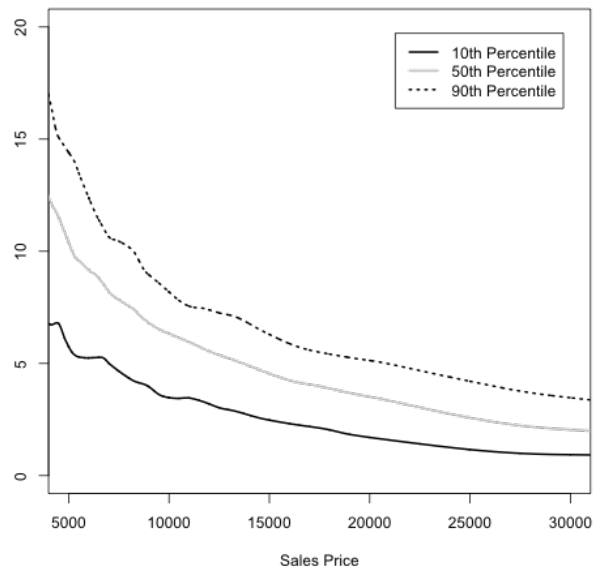
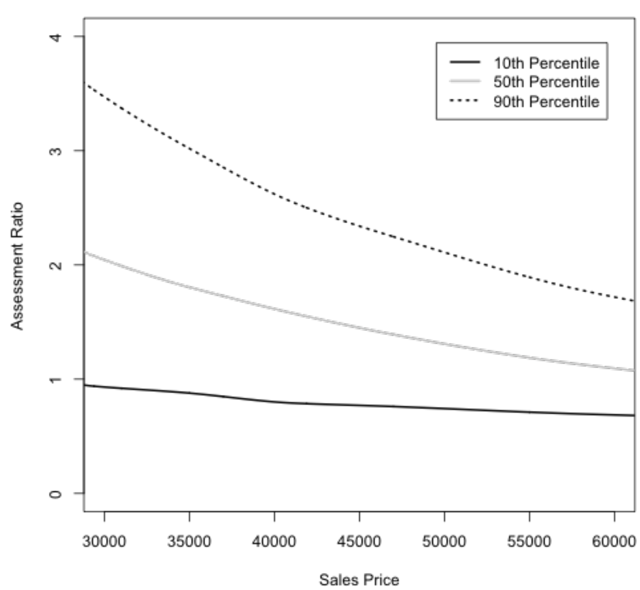


Figure 6:



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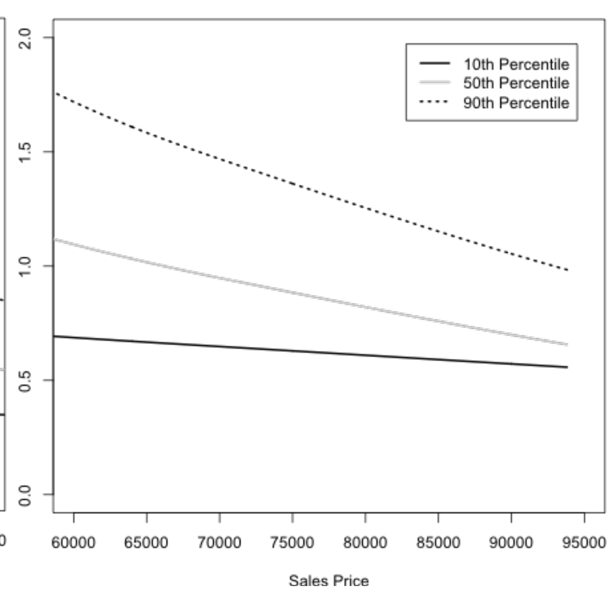


Figure 8: Conditional Quantile Distributions, by Sale Price Quintiles

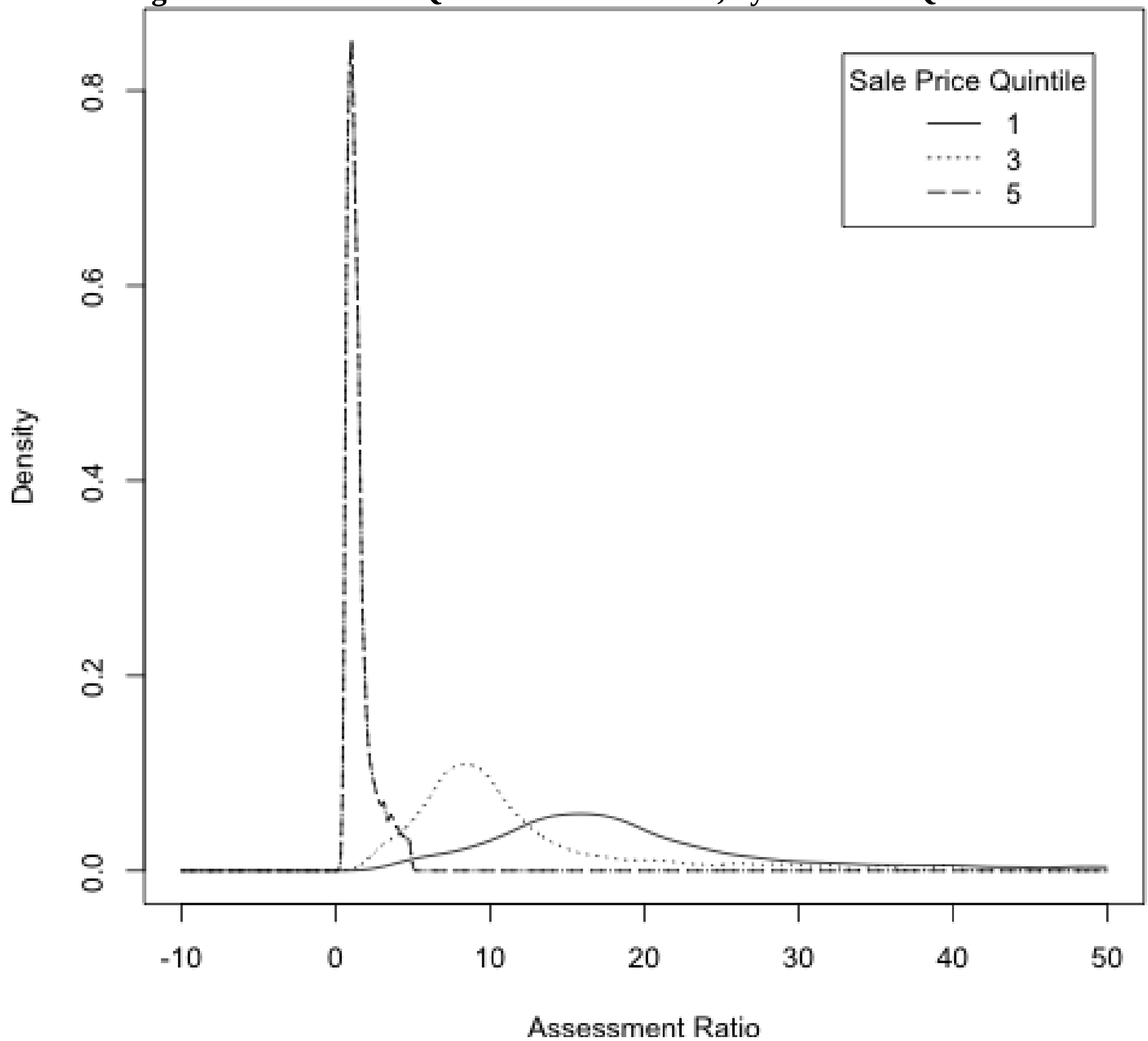


Figure 9: Quantile Distributions, Age

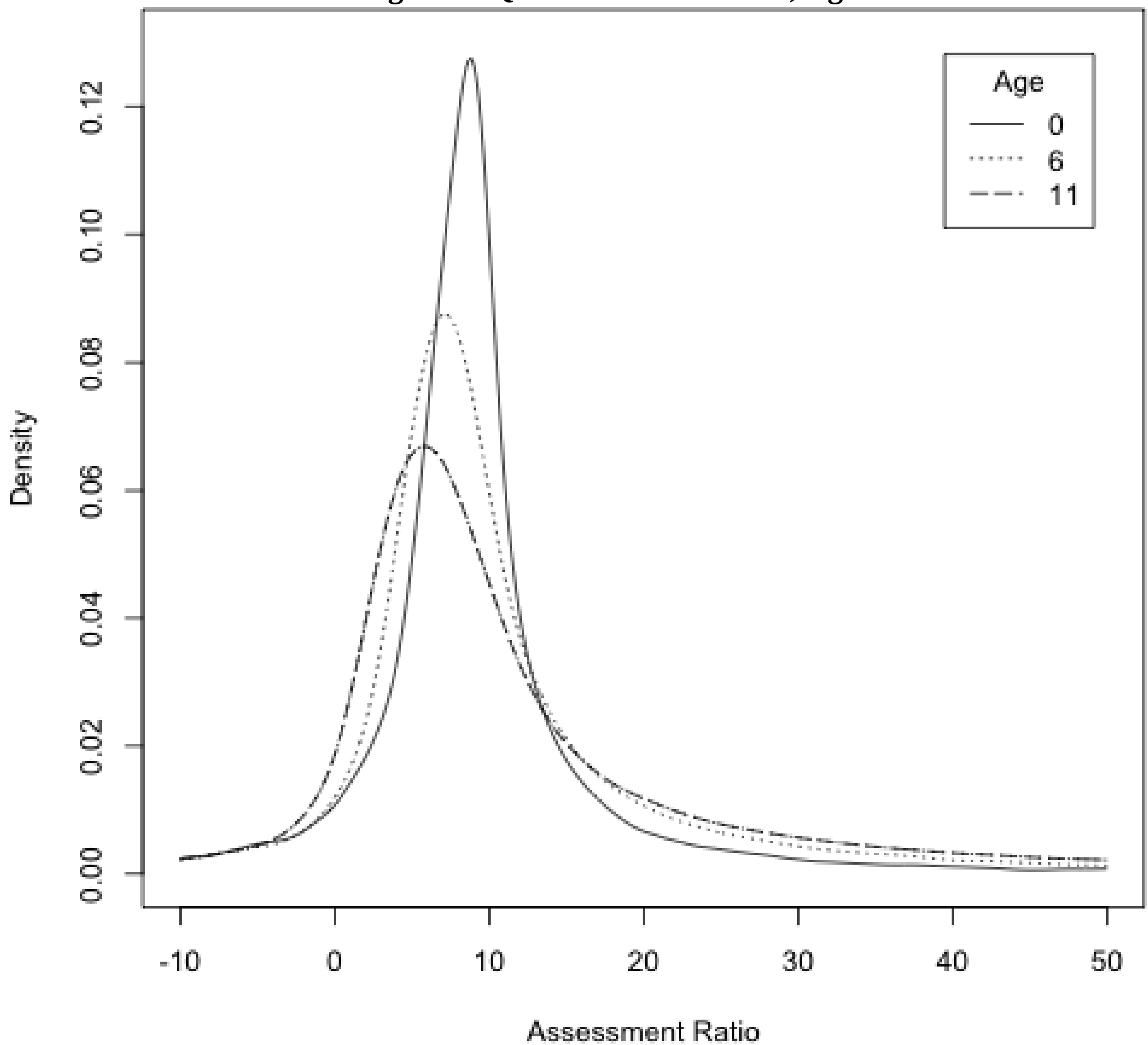


Figure 10: Quantile Distributions, Living Area

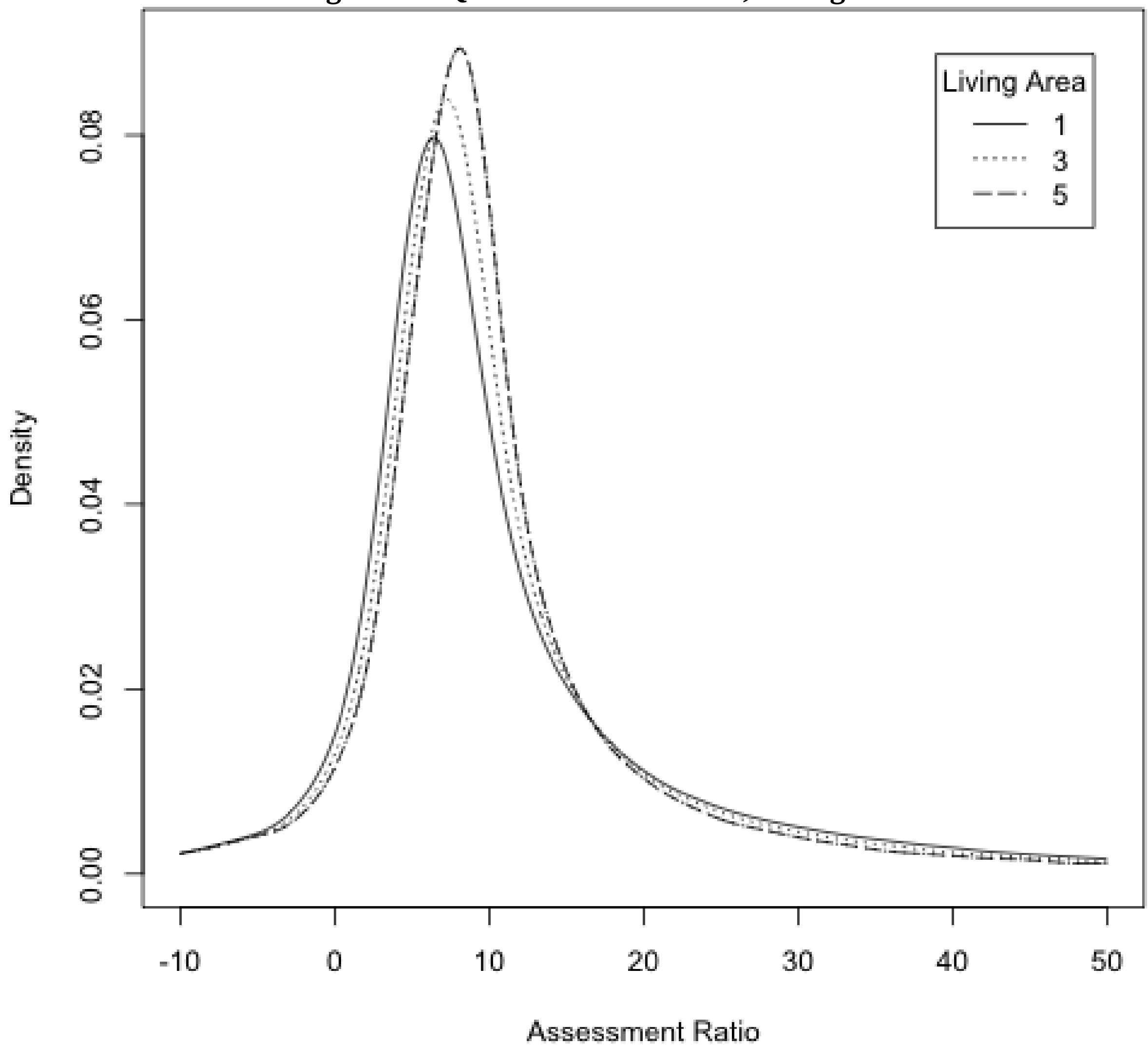


Figure 11: Quantile Distributions, Lot Size

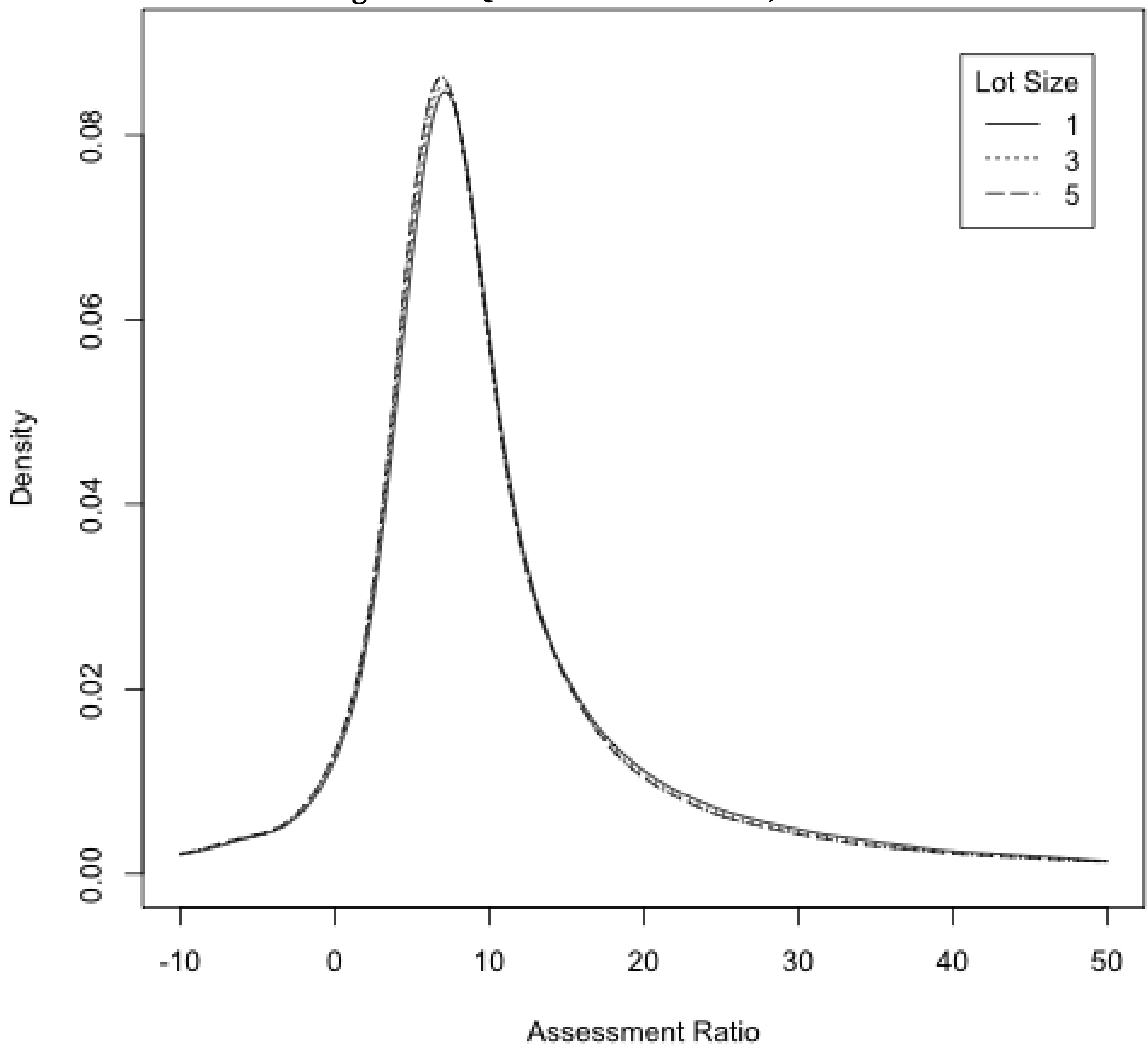


Figure 12: Quantile Distributions, MI Resident

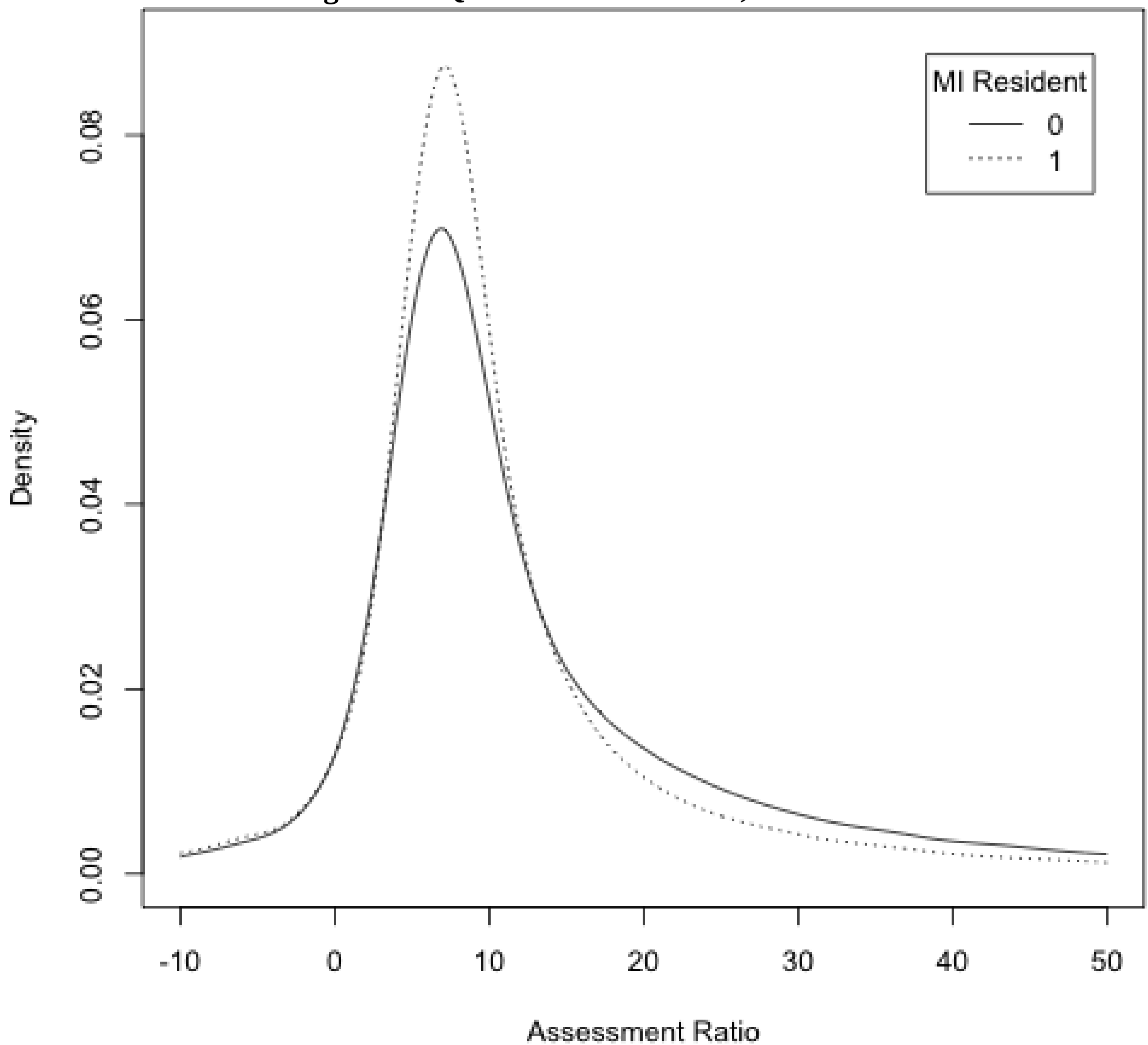


Figure 13: Quantile Distributions, PRE

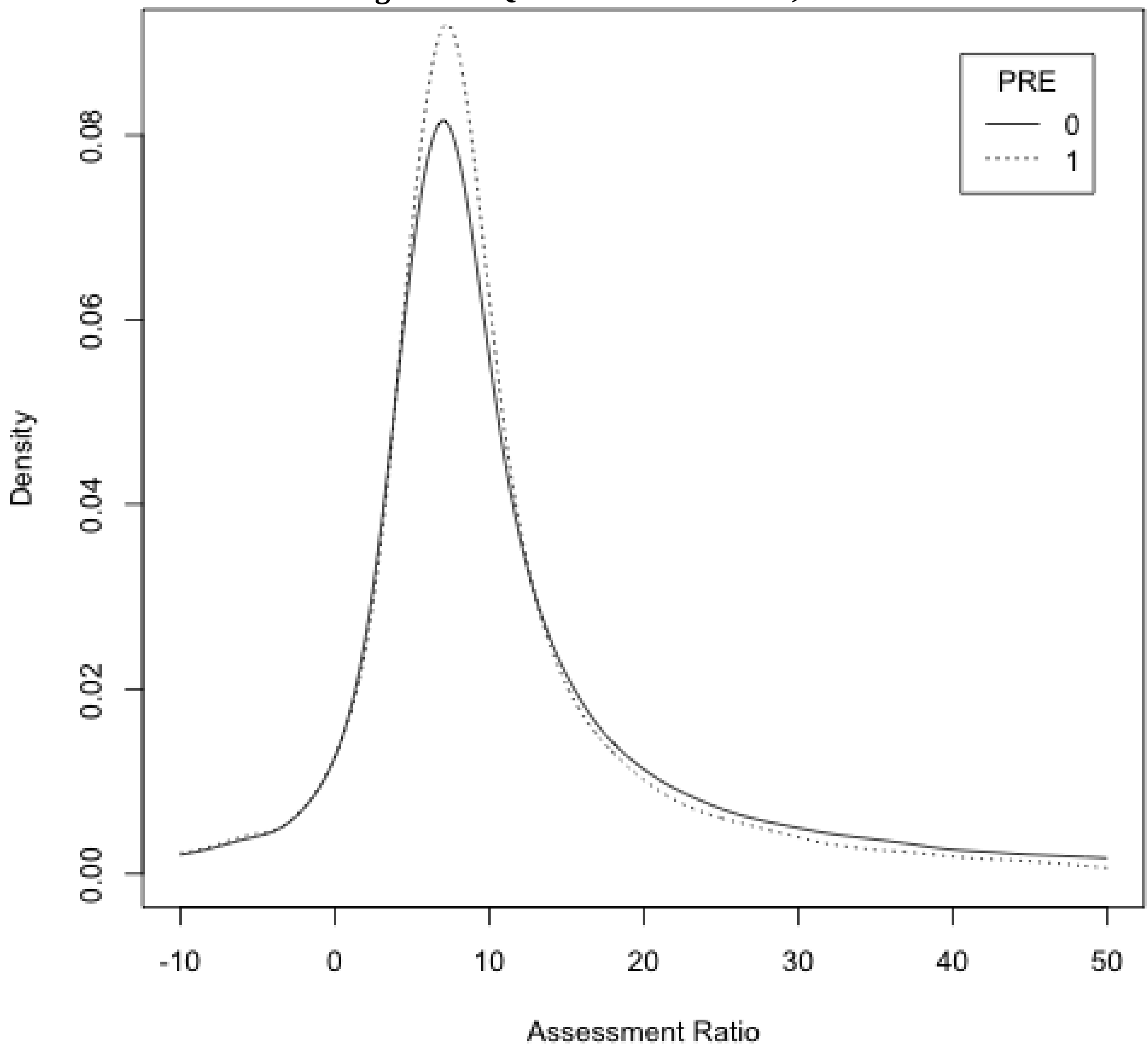


Figure 14: Quantile Distributions, Districts 1 through 4

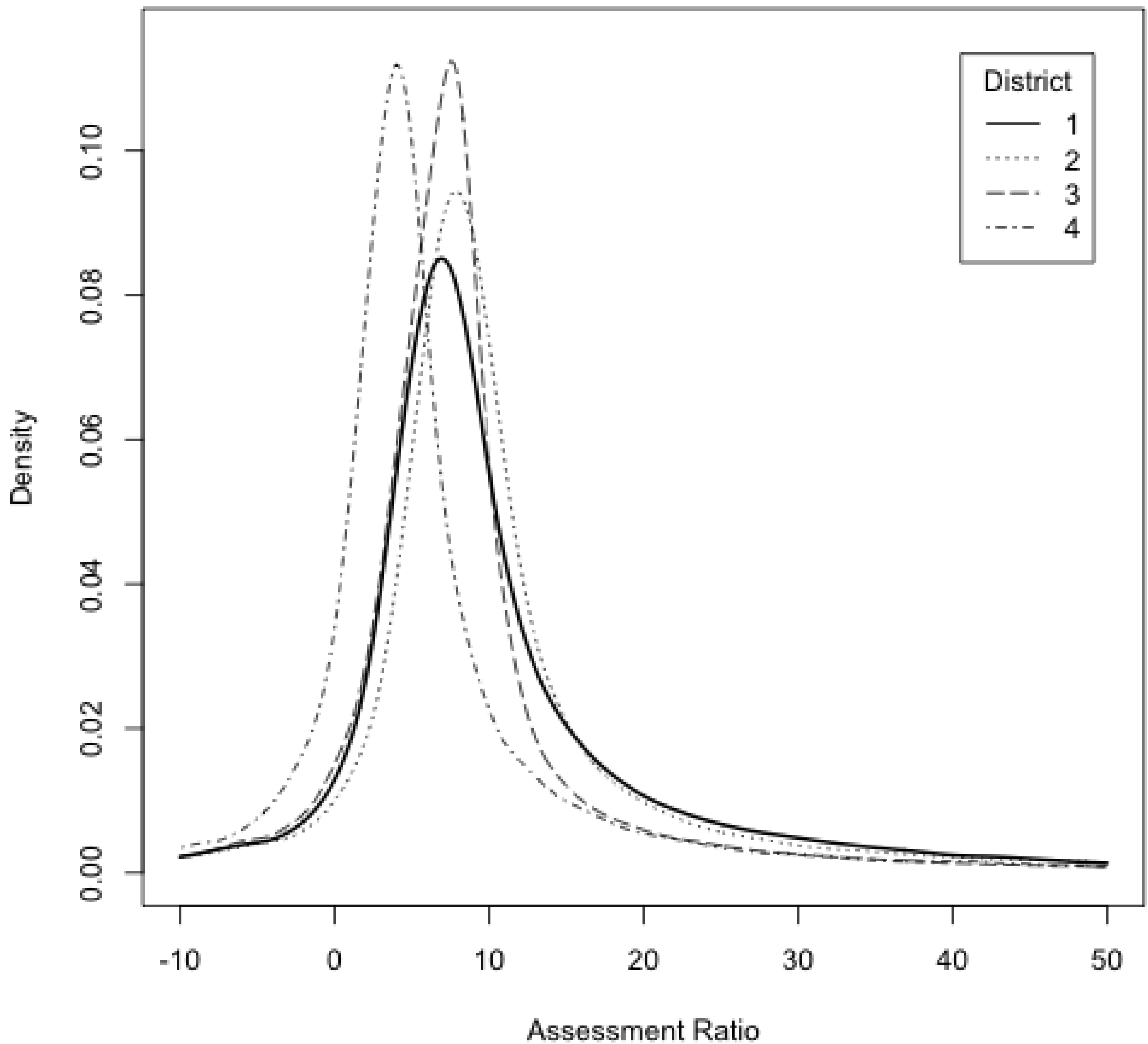


Figure 15: Quantile Distributions, Districts 5 through 7

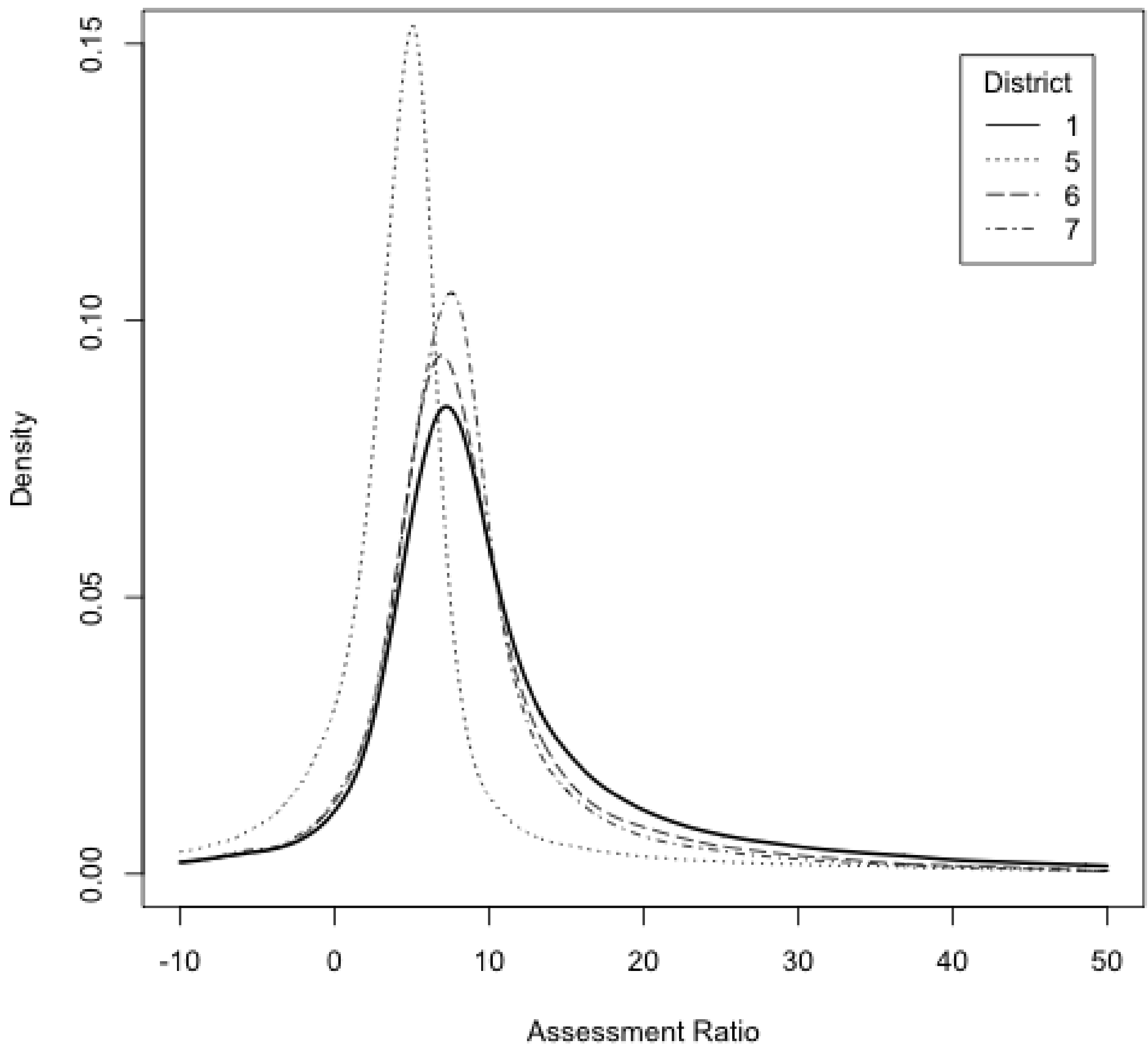
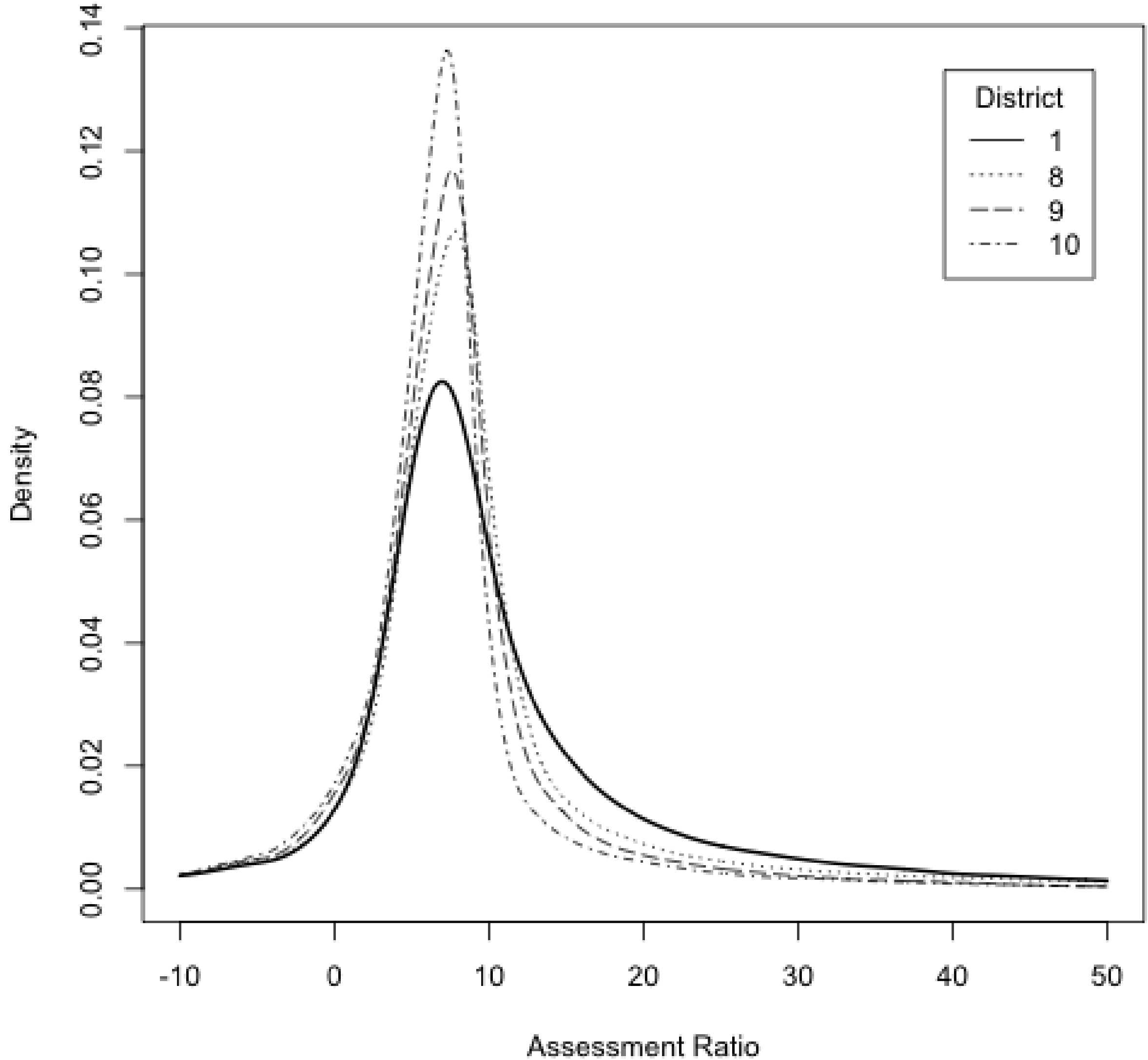


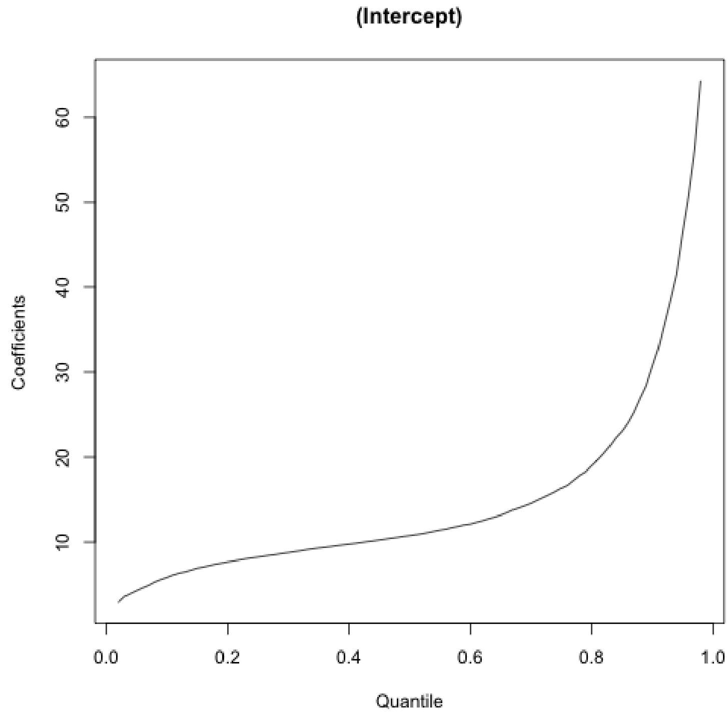
Figure 16: Quantile Distributions, Districts 8 through 10

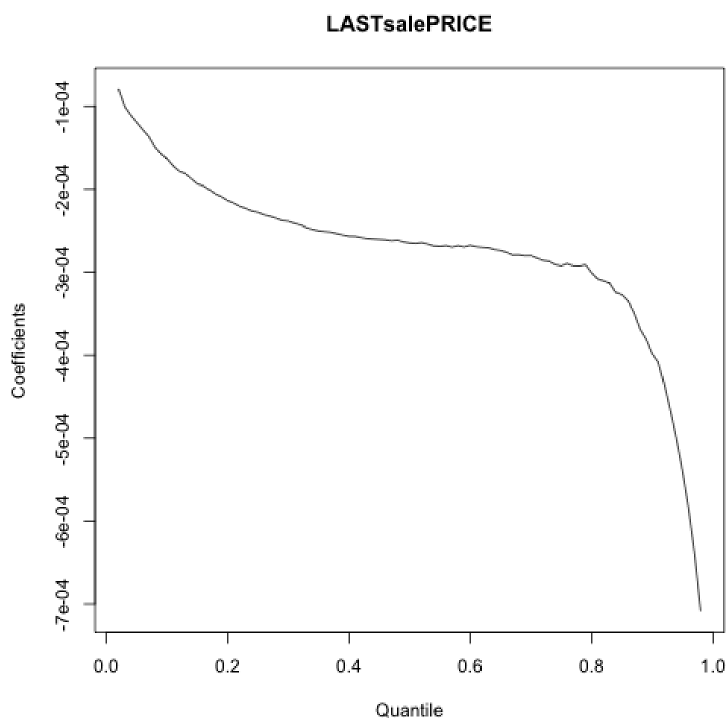


Appendix 1: Variable Definitions

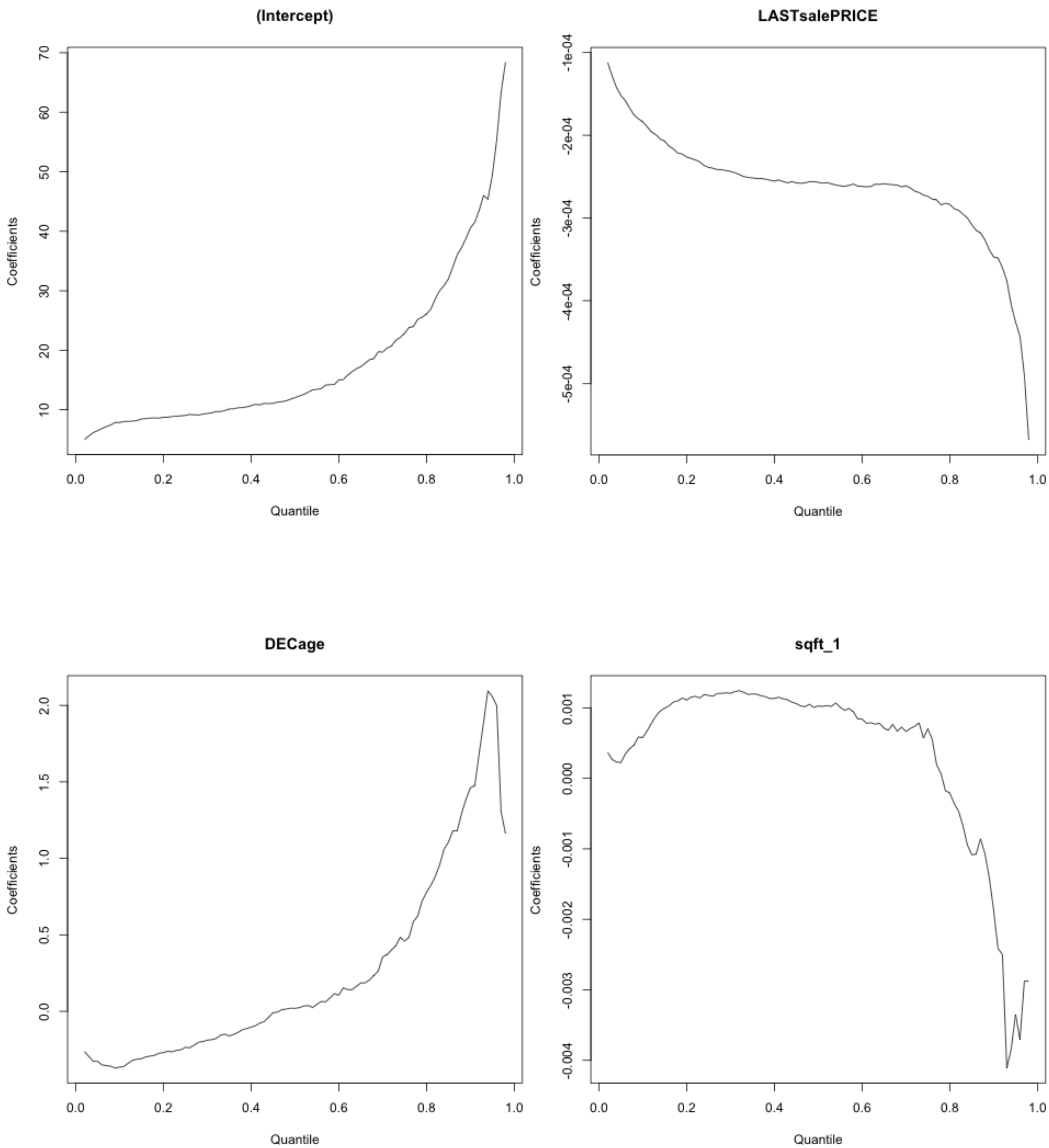
Variable	Definition
Assessment Ratio	*SEV (x2)* divided by *Sale Price*.
SEV (x2)	The 2010 state equalized value (or assessed value) of the property, multiplied by two to be comparable to the sale price.
Sale Price	The 2009 sale price of the property.
Age	Age of the residential structure, estimated as a continuous variable with each successive number representing an additional decade.
Living Area	Size of the residential structure (square feet).
Lot Size	Size of the property associated with the residential structure (acres).
MI Resident	Indicator variable to distinguish whether the property owner lives in Michigan (1 = property owner lives in Michigan, and 0 otherwise).
PRE	Indicator variable to distinguish whether the property owner lives in the property and claims the property as their principal residence (1 = property owner claims the property as their principal residence, and 0 otherwise).

Appendix 2: Standard Quantile Coefficient Estimates (Vertical Equity)

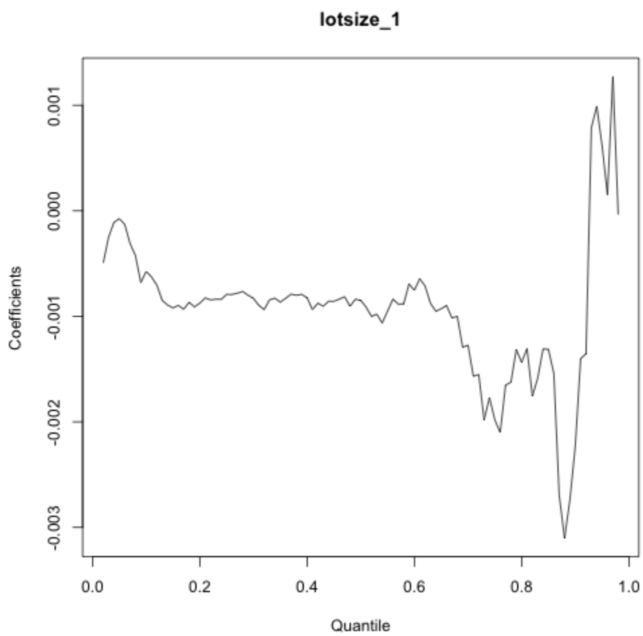


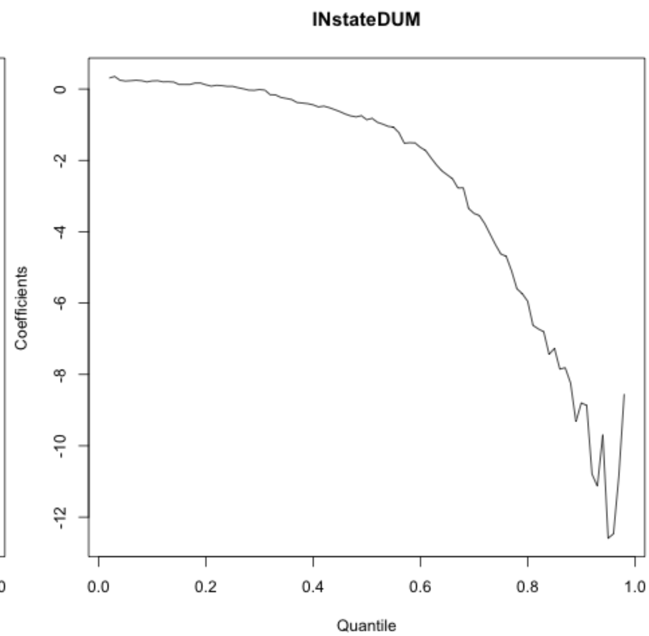


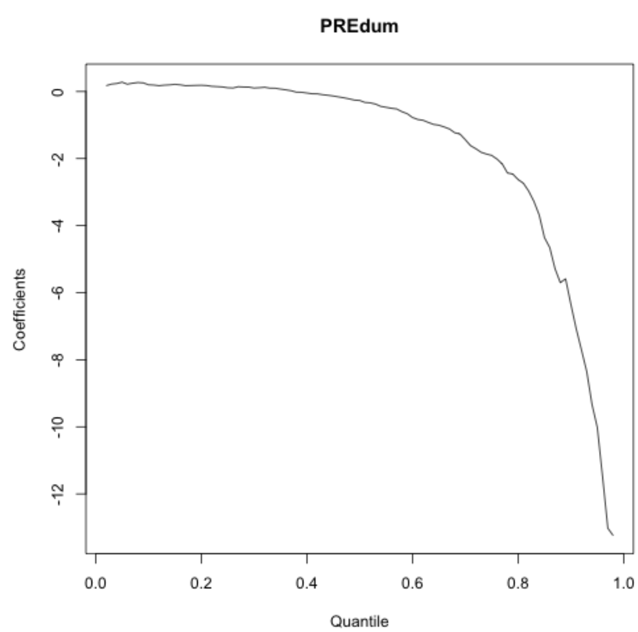
Appendix 3: Standard Quantile Coefficient Estimates (Horizontal Equity)



Appendix 3: (cont'd)







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