Why Are Residential Property Tax Rates Regressive?*

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Abstract

Among single-family homes that enjoy the same set of property tax-funded amenities and pay the same statutory property tax rate, owners of cheap houses pay 50% higher effective tax rates than owners of expensive houses. This pattern appears *throughout* the United States and is caused by systematic assessment regressivity – cheap houses are over-appraised relative to expensive houses. Thirty percent of the observed regressivity can be explained by tax assessors' flawed valuation methods, which ignore variation in priced house and neighborhood characteristics. Infrequent reappraisal explains less than 10% of the regressivity. Heterogeneous appeals behavior and outcomes do not contribute. Over-taxation of disadvantaged households such as minority, low-income, and less educated households is a by-product of model-induced assessment regressivity because these households have low levels of wealth and sort into cheap houses. Taken at face value, correcting assessment regressivity would increase poor homeowners' net worth by almost 15%. These results have important implications for wealth taxation policies.

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1 Introduction

It is a well-known feature of property tax data that assessments appear to be regressive – cheap houses tend to be over-appraised relative to expensive houses (Sirmans et al., 2008). The result of regressive assessments is that owners of cheap houses pay higher effective property tax rates than owners of expensive houses. The literature on assessment regressivity has proposed many explanations: infrequent reappraisal (Paglin and Fogarty, 1972), heterogeneous appeals behavior and outcomes (Weber and McMillen, 2010), and many more. Despite its vast volume, the literature has several large gaps. First, there is no consensus on the cause of regressive assessments. Second, we do not have good estimates of the resulting excess tax payments. Lastly, we do not have a good sense of how much assessment regressivity matters for wealth inequality among homeowners.

This paper uses a comprehensive data set of property taxes and transaction prices of single-family homes in the United States to fill these gaps. I propose and provide empirical evidence for a new explanation for assessment regressivity. I argue that regressive assessments are caused by tax assessors' flawed valuation methods, which ignore priced house and neighborhood characteristics that are difficult to observe or quantify. Tax assessors use statistical valuation methods such as hedonic regressions to assign appraised values to houses en masse. When important pricing characteristics are omitted, predicted prices will be too high for houses that are cheap because of these omitted variables and vice versa.

An advantage of my property tax data set is the fact that each house in the data set is assigned to a tax code area (TCA). A TCA is a small geographic area where all houses pay the same statutory property tax rate and have access to the same set of property tax-funded amenities. The concept of a TCA permits a meaningful discussion of over- or under-taxation that each homeowner faces because I can hold fixed the bundle of public goods that each homeowner in the same TCA buys with his property tax dollars. Among houses in the same TCA, excess tax payments can be calculated as the difference between the observed tax bill and the counterfactual tax bill that would have realized if the house were taxed according to its transaction price and not its flawed appraised value. This method allows me to quantify the amount in which owners of cheap houses are being overtaxed and the amount in which owners of expensive houses are being under-taxed.

I then use these excess tax payments to quantify the impact that assessment regressivity has on wealth inequality.

Since tax code areas are new to the literature on property taxes, I begin my empirical analysis by summarizing tax code area data. The median TCA is small. It contains 65 land parcels and has a total land area of 0.5 square miles. However, there is significant variation in TCA size. Given that the median TCA is small, it is not surprising that there are many TCAs within a small geographic area. The average zip code contains ten TCAs. This fact highlights that, even in a small geographic area, the variation in public goods set and quality that homeowners in the United States have access to can be large.

With the focus of the paper being on assessment regressivity, I move on to quantify the degree of assessment regressivity among single-family homes in the data. Simple summary statistics show that, among houses located in the same TCA and year, owners of cheap houses pay 50% higher effective property tax rate than owners of expensive houses. Next, I estimate the degree of assessment regressivity among houses located in the same TCA and year by regressing log valuation ratio, appraised value divided by transaction price, onto log transaction price with TCA by year fixed effects. The estimated slope coefficent is -0.31, which suggests that assessments are regressive.

However, a negative slope coefficient is to be expected because transaction price is, in principle, true market value plus measurement error, which introduces attenuation bias into the regression estimates (Kochin and Parks, 1982). To overcome this attenuation bias problem, I use an instrumental variable approach where I instrument log transaction price with log leave-one-out average transaction prices from other transaction in the same census tract block group. For a particular transaction, the leave-out approach ensures that the instrument is orthogonal to the measurement error embedded in the observed transaction price, while using average local transaction prices ensures that the instrument is highly correlated with the observed transaction price. The two-staged least squares regression yields a slope coefficient estimate of -0.12, which suggests that assessments are indeed regressive, but approximately 60% of the observed regressivity is caused by attenuation bias.

Having established that assessments among single-family homes are regressive, I provide empirical evidence to show that assessment regressivity is caused by tax assessors' flawed valuation methods. I treat house characteristics such as number of rooms and size as pricing characteristics that are easily observable and often included in tax assessors' regression models. On the other hand, neighborhood characteristics are treated as pricing characteristics that are difficult to quantify and often omitted. The R^2 from a linear regression where transaction price is regressed onto a vector house characteristics captures how well variation in house characteristics can explain variation in realized sale prices. Likewise, the R^2 from a linear regression where transaction price is regressed onto a vector house and neighborhood characteristics captures how well variation in these characteristics can explain variation in realized sale prices. The difference between the second and the first R^2 is a measure of how well variation in neighborhood characteristics can explain variation in realized sale prices, on top of variation in house characteristics. The main empirical evidence of the flawed valuation methods story is that, in TCA-years where the R^2 difference measure is positive and large, assessments are also more regressive, which is consistent with the conjecture that tax assessors' regression models omit neighborhood characteristics.[1]

A natural follow-up question is – how much of the overall degree of assessment regressivity can be explained by the flawed valuation methods mechanism? To answer this question, I begin by constructing synthetic appraised values for single-family houses that I observe repeated sales. Following Bayer et al. (2017), the synthetic appraised value is the product of the house's most recent transaction price in year $t-k$ and the innovation in its local house price index between year $t-k$ and year t. Intuitively, a house's previous transaction price should capture all of its relevant pricing information in year $t-k$ and innovation in its local house price index should capture changes in priced neighborhood characteristics between year $t-k$ and year t. Assuming that no major renovation took place between the two time periods, the house's synthetic appraised value should be a good proxy of its market value in year t. Among houses with relatively recent previous transaction prices, replacing observed appraised values with synthetic appraised values in the linear regression where log valuation ratio is regressed onto log sale price reduces the absolute value of

[1]Note that including fine geographic area (e.g., census tract block group) fixed effects to tax assessors' regression models would not fix this problem because of two reasons. First, omitted characteristics can be related to both the structure and the neighborhood. The paper uses neighborhood characteristics in the main test because they are difficult to quantify, but I have data to measure them. Second, including such fine geographic area fixed effects is often impractical because of insufficient number of transactions in each census tract block group and year.

the slope coefficient by approximately 30%, which suggests that tax assessors' flawed valuation methods can explain approximately a third of the observed assessment regressivity.

I also evaluate other explanations for assessment regressivity that have been proposed in the literature. First, I consider the infrequent reappraisal explanation by comparing the degree of assessment regressivity among all houses that were sold in year t to the degree of assessment regressivity among houses that were reappraised and sold in the same year. Eliminating houses with stale appraised values from the sample reduces the degree of assessment regressivity by less than 10%, which indicates that infrequent reappraisal is a relatively minor contributor. Second, I use appeals data from Cook County, Illinois, to explore whether heterogeneous appeals behavior and outcomes can explain assessment regressivity. I find that, although owners of expensive homes tend to file more appeal and win more often, they do not receive larger appraised value reductions than owners of cheap homes. The degree of assessment regressivity in Cook County is essentially unchanged when assessment regressivity is estimated using pre-appeal appraised values instead of post-appeal appraised values, which indicates that heterogeneous appeals behavior and outcomes cannot explain the county's regressive assessments.

The penultimate section of the paper quantifies the amount of excess tax payments for each home in the data set and discusses the implications that regressive assessments have on wealth inequality among homeowners. For each house, I calculate the counterfactual tax bill, which is the tax bill that would have realized, if the house were taxed according to its transaction price. Within a TCA and year, the counterfactual tax rate is calculated as the ratio of total property tax revenue raised from all homes that were sold and total transaction price. A house's counterfactual tax bill is calculated as the product the counterfactual tax rate and its transaction price. The difference between the observed property tax bill and the counterfactual tax bill is the amount of over- or under-taxation that each house faces.

Using the 2016 Survey of Consumer Finance to place each house in the nation's house price distribution, I find that the average excess property tax payment amount for houses in the bottom decile of the nation's house price distribution is \$590, which is equivalent to 45% of the average observed tax bill. On the other hand, the average underpayment among houses in the top one percent is \$3,904 or 14% of the average observed tax bill. Since poor households sort into cheap houses while rich households sort into expensive houses, the property tax system ends up being a regressive wealth tax among homeowners. A back-of-the-envelope calculation which assumes that property taxes are fully capitalized into house prices at a discount rate of 4% shows that correcting regressive assessments would, on average, increase poor homeowners' wealth by almost 15%. Thus, a key insight from the paper is that, implementing a wealth tax system that requires the government to use statistical valuation methods would likely increase wealth inequality among asset owners.

Several papers in the property tax literature have documented that disadvantaged households such as minorities and low-income households pay higher effective property tax rates (Black, 1977; Avenancio-León and Howard, 2019). Two potential explanations are direct discrimination against these households and house-price sorting. The discrimination explanation can be thought of as unfair assessments being caused by household-specific traits such as race. The sorting explanation can be thought of as unfair assessments being caused the house's *location* in the house price distribution, i.e., cheap houses are overtaxed and expensive houses are undertaxed due to model-induced assessment regressivity.

In the last part of the paper, I show that over-taxation of disadvantaged households is a by-product of model-induced assessment regressivity because disadvantaged households sort into cheap houses. I begin my analysis by replicating results from the literature, which are that houses in census tract block groups with high minority share, low median household income, and low college graduate share tend to be overtaxed relative to their respective comparison groups. Next, I show that houses located in these disadvantaged census tract block groups are, on average, cheaper, which suggests that households with these characteristics tend to sort into cheaper homes. To test whether the baseline over-taxation results are caused by model-induced assessment regressivity, I compare the degree of over-taxation between similarly priced homes that are located in census tract block groups that have different characteristics (e.g., low versus high-income). The result is that, once I condition on the house's location in the house price distribution, houses in economically disadvantaged census tract block groups are relatively *undertaxed*, which suggests that the baseline result can be entirely explained by house-price sorting and model-induced assessment regressivity.

This article is related to the work by Avenancio-León and Howard (2019), but differs from it in several important ways. First, the current article is focused on documenting and explaining within-TCA-year assessment regressivity, while Avenancio-León and Howard (2019) document and explain assessment gaps between minority and non-Hispanic white homeowners. Second, I use administrative TCA data to quantify differences in effective tax rates across houses in the same taxing jurisdiction, which avoids measurement error introduced by constructing taxing jurisdictions from scratch. Lastly, I extend Avenancio-León and Howard (2019)'s results by showing that an econometrician can differentiate between direct discrimination and house-price sorting by estimating the racial assessment gap among similarly priced homes. In doing so, I find that house-price sorting, and not direct discrimination, is the primary driver of the racial assessment gap.

I contribute to the literature on assessment regressivity in several ways. First, works in the literature use property tax data from several localities (e.g., city and county) to document and explain assessment regressivity (Black, 1977; Smith et al., 2003; Eom, 2008; Weber and McMillen, 2010; Ross, 2012, 2013; McMillen, 2013; Hodge et al., 2017). This article uses a near-nationally comprehensive property tax data set to document that property assessments in the United States are generally regressive. The pervasiveness of this pattern begs for a general explanation that goes beyond idiosyncratic characteristics of local property tax systems such as infrequent reappraisal (Paglin and Fogarty, 1972). I propose a new explanation that is general in nature and show that it is supported by the data. Second, I use a novel instrument to solve the attenuation bias problem that plagues regression-based methods for quantifying assessment regressivity (McMillen and Singh, 2020). Third, I introduce the concept of a tax code area, which allows me to compare effective property tax rate across houses, while holding fixed the bundle of tax-funded amenities that they buy. Other works attempt to accomplish the same goal by constructing taxing jurisdictions from incomplete sets of government entity service boundaries (Avenancio-León and Howard, 2019; Berry, 2021). Lastly, I use tax code area data to calculate excess tax payments and quantify the impact that assessment regressivity has on wealth inequality among homeowners.

This article also adds to a growing body of works that studies unintended consequences of algorithms and statistical procedures (Bartlett et al., 2018; Fuster et al., 2018; Kleinberg et al., 2018). I show that mass appraisal methods employed by county assessor's offices over-appraise inexpensive houses and under-appraise expensive houses. Since individuals with low levels of wealth sort into inexpensive houses, the property tax system ends up overtaxing economically disadvantaged households such as minority, low-income, low-education, and low-wealth households.

2 Institutional Details

2.1 Property Tax Basics

Real estate property tax is a form of ad valorem tax because the tax bill is calculated from the property's assessed value (Lincoln Institute of Land Policy, 2014). The tax bill is the product of two components: the house's assesed value, V_i, and the statutory tax rate , τ^s.

$$T_i = \tau^s \times V_i \tag{1}$$

To compute the house's assessed value, the government first assigns an appraised value to the house. The appraised value should, by law, reflect the house's true market value that would result from an arm's length transaction (Lincoln Institute of Land Policy, 2014). The appraisals are periodically done by the county's or city's assessor's office. The assessed value, which is the quantity that the tax rate is to be applied to, is a proportion of the house's appraised value. This proportion, the assessment ratio, is arbitrarily chosen by a local government entity (Lincoln Institute of Land Policy, 2014). For example, Washington D.C. uses an assessment ratio of one, while the state of Illinois uses an assessment ratio of one third (Lincoln Institute of Land Policy, 2014). This piece of institutional detail adds an additional layer of complexity to the property tax system but has no economic meaning in the following analyses because the assessment ratio is constant within tax code areas. To arrive at each house's final assessed value, relevant exemptions are applied. Each local jurisdiction has its own set of idiosyncratic property tax exemptions.[2] With an assessed value assigned to each house in its taxing jurisdiction, the taxing entity can calculate the total tax base, which it uses to compute the statutory tax rate that is applied to each house's assessed value.

[2]For example, per Ala. Code 6-10-2, 27-14-29, Alabama has a homestead exemption that allows homeowners to substract $15,000 from their houses' assessed values.

The statutory tax rate is computed by dividing the taxing entity's property tax revenue target for the year by its tax base. The entity's total revenue from property taxes in each year is either decided by a vote at the ballot box or by an elected official (Avenancio-León and Howard, 2019). The property tax bill for a house that is taxed by a single entity is calculated in the following way.

$$T_i = \frac{R}{\sum_{i=1}^{n} V_i} \times V_i = \tau^s \times V_i \tag{2}$$

R is the total revenue that the taxing entity wishes to raise from residential property taxes and $\sum_{j=1}^{n} V_i$ is the entity's total property tax base.

2.2 Tax Code Areas

In practice, each house is served and taxed by many local government entities (e.g., school districts and local fire departments). Each taxing entity has its own service jurisdiction, which encompasses a certain set of houses. Using assessed value data from the local assessor's office, each taxing entity calculates its total tax base and comes up with its own revenue target and, hence, its own statutory property tax rate. With overlapping service boundaries, each house is assigned to a tax code area (TCA), which is a geographic region that has a unique set of local government entities that serve and tax it. Every house in a TCA pays the same statutory property tax rate, which is the sum of the tax rates imposed by each taxing entity, and, in turn, enjoys the same set of property tax-funded services. In practice, a house's property tax bill is calculated as follows.

$$T_{ik} = \sum_{j=1}^{m} \tau_j^s \times V_{ik} = \tau_k^s \times V_{ik} \tag{3}$$

k is the index for TCAs, j is the index for taxing entities within a TCA. Figure 3 shows a list of all local government entities that collect property taxes from houses in three TCAs in Snohomish County, WA, for the 2020 tax year. Each TCA has different statutory tax rates. The statutory property tax rate in TCA number 18 is \$11.026 per \$1,000 of assessed value, while the rate in TCA number 20 is \$11.225. The difference in tax rates stems from the fact that houses in each TCA are being served by a different sets of local governments. For example, houses in TCA number 21 pay a higher property tax rate than houses in TCA number 20 because houses in TCA number 21 have access to the Central Puget Sound Regional Transit Authority, which is a network of commuter rails and buses that serve the area. This additional public amenity comes with an additional cost of 0.23 cents per \$1,000 of assessed value.[3]

2.3 Tax Rate Uniformity

Within-TCA effective property tax rates across houses are not equal because valuation ratios are not uniform. Define the valuation ratio as $\frac{A_i}{M_i^*}$ where M_i^* denotes house i's true market value and A_i denotes house i's appraised value. If there is a negative relationship between valuation ratios and true market values, then inexpensive houses are relatively over-assessed and effective property tax rates are regressive.

Researchers have documented assessment regressivity among houses in the same city and county (Hodge et al., 2017; McMillen and Singh, 2020; Smith et al., 2003). However, without looking within TCAs, these findings do not necessarily show that effective property tax rates are regressive. Cheap houses are likely to be located in an area served by a set of local governments that differs from areas where expensive houses are located. Hence, the comparison of relative valuation ratio disparity between these two groups of houses is not an apples-to-apples comparison. A researcher could find a negative relationship between valuation ratios and house prices among houses in the same city, while there may not be such relationship within each TCA. The intra-city assessment regressivity result suggests regressive effective *city* property tax rates, but not necessarily, effective *total* property tax rates, which is the more important economic quantity. In addition, it is difficult to make meaningful comparison of two houses that pay different effective property tax rates and enjoy different sets of property-tax-funded amenities because higher effective tax rate may also mean higher quality of amenities. By comparing houses within the same tax code area, variation in effective tax rates across houses becomes meaningful because the bundle of public goods that

[3]To see what tax code areas look like, please refer to Appendix A.1.

those tax dollars buy remain constant.

3 Empirical Strategy

To measure assessment regressivity among a set of transacted houses within a TCA and year, I run the following within-TCA-year regression.

$$logA_{it} - logM_{it} = \alpha + \beta logM_{it} + \epsilon_{it} \tag{4}$$

A_{it} denotes appraised value, M_{it} denotes sale price, i indexes houses, and t indexes years. Log valuation ratio is regressed onto log sale price and β captures the degree of assessment regressivity. A negative β coefficient suggests that assessments are regressive. In the nontrivial case where the covariance between log appraised value and log sale price is positive, β is negative when $Cov(a, m) < \sigma_m^2$.

$$\beta = \frac{Cov(a-m, m)}{\sigma_m^2} = \frac{Cov(a, m)}{\sigma_m^2} - 1 \tag{5}$$

However, it is important to note that the regression shown in Equation 4 is biased towards finding a negative slope coefficient (Kochin and Parks, 1982; McMillen and Singh, 2020). Consider the case where appraised values are exactly equal to true market values, but sale price is equal to true market value plus measurement error. Then, mechanically, β is negative, even though, by assumption, assessments are not regressive.

I use the instrumental variable approach to address this attenuation bias problem. Suppose that house i's sale price in year t equals its true market value in year t plus a measurement error term that is identically and independently distributed, then a valid instrument for house i's observed sale price in year t is the leave-one-out average sale price of other transactions in house i's census tract block group. The leave-one-out average sale price should be highly correlated with house i's sale price, which ensures that the instrument should be sufficiently strong. Furthermore, the leave-one-out approach satisfies the exclusion restriction because, by leaving out the transaction that is being considered, the correlation between the instrument and the measurement error term embedded in the transaction's sale price should be zero. With this estimation strategy, the true degree of assessment regressivity is captured by β^{IV} in the following two-stage least squares regression.

$$logM_{it} = \alpha' + \beta' \overline{logM_{it}} + \epsilon'_{it} \tag{6}$$

$$logA_{it} - logM_{it} = \alpha + \beta^{IV} \widehat{logM_{it}} + \epsilon_{it} \tag{7}$$

$\overline{logM_{it}}$ denotes the log leave-one-out average sale price of other transactions in house i's census tract block group. $\widehat{logM_{it}}$ denotes the predicted value of house i's log sale price from the first-stage regression. A negative β^{IV} would indicate that assessments are indeed regressive.

4 Data

4.1 Data Sets

The first main data set that the paper uses is the CoreLogic Tax data set, which contains property tax-related data and parcel characteristics for approximately 150 million property parcels in the United States. The data set covers every type of real estate parcels, e.g., residential, commerical, industrial, agricultural, vacant, and tax-exempt. This study focuses on single family residential real estate parcels. For most parcels, the data set contains 10 years of tax data, spanning different year intervals. The main sample that this article uses covers observations from 2007 to 2019. Tax-related variables include property tax bill, tax year, appraised value, assessed value, appraisal year, exemption indicators, and tax code areas. Parcel characteristics include land and property information such land area size, total living area, number of bedrooms, number of bathrooms, etc.

A key innovation in this paper is the tax code area (TCA) data. In county records and in the CoreLogic Tax data set, each parcel is assigned to a TCA. For example, each house in Snohomish

County that appears in the data set is assigned to a TCA numbered similarly to the ones displayed in Figure 3.[4] The CoreLogic data set has TCA data for all states, except for Massachusetts, which I exclude from my analysis.[5] TCA "names" contain numbers, letters, and special characters. Furthermore, there are instances where TCA names appear with preceding zeroes in some years and not in other years. It is important that TCA names are entered cleanly and consistently because houses need to be correctly grouped into their appropriate tax code areas. I clean area names in two steps. First, I remove spaces, preceding zeroes, and special characters. Then, based on the reasoning that county governments are usually the government unit that is responsible for property tax assessments and collection, I treat TCAs that share the same county and have the same name as the same TCA. Figure 1 uses the sample of all transacted homes to plot median scaled statutory tax rates, observed property tax bill divided by assessed value, against within-TCA house price bins. Each house's statutory tax rate is scaled by the TCA's median statutory tax rate. The plot shows that the median house in every price bin pays the same statutory tax rate, which verifies that the cleaned TCA data are accurate.[6]

The second main data set that the paper uses is the CoreLogic Deeds data set, which contains transaction information on real estate properties in the United States. The transaction information includes sale price, sale date, transaction type, mortgage amount, and lender name. I only use arm's length transactions in my analyses. The CoreLogic Tax data set can be merged with the CoreLogic Deeds data set by using unique county-provided parcel identifiers that link land parcels across data sets.

Five-year averages of census tract block group characteristics provided by the Census Bureau's American Community Surveys (ACS) are used to construct neighborhood characteristic

[4] This data set differs from the one used by Avenancio-León and Howard (2019) because I observe TCA assignments collected from county assessor's offices. Avenancio-León and Howard (2019) use GIS area files to construct "taxing jurisdictions" by overlaying taxing boundaries of each local government entity. This methodology will likely produce errors if the list of taxing entities is incomplete or the GIS files are not accurate at every point in time, which is possible because service boundaries do change over time through annexation and addition. If taxing jurisdictions are constructed incorrectly, then the authors are not actually making a comparison of effective tax rates across houses that have access to the same set of tax-funded amenities. My conversations with the Muni Atlas Research, the company which distributes the GIS files, reveal that the data set do not contain service boundaries of all local government entities.

[5] Many parcels in Rhode Island and Michigan are missing tax code area data.

[6] Medians are plotted instead of means because I observe pre-exemption assessed values and actual tax bills, which includes idiosyncratic exemptions such as exemptions for the elderly. Therefore, plotting the means would not give the same picture because these exemptions introduce deviations in statutory rates around the true statutory tax rate.

variables. I follow the urban economics literature and make the implicit assumption that a census tract block group is a neighborhood (Davis et al., 2019). As shown in the previous section, TCAs can be large and contain multiple census tract block groups, which allows me to study within-TCA variation in neighborhood characteristics.

4.2 Sample Construction

The sample of homes used in the analyses below consists of homes that were sold in whole single-parcel arm's-length transactions between 2000 and 2019. Specifically, I exclude nominal sales, inter-family transfers, multi-parcel sales, partial parcel sales, and foreclosure sales. To make it into the sample, the home must have a positive property tax bill, appraised value, and tax code area information in the year that it was sold. I drop houses with transaction prices less than $10,000 and greater than $10,000,000. The lower bound filter lowers the probability that mislabeled non-arms length transactions are included. The upper bound filter lowers the chance that mislabeled multiple-parcels sales are included.[7] Both new and existing constructions are included in the sample. I exclude condominiums from the sample because of poor data quality on unit numbers, which, in some instances, makes it impossible to merge a given unit's transaction data to its tax records. In analyses where I use the instrumental variable approach outlined in Section 3, I drop transactions where I do not have at least 30 transactions to calculate average sale price. Lastly, because of Proposition 13, I exclude single-family home transactions in California from the analysis.[8]

4.3 Tax Code Area Summary Statistics

How much land area do TCAs have? How many parcels belong to a TCA? How many TCAs are there in a county? This section uses tax data from 2018 to compute summary statistics on tax code area characteristics and answer these questions. I use 2018 data because it is the year in which the CoreLogic Tax data set contains the largest number of parcels, which means that it should be the

[7] All results are qualitatively and quantitatively similar without these filters.

[8] All results hold when I include single-family home transactions in California. Although Proposition 13 uses past transaction prices as assessed values, biases introduced by flawed valuation methods would still manifest in Californian homes through new constructions and renovation-induced reappraisals.

year in which I could get the most representative snapshot of TCA characteristics and the number of tax code areas at different levels of geographic granularity (e.g., state, county, zip code, and census tracts).

Table 1 presents the resulting summary statistics. Massachsetts and Rhode Island are excluded from the sample because TCA data are missing for parcels in these two states. In this sample, there are close to 140,000 tax code areas. The average TCA contains 930 land parcels and has a land area of approximately 17.5 square miles. For each TCA, land area is calculated by summing parcel land area over all parcels that belong to the TCA.[9] The distributions of these size measures are highly skewed. The median number of parcels is 65 and the median land area is 0.49 square miles, indicating that most TCAs are much smaller than the means suggest. Number of parcels and land area have large standard deviations, which indicates that there is significant cross-sectional variation in TCA size.

The next set of statistics show the land use mix within tax code areas. Using land use codes in the CoreLogic Tax data set, I classify land parcels and properties into six categories – residential, commercial, industrial, agricultural, vacant, and tax-exempt.[10] On average, 45% of all parcels within a TCA are residential parcels, while the majority of the remaining parcels are commercial, agrigultural, and vacant. This observation suggests that, within a TCA, there is a large variation in neighborhood characteristics and local amenities. For example, there are homes that are located near commercial districts, while others are located near agricultural districts. The key implication is that these difficult-to-quantify factors could significantly contribute to within-TCA variation in house prices.

The bottom panel of Table 1 presents summary statistics on the number of TCAs within different levels of geographic units. The goal of this exercise is to shed light on the fragmentation of local government taxing jurisdictions. The first row summarizes the number of tax code areas within states. On average, a state has almost three thousand tax code areas. The average county has 49 TCAs and the average zip code has 10. Even a small geographic area such as a census tract

[9] I fill in missing parcel land area with the TCA's median parcel land area. Results are similar when I use average parcel land areas to impute missing land area data.

[10] Tax-exempt parcels are land and property owned by local or federal government entities.

block group has multiple tax code areas. These summary statistics suggests that, even in small areas, the set and the quality of public goods that homeowners enjoy may vary significantly.

5 Flawed Valuation Methods and Assessment Regressivity

5.1 Baseline Assessment Regressivity Results

This section documents baseline facts about assessments and effective property tax rates regressivity among houses in the same TCA and year. Figure 2 uses data from over 21 million single-family home sales to show the relationship between effective property tax rate and house price. To construct this plot, I use sale prices to evenly sort houses in the same TCA that were sold in the same year into twenty price bins. For each house, I calculate its effective tax rate, which is the ratio between its property tax bill and its sale price. Next, each effective tax rate is scaled by the median effective tax rate in its TCA-year. Finally, I plot the median scaled effective tax rate for each house price bin.

The figure shows a clear downward-sloping relationship between effective tax rate and house price, which suggests that, holding constant the bundle of public goods, cheaper homes are taxed at higher rates than more expensive homes.[11] The disparity in effective tax rates between cheap and expensive homes is large. The median effective tax rate of houses in the bottom decile of the TCA-year price distribution is 46% higher than the median effective tax rate of houses in the top decile. Therefore, if effective tax rates are prices, then, to gain access to the same bundle of public goods, owners of cheaper houses are paying a much higher price than owners of expensive houses.

Section 3 alludes to the fact that the downward-sloping relationship between effective tax rate and house price could just be a statistical artifact that results from measurement error embedded in transaction prices. In other words, we see this pattern because houses that were sold for unexpectedly low prices would appear to have high effective tax rates, while houses that were sold for unexpectedly high prices would appear to have low effective tax rates. I use the empirical stra-

[11] I get a similar picture when I scale effective tax rates by mean TCA-year effective tax rate and plot mean scaled effective tax rates for each price bin.

tegy proposed in Section 3 to address this issue. Table 2 presents these regression results. Column 1 shows the ordinary least sqaures (OLS) regression result where log valuation ratio is regressed onto log sale price and TCA-year fixed effects. The slope coefficient estimated by this regression is -0.31. The two-stage least squares (2SLS) regression in Column 2 addresses the attenuation bias concern by instrumenting log sale price with log leave-one-out average sale prices from other transactions in house i's census tract block group. The estimated slope coefficient is -0.12, which suggests that assessments are indeed regressive, but approximately 60% of the observed regressivity is caused by attenuation bias.[12]

5.2 Flawed Valuation Method Explanation

The intuition for the flawed valuation methods explanation is the following. Consider two houses that have the exact same set of observable structure attributes (e.g., number of bedrooms, number of bathrooms, and living area square footage) and are located in the same TCA. One house is located in a desirable neighborhood, while the other is located in a less desirable one. An appraisal method that ignores neighborhood quality would assign the same appraised values to these houses. On the other hand, the market would assign very different prices to these houses because the one in the less desirable neighborhood would receive a much lower price. Upon sales, the econometrician would observe that β calculated from these two houses is negative. The same intuition applies if the overlooked characteristics are structural in nature (e.g., construction quality).

In the rest of the paper, I treat neighborhood characteristics as omitted variables because assessors often exclude them from regression models, but I can measure them with ACS data. Neighborhood characteristics that I have in mind can be thought of as very fine geographic area fixed effects that capture variation in variables such as crime rate and pollution. Variation in neighborhood characteristics within a small geogrpahic area can be large (Ananat, 2011), which explains why using fine geographic fixed effects (e.g., census tract block group) would not solve assessment regressivity. In the following subsection, I explain why a common valuation method used by county assessors tend to produce regressive assessments.

[12]The Kleibergen-Paap Wald F-Statistic passes the weak instrument test suggested by Stock et al. (2005).

5.3 Hedonic Pricing Method

The hedonic pricing method (HPM) regresses sale prices observed in year t onto measurable house and neighborhood characteristics associated with the house observed in the same year (Rosen, 1974). Coefficients from this regression model are used to calculate appraised values for all houses. HPM fails to capture relavant variation in neighborhood quality when the appraiser does not include good proxies for neighborhood quality in the regression equation. The International Association of Assessing Officers (IAAO) provides a guideline on which variables should be included in the appraiser's regression model (IAAO, 2014). The guideline suggests that type of dwelling, living area, construction quality, age, secondary areas, land size, available utilities, market area, zone, neighborhood, location amenities, and location nuisances be included in the model. Clearly, variables such as construction quality and location amenities are very difficult to quantify and appraisers would likely omit them.[13]

Formally, if appraised values are predicted sale prices from an OLS regression where log sale price m is regressed onto an arbitrary vector of house and neighborhood characteristics, then the expression for β can be written as follows.

$$\beta^{HPM} = \frac{Cov(\hat{m}, m)}{\sigma_m^2} = \frac{\sigma_{\hat{m}}}{\sigma_m} \times \rho_{\hat{m},m} - 1 = \sqrt{R_{\hat{m}}^2} \times \sqrt{R_{\hat{m}}^2} - 1 = R_{\hat{m}}^2 - 1 \tag{8}$$

$\hat{m}$ denotes appraised values. $R_{\hat{m}}^2$ denotes the coefficient of determination from the same regression. The derivation of β above assumes that $\rho_{\hat{m},m} > 0$ and uses the definition of an OLS regression R^2, which can be expressed as (1) the ratio of the explained variance and the total variance of the dependent variable and (2) the square of the Pearson correlation coefficient between the predicted values and the dependent variable. Here, β is always negative except for the knife-edge case where the appraiser's OLS regression model yields an R^2 of 1.[14]

[13] To provide a concrete example of the list of variables that appraisers use in their linear regression model, I turn to Cook County, Illinois, which makes its appraisal data public at https://datacatalog.cookcountyil.gov/Property-Taxation/Cook-County-Assessor-s-Residential-Property-Charac/bcnq-qi2z. The data set contains 82 variables and only a few are related to neighborhood characteristics, while the rest are related to house and parcel characteristics. The neighborhood variables are O'Hare noise indicator, floodplain indicator, and proximity to a major road indicator. Although these neighborhood characteristics may contain important pricing information for houses in the county, it is clear that a regression model that uses these variables would omit many other important neighborhood characteristics.

[14] Other appraisal methods commonly used by tax assessors and how they produce regressive assessments are

5.4 Testable Predictions

This section outlines testable predictions from the flawed valuation methods explanation. To recap, the proposed explanation asserts that assessment regressivity is caused by tax assessors' valuation models overreliance on observable house characteristics such as size and omission of difficult-to-observe characteristics such as neighborhood quality. This statement yields two testable predictions. The first testable prediction is, in instances where house characteristics cannot predict house prices well, assessments are more regressive.

Prediction 1 *Let* $R^2_{\hat{m}(\mathbf{h}^*)}$ *denote the coefficient of determination calculated from the following TCA-year-level regression.*

$$logM_{it} = \theta + \gamma' \mathbf{h^*_{it}} + \delta_{it} \tag{9}$$

M_{it} *denotes the observed sale price for house* i *in period* t *and* $\mathbf{h^*_{it}}$ *is a vector of house characteristics associated with house* i *in the same time period.* $\hat{m}(\mathbf{h}^*)$ *denotes predicted log of sale price from the regression above. The asterisk highlights the fact that this is an arbitrary vector of house characteristics chosen by the econometrician that may differ from the vector of house characteristics in true model of house prices. Let* β *be the slope coefficient estimated from the following TCA-year-level regression.*

$$logA_{it} - logM_{it} = \alpha + \beta logM_{it} + \epsilon_{it} \tag{10}$$

k *is the index for TCAs. Then across TCA-years,* $R^2_{\hat{m}(\mathbf{h}^*),kt}$ *should be positively correlated with* β_{kt}*.*

Intuitively, $R^2_{\hat{m}(\mathbf{h}^*)}$ captures how well variation in house characteristics can explain variation in observed sale prices of houses in a particular TCA-year and β is a measure of assessment regressivity among those houses. Note that a positive correlation between β and $R^2_{\hat{m}(\mathbf{h}^*)}$ is not me-

discussed in the online appendix.

chanical. This is because I do not know the exact appraisal models that local tax appraisers used to produce appraised values that I observe in the data. The existence of this positive correlation verifies that (1) variation in house characteristics explains variation in appraised values well and (2) assessment regressivity is driven by how well house characteristics serve as predictors of sale prices. Together, these two statements verify that house characteristics-based appraisal methods produce assessment regressivity, which is worse in TCA-years where house characteristics cannot reliably predict realized sale prices.

However, a positive correlation between β and $R^2_{\hat{m}(\mathbf{h}^*)}$ alone does not confirm the proposed story because it is also consistent with the story where cross-TCA-year variation in β is solely driven cross-TCA-year variation in transaction price noise. The second part of the flawed valuation methods story asserts that tax assessors' valuation models produce regressive assessments because they exclude neighborhood characteristics. Hence, the second testable prediction is that assessment regressivity should be worse in TCA-years where, on top of variation in house characteristics, variation in neighborhood characteristics is very important in explaining variation in realized sale prices. To fix ideas, suppose that log sale price m is a linear function of J house characteristics h_j and K neighborhood characteristics n_k.

$$m_i = \sum_{j=1}^{J} \lambda_j^h h_j + \sum_{k=1}^{K} \lambda_k^n n_k \tag{11}$$

λs are arbitrary constants. Let $\hat{m_i}(\mathbf{h}^*, \mathbf{n}^*)$ be the predicted log sale prices from regressing log sale price onto a set of house and neighborhood characteristics. The asterisks highlight the fact that this set of house and neighborhood characteristics is not the same as the one shown in Equation 11. A measure of the incremental explanatory power that neighborhood characteristics bring to the regression model is the following.

$$\Delta R^2_{kt} = R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*)} - R^2_{\hat{m}(\mathbf{h}^*)} \tag{12}$$

Prediction 2 *Let* $R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*)}$ *denote the coefficient of determination calculated from the following*

TCA-year-level regression.

$$logM_{it} = \theta + \gamma_{\mathbf{1}}'\mathbf{h}_{\mathbf{it}}^{*} + \gamma_{\mathbf{2}}'\mathbf{n}_{\mathbf{it}}^{*} + \delta_{it} \tag{13}$$

$\mathbf{n}_{\mathbf{it}}^{*}$ *is a vector of nieghborhood characteristic associated with house i in the same time period and everything else is defined as before. Then,* β *from Equation 10 should be negatively correlated with* $\Delta R^2_{kt} = R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*)} - R^2_{\hat{m}(\mathbf{h}^*)}$ *across TCA-years.*

Intuitively, ΔR^2_{kt} is large in places where variation in neighborhood characteristics can offer significant additional explanatory power to the regression model. If variation in neighborhood characteristics cannot help explain variation in realized sale prices, then the correlation between β_{kt} and ΔR^2_{kt} would be zero. A negative correlation between these two parameters confirms the flawed valuation methods story because it shows that assessment regressivity is caused by valuation models that omit neighborhood characteristics.

5.5 Testing the Predictions

The previous section proposes that, if assessment regressivity is driven by appraisers ignoring a set of important pricing characteristics, then there should be a positive relationship between β and $R^2_{\hat{m}(\mathbf{h}^*)}$ across TCA-years. To test this prediction, I begin by constructing a data set of transacted houses that I observe house characteristics, neighborhood characteristics, sale prices, and appraised values. Using this data set, I estimate β for each TCA-year by running the regression from Equation 10 and I estimate β^{IV} by using the approach outlined in Section 3. Next, I estimate $R^2_{\hat{m}(\mathbf{h}^*)}$ by running the regression from Equation 9. The house characteristics that I use are log number of bedrooms, log number of bathrooms, log living area square footage, and log age.[15]

Table 3 presents summary statistics for the estimated parameters. There are 10,974 TCA-years in the sample. The average β_{kt} is -0.42 and the average β^{IV}_{kt} is -0.21, which is consistent with the observation that assessments tend to be regressive. The degree of regressivity varies

[15] The choice of house characteristics follows the appraisal guideline from the International Association Of Assessing Officers (IAAO, 2010).

significantly across TCA-years. β_{kt} ranges from -1.03 to 0.19, while β_{kt}^{IV} ranges from -1.91 to 1.35. The average $R^2_{\hat{m}(\mathbf{h}^*)}$ is 0.41, which means that the list of house characteristics, on average, explains a substantial portion of house price variation within a TCA-year. Similarly to measures of assessment regressivity, there is significant variation across TCA-year in $R^2_{\hat{m}(\mathbf{h}^*)}$, which ranges from 0.05 to 0.81.

Figure 4 presents a binned scatter plot of β_{kt} on $R^2_{\hat{m}(\mathbf{h}^*),kt}$ with county-year fixed effects. Including county-year fixed effects is important because the thought experiment is, holding fixed valuation methods and other attributes related to the county assessors' office that may affect appraisal quality, does assessment regressivity decrease as house characteristics' ability to explain variation in realized sale prices increase? Figure 4 show that this is the case. There is a near-linear and positive relationship between β_{kt} on $R^2_{\hat{m}(\mathbf{h}^*),kt}$. I formally test this relationship by regressing β_{kt} on $R^2_{\hat{m}(\mathbf{h}^*),kt}$ with county-year fixed effects. Column 1 of Table 4 presents the result. As expected from the plot, there is a positive and significant relationship between β_{kt} and $R^2_{\hat{m}(\mathbf{h}^*),kt}$. The conclusion holds when I use β_{kt}^{IV} as the dependent variable. Column 2 presents this result.

To show that variation in neighborhood characteristics is the unaccounted component that drives the relationship between β_{kt} on $R^2_{\hat{m}(\mathbf{h}^*),kt}$, I compute $R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt}$ by estimating regression Equation 13.[16] Table 3 presents summary statistics for $R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt}$ and ΔR^2_{kt}. The average value of $R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt}$ is 0.54, which indicates that this set of house and neighborhood characteristics can explain, on average, half of the variation in realized sale prices. The average value of ΔR^2_{kt} suggests that adding neighborhood characteristics to the linear regression model can help improve its predictive power. There is substantial cross TCA-year variation in ΔR^2_{kt}, which shows that there are TCA-years where neighborhood characteristics are important and those where they are not.

Figure 5 presents a binned scatter plot of β_{kt} on ΔR^2_{kt} with county-year fixed effects. The plot shows a clear negative relatioship. The third column of Table 4 shows the estimated OLS

[16] Neighborhood characteristics that I use are minority share, log median household income, unemployment rate, percentage of adult with a college degree, percentage of households that participate in SNAP, median gross rent as a percentage of household income, homeownership percentage, home vacancy percentage, percentage of commerical parcels, percentage of industrial parcels, and percentage of agricultural parcels. Neighborhood characteristics are measured at the census tract block group-level.

coefficient from regressing β_{kt} onto ΔR^2_{kt} with county-year fixed effects. The estimated coefficient is negative and statistically significant, which confirms that omitted neighborhood characteristics drive the panel variation in assessment regressivity. The result holds when I use β^{IV}_{kt} as the dependent variable. Column 4 presents this result.[17]

5.6 How Much Do Flawed Valuation Methods Matter?

This section quantifies the proportion of assessment regressivity that can be explained by the flawed valuation method mechanism. I begin by constructing synthetic appraised values for houses that were sold.[18] For each transaction associated with a certain house i, I grow house i's most recent sale price by innovation in its local single-family house price index.[19]

$$A^{syn}_{i,t} = M_{i,t-k} \times \frac{HPI_t}{HPI_{t-k}} \tag{14}$$

$M_{i,t-k}$ is house i's previous sale price in year $t-k$ and $\frac{HPI_t}{HPI_{t-k}}$ is the change in its census tract house price index between year $t-k$ and year t.[20] This approach makes two implicit assumptions. First, house i's previous sale price captures house i's priced house and neighborhood characteristics in year $t-k$. In other words, past transaction price is a good predictor of current transaction price. Second, innovations in the local house price index sufficiently account for changes in priced neighborhood characteristics that occurred between year $t-k$ and year t.

The next step is to construct synthetic valuation ratios from taking the difference between log of house i's synthetic appraised value and log of its sale price. I then estimate the degree of assessment regressivity among houses in my sample by regressing log observed valuation ratio, the difference between log observed appraised value and log sale price, onto log sale price. The

[17] All results hold when standard errors are calculated from a bootstrapping procedure that creates 100 random samples from the original data set, estimates all parameters, and runs the test regression 100 times.

[18] This method is similar to the approach taken by Bayer et al. (2017).

[19] House price index data are from https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx.

[20] Missing census tract house price indexes are substituted with zip code house price indexes. Missing zip code house price indexes are substituted with county house price indexes. Results are not sensitive to the choice of house price index.

estimated slope coefficient β captures the observed degree of assessment regressivity that needs to be explained. Next, I estimate the degree of assessment regressivity using the instrumental variable approach outlined in Section 3. β^{IV} captures the degree of assessment regressivity that is free from attenuation bias. The difference between β and β^{IV} is the amount of assessment regressivity that can be explained by attenuation bias. Lastly, I run the 2SLS regression where log synthetic valuation ratio, the difference between log synthetic appraised value and log sale price, is regressed onto log sale price and log sale price is instrumented with log leave-one-out average sale price. The resulting slope coefficient captures the degree of assessment regressivity that is free from attenuation bias and some degree of model-induced valuation error. The difference between β^{IV} and the third slope coefficient, β^{IV}_{syn}, is the amount of assessment regressivity that can be explained by flawed valuation methods. Any remaining regressivity, the difference between β^{IV}_{syn} and zero, could come from the fact that Equation 14 does not account for renovations between year $t-k$ and year t or some other explanation. Hence, the difference between β^{IV} and β^{IV}_{syn} can be interpreted as the lower bound of the amount of assessment regressivity that can be explained by flawed valuation methods.

Table 5 presents the regression results. The sample used in these regressions include transactions in year t where the previous transaction in year $t-k$ is not more than 5 years old. This filter ensures that previous transaction prices are reasonable predictors of current transaction prices. The first column presents the baseline OLS regression result. The slope coefficient is -0.24. Column 2 presents the 2SLS regression result where log observed valuation ratio is regressed onto log sale price. The estimated slope coefficient is -0.07. The last column presents the 2SLS regression result where log synthetic valuation ratio is regressed onto log sale price. The slope coefficient is -0.01 and is not statistically different from zero. Comparing these three slope coefficients shows that, for this sample of transactions, 70% of the observed assessment regressivity can be explained by attenuation bias and the remaining 30% can be explained by flawed valuation methods.[21]

[21] Please refer to the online appendix for results using transactions with older previous transaction prices.

6 Other Explanations

6.1 Infrequent Reappraisals

It is a well known fact in the property tax literature that appraised values often lag sale prices because houses do not get reappraised every year (Engle, 1975; Heavey, 1978). Infrequent reappraisal can cause assessment regressivity in the following way. Suppose that, initially, appraised values equal sale prices for all houses. Each year, houses experience random i.i.d. mean-zero price shocks. Appraisers can perfectly predict these shocks but do not regularly update appraised values to reflect these changes. The result is low covariance between appraised values and sale prices, which makes assessments regressivity.

To quantify how much of the observed assessment regressivity can be explained by infrequent reappraisal, I run the regression shown in Equation 4 with TCA by year fixed effects and its 2SLS version for all houses sold and a subsample of houses that were reappraised and sold in the same year. I consider a house to have stale appraised value if its current appraised value equals its 1-year lagged appraised value. Table 6 presents these regression results.[22] Column 1 presents the OLS result for all houses sold. The estimated slope coefficient is -0.28. Column 2 presents the 2SLS result. The corrected slope coefficient is -0.06. Column 3 presents the 2SLS result for homes that were sold and reappraised in the same year. The estimated slope coefficient is -0.04 and it is statistically different from the slope coefficient reported in Column 2. Comparing the slope coefficients from Columns 2 and 3 shows that removing houses with stale appraised values from the sample decreases assessment regressivity by approximately 7%. This exercise shows that, despite being a common feature of property tax administration, infrequent reappraisal is a relatively small contributor to assessment regressivity.

[22] The sample size used in these regressions is smaller than the sample size used in the baseline regressivity regression because, for a transaction to be included, I must be able to observe its 1-year lagged appraised value.

6.2 Heterogeneous Appeals Behavior and Outcome

This subsection evaluates the heterogeneous appeals behavior and outcome explanation. Suppose that individuals who own cheaper homes are less likely to appeal their county-proposed appraised values, relative to individuals who own more expensive homes. Furthermore, suppose that owners of cheaper homes are also relatively less successful in winning appeals. These two factors could give rise to assessment regressivity.

To explore whether the appeals hypothesis could explain within-TCA assessment regressivity, I use publicly available tax, transaction, and appeals data from Cook County, Illinois.[23] I use unique parcel identifiers to merge Cook County's transaction data with Cook County's appeals data. Using the same identifiers, I merge TCA data from CoreLogic into the merged Cook County data set. Next, I use the procedure from Section 5.6 to impute market prices for homes that were not sold at least twice in the sample. The resulting data set is a panel of more than 3.8 million transactions with annual appeals information, appraised values, imputed market values, and, where available, sale prices. Finally, I assign houses to 1 of 20 price bins within their TCA-year to explore how appeals behavior and outcome vary across price bins.

Figure 6 plots average appeal probability against within-TCA-year house price bins. If differences in appeals behavior were to explain the negative relationship between valuation ratio and house price, then there should be a positive relationship between appeals probability and house price. The plot shows that, although not monotonically, there is a positive relationship between appeals probability and house price, which lends support to the heterogeneous appeals behavior story.

Next, I investigate the relationship between win probability and within-TCA house prices. Figure 7 plots average win probability against within-TCA-year house price bins. This sample includes only houses that filed an appeal in a given year. If differences in win probability were to explain assessment regressivity, then there should be a positive relationship between win probability and house price. Similarly to appeals behavior, I find an almost monotonically increasing relationship between win probability and house price.

[23] https://datacatalog.cookcountyil.gov/

Lastly, I investigate how, conditional on appealing, appraisal reduction percentage varies with house price. Figure 8 plots average percentage appraised value reduction against within-TCA-year house price bins. This sample includes only houses that filed an appeal in a given year. If differences in degrees of appeals success were to explain assessment regressivity, then there should be a positive relationship between appraised value reduction and house price. However, the relationship is U-shaped, with houses near the top of the within-TCA-year price distribution receiving only slightly more appraisal reduction than houses at the bottom of the distribution. In conclusion, although owners of more expensive homes are more likely to appeal and win, the resulting pattern of appraisal reduction cannot explain the downward-sloping relationship between valuation ratio and house price.[24]

7 Property Tax and Wealth Inequality

7.1 Property Tax Burden and Wealth

To show how property tax burden fall on homeowners with different wealth levels, I combine data from CoreLogic with data from the 2016 Survey of Consumer Finance (SCF).[25] I first use data from the SCF to divide homeowners into eleven groups, according to the value of their primary residences. These groups are, approximately, the ten deciles of primary residence value and the top one percent. Table 7 shows the lower and upper bound values for each group. Using the same data set, I calculate average homeowners' net worth for each group. Using the CoreLogic data set, each group's average property tax bills are calculated from single-family house transactions in 2016.[26] The final column presents average property tax bill as a percentage of net worth. The key observation is that property taxes are regressive with respect to wealth. Sorted this way, the data shows a near-monotonically decreasing relationship between property tax bill as a percentage of net worth and net worth. Homeowners in the bottom decile of the house price distribution pay

[24] Appendix A.3 provides additional analyses that support this conclusion.

[25] https://sda.berkeley.edu/sdaweb/analysis/?dataset=scfcomb2019

[26] To match the SCF's house price distribution, I do not drop houses that were sold for less than $10,000 and those that were sold for more than $10,000,000. Results are qualitatively and quantitatively similar when I drop these transactions.

average annual property tax that is equivalent to 1.31% of their net worth. On the other hand, homeowners in the top 1% of the house price distribution pay average annual property tax that is equivalent to 0.12% of their net worth. These numbers show that the property tax system in the United States is effectively a regressive wealth tax, which aligns with results from Levinson (2020).

The regressivity in property tax burden with respect to wealth comes from three sources – (1) correlation between homeowners' wealth and primary residence value, (2) homeowners' wealth composition, and (3) assessment regressivity. Homeowners sort into differentially priced homes such that there are systematic correlations between wealth, income, and house price. Homeowners with low levels of wealth sort into cheaper homes, while homeowners with high levels of wealth sort into more expensive homes. This fact is clear from the average net worth tabulation in Table 7. Furthermore, as shown in Table A4, home equity makes up a larger percentage of homeowners' asset portfolio for those in the lower part of the house price distribution, compared to those in the upper part of the distribution. The combination of these two facts and assessment regressivity makes property taxes regressive with respect to wealth. Low-wealth individuals buy cheap homes that tend to be over-appraised and their property tax bills are large relative to their total wealth because their primary residences make up a large part of their wealth portfolio.

7.2 Excess Tax Payments and Wealth Inequality

This section quantifies the amount of regressivity that comes from assessment regressivity and discusses implications for wealth inequality. I begin by calculating excess tax payments (ETP) for each house that was sold in 2016. Excess tax payment is calculated as the difference between the observed tax bill and the counterfactual tax bill, which would have resulted if houses were taxed according to their sale prices.

$$ETP_{ik} = \underbrace{T_{ik}}_{\text{Observed Tax Bill}} - \underbrace{\frac{\sum_{i=1}^{n} T_{ik}}{\sum_{i=1}^{n} M_{ik}}}_{\text{Counterfactual Tax Rate}} \times \underbrace{M_{ik}}_{\text{Sale Price}} \tag{15}$$

Within a TCA k, for all houses that were sold, I compute total tax revenue and total sale value. Total tax revenue divided by total sale value gives the counterfactual statutory tax rate.[27] The counterfactual tax rate is multiplied to each house's sale price to arrive at the counterfactual tax bill. A positive ETP value means that the observed tax bill is too high and a negative value means that it is too low, relative to the sale price-based benchmark. For this exercise, I exclude TCAs that have fewer than thirty transactions in 2016.[28]

Table 8 presents the result of these back-of-the-envelope calculations for the average household in each home-value group. On average, households whose primary home values are in the bottom decile pay \$590 in excess tax payment per year. This amount is equivalent to 45% of the average property tax bill for this group of homeowners, which means that regressive assessments almost doubled their property tax burden. The percentage of assessment-regressivity-induced overtaxation is also large for homeowners in the next two deciles. These percentages are 21% and 9.3%, respectively. Not surprisingly, these ETP values decrease monotonically with house price and turns negative for homeowners whose primary residence is valued above the 60th percentile. At the top part of the distribution, homeowners in the very most expensive homes receive a tax break of approximately 14% from regressive assessments. The main takeaway is that the degree of over and under-taxation that result from regressive assessments is large.

The fourth column reports mean excess tax payment as a percentage of mean net worth for each group. I can use these percentages to decompose the amount of wealth tax regressivity that comes from assessment regressivity. I begin by calculating the obesrved wealth tax rate gap between rich and poor homeowners. Table 7 shows that the gap in wealth tax rates between homeowners in the bottom decile and those in the top 1% is 1.19% (1.31% - 0.12%). This gap is a measure of wealth tax regressivity. Next, I adjust these wealth tax rates by subtracting the excess tax payment as percentages of mean net worth numbers. The resulting adjusted wealth tax rates can

[27] Note that this calculation is analogous to the formula for statutory tax rate, which is the ratio of total property tax revenue raised (sum of all tax bills) and the local government's tax base (sum of all assessed values).

[28] Due to data limitations, the calculations in this section make several simplifying assumptions. The first assumption is that redistributing tax burdens among houses that were sold is close enough to the tax burden distribution that would have realized if, instead, all houses were sold and the calculations were repeated on the population. Secondly, these calculations make the assumption that every government entity that collects property taxes from a TCA shares the same property tax base, which is made up of all single-family homes in the TCA. In practice, this is not true. Each government entity has its own service boundary, which are overlaid onto each other to form TCAs. Therefore, a better method to calculate counterfactual tax rates requires a data set that contains the complete set of property-tax-collecting government entities, each government's tax base, and each government's statutory tax rate. Given currently available data, these calculations give the best estimates of excess tax payments known to the literature.

be interpreted as the wealth tax rates that are free of assessment regressivity. Using the adjusted wealth tax rates, I calculate the adjusted wealth tax rate gap, which is 0.59%.[29] Comparing the adjusted gap to the original gap shows that approximately half of the wealth tax regressivity comes from regressive home assessments.[30]

If we can correct assessment regressivity, how would the wealth distribution among homeowners change? I can answer this question in the following way. By treating each house's excess tax payment as a perpetuity and assuming that property taxes are fully capitalized into house prices at a discount rate of 4%, these excess tax payments can be converted into changes in home equity (Do and Sirmans, 1994).[31] These changes are the amount of home equity that would accrue to homeowners, if assessment regressivity were fully corrected. For homeowners in the bottom decile of the house price distribution, average over-taxation of $590 per year is equivalent to a present value amount of $14,756 or approximately 15% of average net worth. The interpretation is that, if regressive assessments were fully corrected, then these homeowners would see their net worth increase by almost 15% because the value of their primary residence would increase by $14,756.

Likewise, for homeowners in the top 1% of the house price distribution, a $3,904 property tax break is equal to $97,600 in present value term or 0.4% of average net worth. The interpretation is that correcting assessment regressivity would, on average, decrease the net worth of this group of homeowners by 0.4%. These calculations show that correcting assessment regressivity would decrease the wealth gap between owners of cheap homes and owners of expensive homes by transferring wealth from rich homeowners to poor homeowners. For instance, the ratio of wealth between the average top-group homeowner and the average bottom-group homeowners would decrease by 13%.[32]

[29] $(1.31\% - 0.58\%) - (0.12\% + 0.02\%) = 0.59\%$

[30] $1 - \frac{0.59\%}{1.19\%} = 49.6\%$

[31] A $1 excess tax payment per year, if eliminated, would increase home equity by $25.

[32] It is important to note that these calculations do not account for additional savings that poor homeowners get, additional disavings that rich homeowners experience, and other general equilibrium effects that could influence the distribution of homeowners' wealth.

8 Sorting and Overtaxation of Disadvantaged Households

In this section, I argue that over-taxation of disadvantaged households is a *by-product* of assessment regressivity. In a world where there is assessment regressivity and no direct discrimination by tax assessors towards any group, any group that sort into cheap houses would *mechanically* face unfavorable assessment gaps, relative to groups that sort into expensive houses. Therefore, despite the existence of assessment gaps between racial groups, the only form of discrimination that truly exists in this hypothetical world is discrimination with respect to house price.

To make this point, I begin by replicating results from the literature, which documents that minorities and low-income households live in houses that are relatively overtaxed (Baar, 1981; Black, 1977; Avenancio-León and Howard, 2019). I also add level of education as the third indicator for socioeconomic status. Following the literature, I merge census tract block group characteristics with single-family home transactions and tax records into a panel data set that I can use to run variants of the following regression.

$$logT_{it} - logT_{it}^{M} = \alpha + \gamma Demographic\,Indicator_{it} + TCA \times Year\,FE + \epsilon_{it} \tag{16}$$

The log difference between the observed tax bill and the counterfactual tax bill is regressed onto a demographic indicator variable, along with TCA by year fixed effects. The counterfactual tax bill is calculated in the same way as in Section 7. T_{it} denotes house i's observed property tax bill in year t and T_{it}^{M} denotes its counterfactual tax bill. The log difference of these two quantities is a measure of excess tax payment, which I call taxation gap. The demographic indicator variables that I use are Low Income, Low College Share, and High Minority Share. Low Income equals 1 if the home is located in a census tract block group where its median household income is lower than the sample's median in that year. Low College Share equals 1 if the home is located in a census tract block group where its share of college-educated adults is lower than the sample's median in that year. High Minority Share equals 1 if the home is located in a census tract block group where its minority share is higher than the sample's median in that year. Minority share is defined as the percentage of the census tract block group's population that is black, Hispanic, or Native American. In line with results from the literature, I find that houses in relatively disadvantaged census tract block groups have higher excess tax payments than houses in more advantageous block groups.

Next, I show that disadvantaged households tend to sort into cheap houses. Using the same data set, Table 10 presents average mortgage holder characteristics by TCA-year price decile. First, note that within TCA-year house price variation is large. Average house price in the top TCA-year decile is more than five times greater than the average house price in the bottom decile. Second, degree of over-taxation decreases with house price. The average homeowner in the bottom price decile are overtaxed by 67%, while the average homeowner in the bottom price decile is undertaxed by 9%. Crucially, block group characteristics that are correlated with socioeconomic advantages (e.g., household income and education) increase with house price, while those that are associated with socioeconomic disadvantages decrease with house price (e.g., minority share). This exercise shows that households sort into differentially priced homes in such a way that socioeconomic characteristics systematically correlate with house price.

To investigate whether the taxation gaps shown in Table 9 are purely a function of sorting by price, I run variants of the following regression.

$$
\begin{aligned}
logT_{it} - logT_{it}^{M} = \alpha &+ \gamma Demographic\,Indicator_{it} \\
&+ \theta_1 Price\,Decile\,2_{ijt} + \theta_2 Price\,Decile\,3_{ijt} + ... \\
&+ \lambda_1 Demographic\,Indicator_{it} \times Price\,Decile\,2_{ijt} + ... \\
&+ TCA\ \times Year\,FE + \epsilon_{it}
\end{aligned}
\tag{17}
$$

j is the index for TCA. Log excess tax payment is regressed onto a demographic indicator variable, within-TCA-year house price decile indicator variables, and their interaction terms. This specification controls for where each home is located in the within-TCA-year house price distribution. If after conditioning on house price, disadvantaged households are still overtaxed relative to other households, then the data suggests that direct discrimination along certain household characteristics may exist. If taxation gaps disappear after I control for house price, then the data suggests that the results shown in Table 9 can be completely explained by house price sorting and model-induced assessment regressivity.

Table 11 presents the results. Statistical significance tests are performed on the estimated coefficients to determine whether, conditional on house price, the taxation gaps shown in Table 9 remain positive and statistically different from zero. Table 12 presents t-test results on the taxation gaps in each price decile and F-statistics from joint tests against the null hypothesis that the taxation gap is equal to zero in all ten price deciles. Figures 9, 10, and 11 plot the estimated coefficients relative to the reference group's average log taxation gap along with 95% confidence interval bars based on results shown in Table 12.

Column 1 of Table 12 shows that the low-income taxation gap is negative in nine out of ten house price deciles. The joint test rejects the null hypothesis that the coefficients are jointly equal to zero, which indicates that, on average, the low-income taxation is negative. These results show that the low-income taxation gap shown in Table 9 is purely a function of low-income households sorting into over-appraised cheap houses. Furthermore, it is actually the case that low-income households are being *undertaxed*, relative to higher-income households. It is beyond the scope of this paper to explore why this pattern appears in the data. Columns 2 and 3 show similar results for houses located in low-education and high-minority areas. Another way to interpret this second set of results is that the baseline regression results suffer from omitted variable bias where the omitted variable is house price.

Avenancio-León and Howard (2019) document that minorities (e.g., black and non-white Hispanic households) pay higher effective tax rates than non-Hispanic white households and assert that an econometrician cannot identify whether this taxation gap is the result of direct discrimination against minorities or flawed valuation methods. In this section, I show that, by conditioning on house price, an econometrician can indeed differentiate between the two explanations. Although the data show that, on average, assessors do not directly discriminate against minority homeowners, I cannot say that direct discrimination does not exist in specific parts of the country. More importantly, the results suggest that wealth inequality across racial groups, which is likely a result of systemic racism (Aaronson et al., 2020), forces minorities into cheaper homes and is the key driver of inequitable property tax burdens.

9 Conclusion and Discussion

This article uses data from more than 20 million single-family home transactions to document assessment regressivity among houses that pay the same statutory property tax rate and have access to the same set of property-tax funded amenities. Flawed valuation methods, which ignore priced latent characteristics, can explain a large portion of this phenomenon, which suggests that assessment regressivity could be alleviated by improving appraisal techniques. A simple solution that can reduce the degree of assessment regressivity among houses with relatively recent transaction prices is to calculate appraised values as the product of their previous sale prices and the innovation in their local house price indexes.

Although this article focuses on single family home assessments, it is likely that assessment regressivity also exists among other types of properties (e.g., commercial, industrial, and agricultural). For these properties, assessors use the income approach to assign appraised values. To appraise a given property, the assessor calculates average price-to-rent ratio from comparable properties and applies it to the property's annual rent. The income approach uses overly coarse average unobservable characteristics to value properties, which, under weak assumptions, produces regressive assessments in the same way that the comparable sales approach does.[33]

The results from this paper have several implications for economic inequality in the United States. In line with Levinson (2020), I find that the property tax system serves as a regressive wealth tax among homeowners. Furthermore, I show that overtaxation of disadvantaged households is a mechanical result of model-induced assessment regressivity because, due to low levels of wealth, these households sort into cheap houses that tend to be overappraised. This result highlights the role that wealth inequality plays in driving low-wealth individuals into situations where other types of inequality manifest and worsen their economic position.

Lastly, a general lesson from this article is that a wealth tax system that requires the

[33] Refer to the online appendix for a detailed discussion.

government to value and tax assets with no readily available market prices would tend to increase wealth inequality among asset holders. This is because households with low levels of wealth tend to hold cheaper assets (e.g., cheap cars, cheap houses, and small businesses with low growth potential), while households with high levels of wealth tend to hold more expensive assets. Since statistical valuation methods tend to overappraise cheap assets and under-appraise expensive assets, it follows that imposing such a tax regime would increase wealth inequality among these two groups via the tax capitalization channel.

Figure 1: Median Scaled Statutory Tax Rate by TCA-Year House Price Bin

This figure presents a binnned scatter plot of median scaled statutory tax rate for houses in each TCA-year price bin. Statutory tax rate is calculated as house i's observed tax bill in year t divided by its appraised value in year t. Tax code areas (TCA) are small geographic areas where every house has access to the same set of property-tax funded government services and pay the same statutory tax rate. Each house's statutory tax rate is scaled by the median statutory tax rate in its TCA-year. Houses in each TCA-year are evenly sorted into twenty price bins. The cheapest houses are in the first bin and the most expensive houses are in the twentieth bin. The sample contains single-family houses in 49 states and the District of Columbia that were sold between 2000 and 2019.

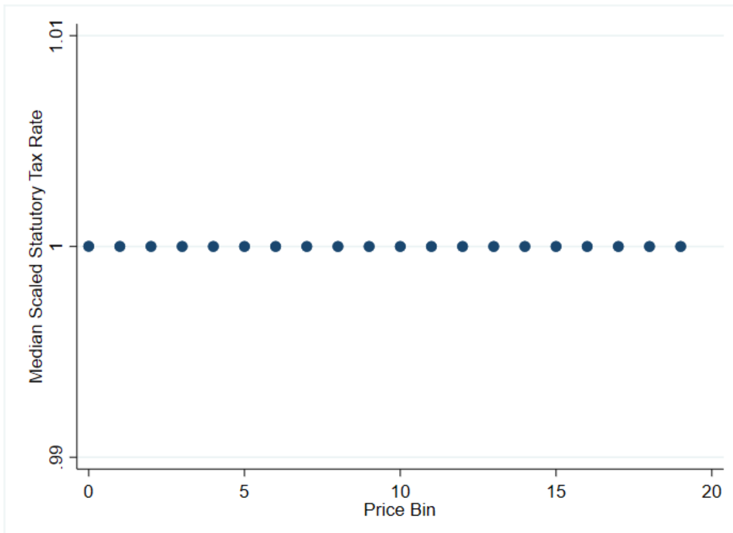


Figure 2: Median Scaled Effective Tax Rate by TCA-Year House Price Bin

This figure presents a binnned scatter plot of median scaled effective tax rate for houses in each TCA-year price bin. Effective tax rate is calculated as the house's observed tax bill in year t divided by its sale price in year t. Tax code areas (TCA) are small geographic areas where every house has access to the same set of property-tax funded government services and pay the same statutory tax rate. Each house's effective tax rate is scaled by the median effective tax rate in its TCA-year. Houses in each TCA-year are evenly sorted into twenty price bins. The cheapest houses are in the first bin and the most expensive houses are in the twentieth bin. The sample contains single-family houses in 49 states and the District of Columbia that were sold between 2000 and 2019.

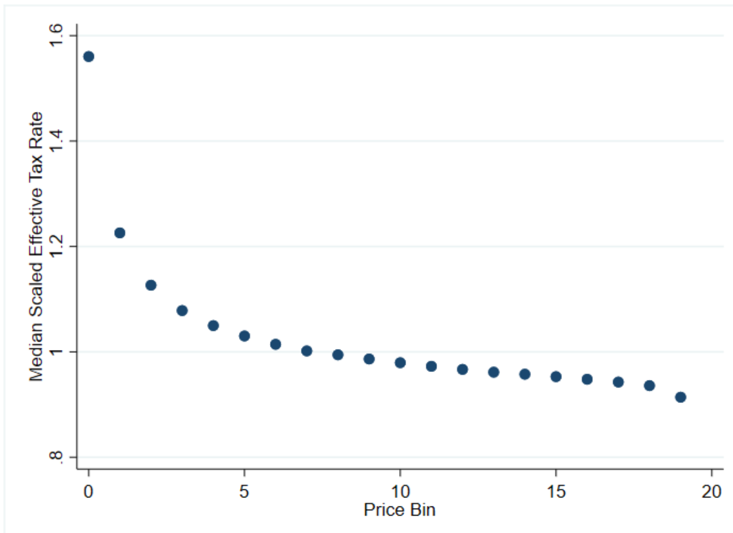


Figure 3: 2020 Tax Code Areas in Snohomish County, WA

This figure presents the list of all local government entities that collect property taxes in three tax code areas (TCA) in Snohomish County, WA. Statutory tax rates are presented as \$1 USD of tax per \$1,000 USD of assessed value.

TAX CODE AREAS & RATES FOR TAX YEAR 2020

"TCA's" (Tax Code Areas) designate a unique set of taxing districts. They appear on tax statements. These columns list the Tax Code Area, district/levy, and regular and excess levy rates within that TCA. All rates are expressed in dollars per thousand dollars of assessed value. Totals are accurate, but may not agree to sum of detail because of rounding.

TCA	District Abbrev.	District/Levy Name	Regular/Excess	Rate
00018	CNT	COUNTY REGULAR	Regular Levy	0.63749375727
	CNT	COUNTY CONSERVATION FUTURES	Regular Levy	0.02796182191
	CTYEVT	EVERETT	Regular Levy	1.90529928265
	CTYEVT	EVERETT EMS PERMANENT 2001-ON	Regular Levy	0.46801912362
	PRTEVT	PORT OF EVERETT MAINTENANCE	Regular Levy	0.23664019462
	SCH002EVT	SCHOOL 002 BONDS	Excess Levy	2.41352285021
	SCH002EVT	SCHOOL 002 CAPITAL PROJECTS	Excess Levy	0.54775496112
	SCH002EVT	SCHOOL 002 ENRICHMENT	Excess Levy	1.92148220699
	STASCH	STATE SCHOOL 1	Regular Levy	1.86415073934
	STASCH	STATE SCHOOL 2	Regular Levy	1.00352181207
			Sum of Regular Levy Rate	6.14308673148
TCA Value:	\$250,619		*Sum of Excess Levy Rate*	4.88276001832
			Sum of TCA 00018	***11.02584674980***
00020	CNT	COUNTY REGULAR	Regular Levy	0.63749375727
	CNT	COUNTY CONSERVATION FUTURES	Regular Levy	0.02796182191
	CTYEVT	EVERETT	Regular Levy	1.90529928265
	CTYEVT	EVERETT EMS PERMANENT 2001-ON	Regular Levy	0.46801912362
	PRTEVT	PORT OF EVERETT MAINTENANCE	Regular Levy	0.23664019462
	RTACPS	CENTRAL PUGET SOUND REGIONAL TRANSIT AUTHORITY	Regular Levy	0.19937000000
	SCH002EVT	SCHOOL 002 BONDS	Excess Levy	2.41352285021
	SCH002EVT	SCHOOL 002 CAPITAL PROJECTS	Excess Levy	0.54775496112
	SCH002EVT	SCHOOL 002 ENRICHMENT	Excess Levy	1.92148220699
	STASCH	STATE SCHOOL 1	Regular Levy	1.86415073934
	STASCH	STATE SCHOOL 2	Regular Levy	1.00352181207
			Sum of Regular Levy Rate	6.34245673148
TCA Value:	\$188,410,518		*Sum of Excess Levy Rate*	4.88276001832
			Sum of TCA 00020	***11.22521674980***
00021	CNT	COUNTY REGULAR	Regular Levy	0.63749375727
	CNT	COUNTY CONSERVATION FUTURES	Regular Levy	0.02796182191
	CTYEVT	EVERETT	Regular Levy	1.90529928265
	CTYEVT	EVERETT EMS PERMANENT 2001-ON	Regular Levy	0.46801912362
	HSP001VAL	HOSPITAL DIST 1 MAINTENANCE	Regular Levy	0.23340678097
	PRTEVT	PORT OF EVERETT MAINTENANCE	Regular Levy	0.23664019462
	RTACPS	CENTRAL PUGET SOUND REGIONAL TRANSIT AUTHORITY	Regular Levy	0.19937000000
	SCH002EVT	SCHOOL 002 BONDS	Excess Levy	2.41352285021
	SCH002EVT	SCHOOL 002 CAPITAL PROJECTS	Excess Levy	0.54775496112
	SCH002EVT	SCHOOL 002 ENRICHMENT	Excess Levy	1.92148220699
	STASCH	STATE SCHOOL 1	Regular Levy	1.86415073934
	STASCH	STATE SCHOOL 2	Regular Levy	1.00352181207
			Sum of Regular Levy Rate	6.57586351245
TCA Value:	\$148,078		*Sum of Excess Levy Rate*	4.88276001832
			Sum of TCA 00021	***11.45862353077***

Figure 4: Binnned Scatter Plot of β_{kt} Against $R^2_{\hat{m}(\mathbf{h}^*),kt}$

Each observation is a TCA-year, indexed by kt. β_{kt} is estimated for each TCA-year by regressing log valuation ratio onto log sale price. $R^2_{\hat{m}(\mathbf{h}^*),kt}$ is the coefficient of determination from TCA-year regressions where log sale price is regressed onto house characteristics. Both variables are residualized by county-year indicator variables. The sample contains TCA-years where there are at least 30 transactions.

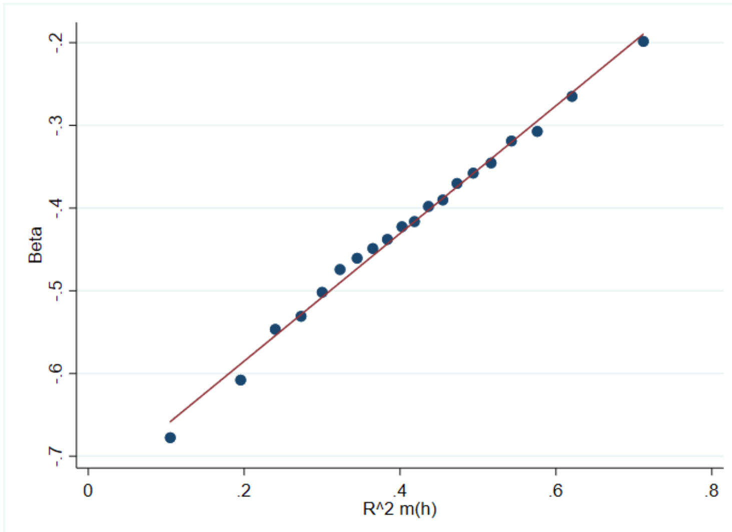


Figure 5: Binnned Scatter Plot of β_{kt} Against ΔR^2_{kt}

Each observation is a TCA-year, indexed by kt. β_{kt} is estimated for each TCA-year by regressing log valuation ratio onto log sale price. $R^2_{\hat{m}(\mathbf{h}^*),kt}$ is the coefficient of determination from TCA-year regressions where log sale price is regressed onto house characteristics. $R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt}$ is the coefficient of determination from TCA-year regressions where log sale price is regressed onto house and neighborhood characteristics. $\Delta R^2_{kt} = R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt} - R^2_{\hat{m}(\mathbf{h}^*),kt}$. Both variables are residualized by county-year indicator variables. The sample contains TCA-years where there are at least 30 transactions.

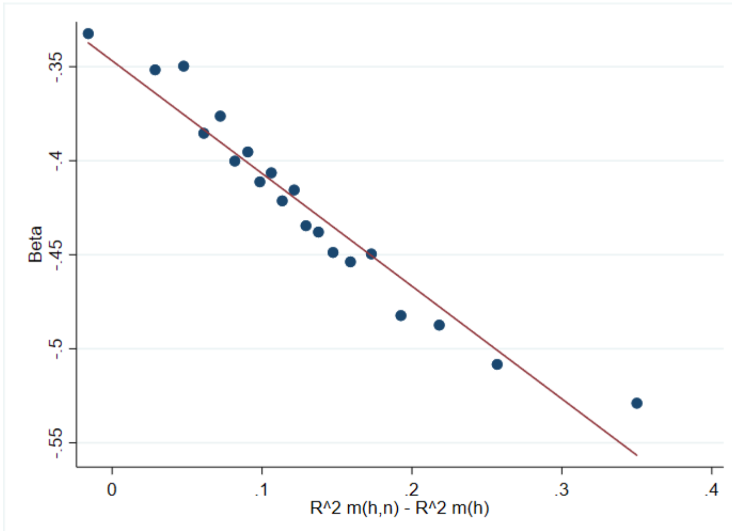


Figure 6: Appeals Probability by TCA-Year House Price Bin

This figure presents a binnned scatter plot of appeals probability against TCA-year house price bins for houses in Cook County, IL. Appeals probability is calculated from an appeal indicator variable, which equals 1 if the homeowner filed an appeal in a given year and zero otherwise. Houses in each TCA-year are evenly sorted into twenty price bins. The cheapest houses are in the first bin and the most expensive houses are in the twentieth bin. The sample includes house-years between 2007 and 2017 where sale prices are observable or where sale prices can be imputed using the procedure from Bayer et al. (2017).

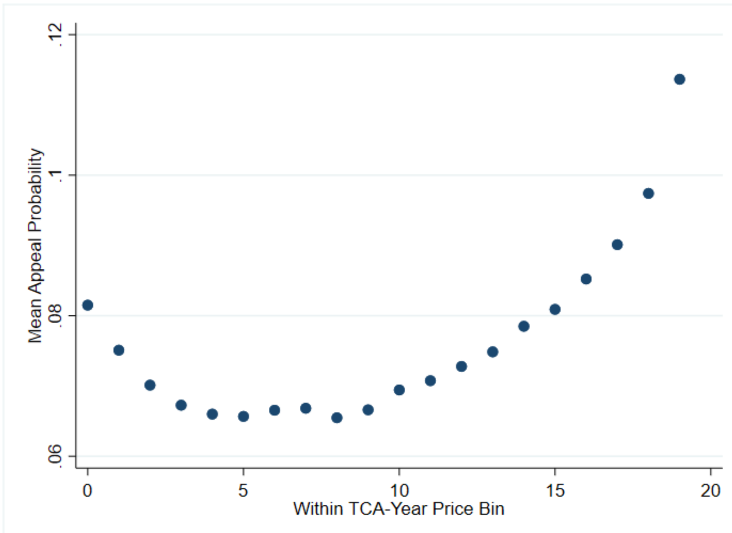


Figure 7: Win Probability by TCA-Year House Price Bin

This figure presents a binnned scatter plot of win probability against TCA-year house price bins for houses in Cook County, IL. The sample includes house-years between 2007 and 2017 where the homeowner filed an appeal and house-years where sale prices are observable or where sale prices can be imputed using the procedure from Bayer et al. (2017). Win probability is calculated from a win indicator variable which equals 1 if the homeowner appealed and won in a given year and zero otherwise. Houses in each TCA-year are evenly sorted into twenty price bins. The cheapest houses are in the first bin and the most expensive houses are in the twentieth bin.

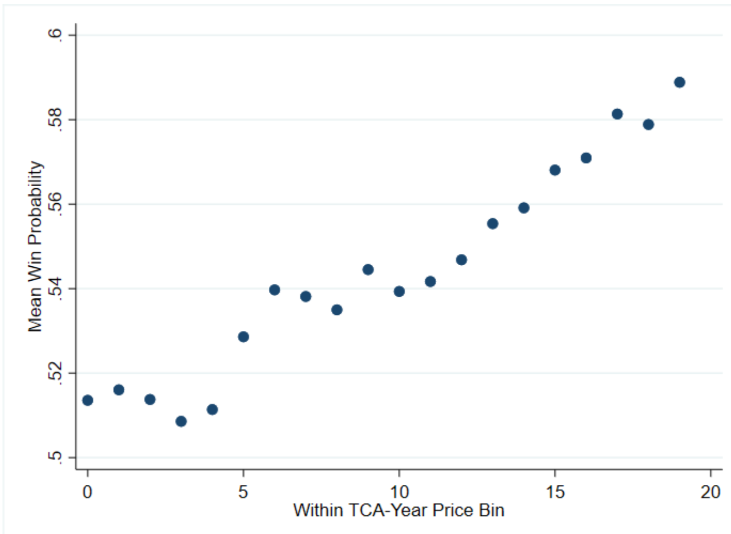


Figure 8: Average Percentage Appraised Value Reduction by TCA-Year House Price Bin

This figure presents a binnned scatter plot of average percentage appraised value reduction against TCA-year house price bins for houses in Cook County, IL. The sample includes house-years between 2007 and 2017 where the homeowner filed an appeal and house-years where sale prices are observable or where sale prices can be imputed using the procedure from Bayer et al. (2017). Appraised value reduction percentage is calculated as the amount of appraised value reduction that the homeowner received divided by the proposed appraised value. Houses in each TCA-year are evenly sorted into twenty price bins. The cheapest houses are in the first bin and the most expensive houses are in the twentieth bin.

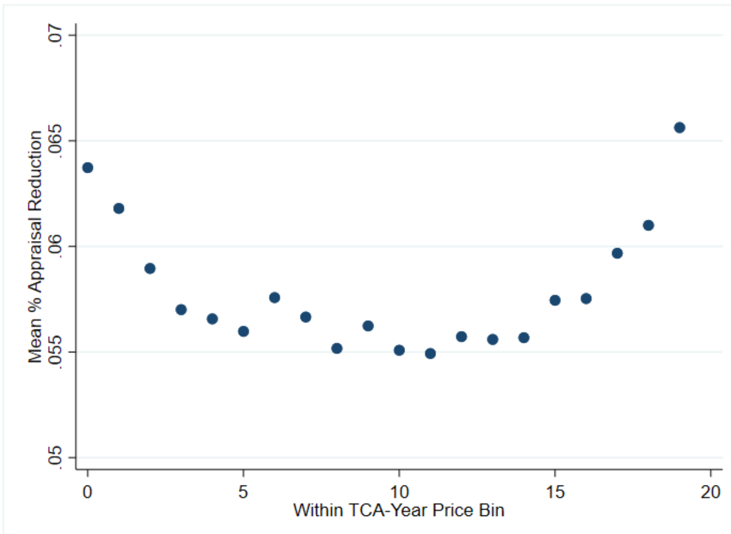


Figure 9: Low-Income Taxation Gap by TCA-Year Price Decile

This plot compares average log taxation gap of houses in low-income census tract block groups to average log taxation gap of other homes, conditional on TCA-year price decile. Taxation gap is defined as the ratio of the observed tax bill and the counterfactual tax bill, if the home were taxed according to its sale price in that year. A census tract block group is considered to be low-income if its median household income is lower than the year's median value. Blue dots are average log taxation gap of houses in low-income census tract block groups in each TCA-year price decile. Red dots are average log taxation gap of other homes in each TCA-year price decile. In each TCA-year price decile, the blue dot is calculated as the sum of the reference group's average log taxation gap and the approriate coefficient from Column 1 of Table 12. The bars are 95% confidence intervals drawn from the same t-tests.

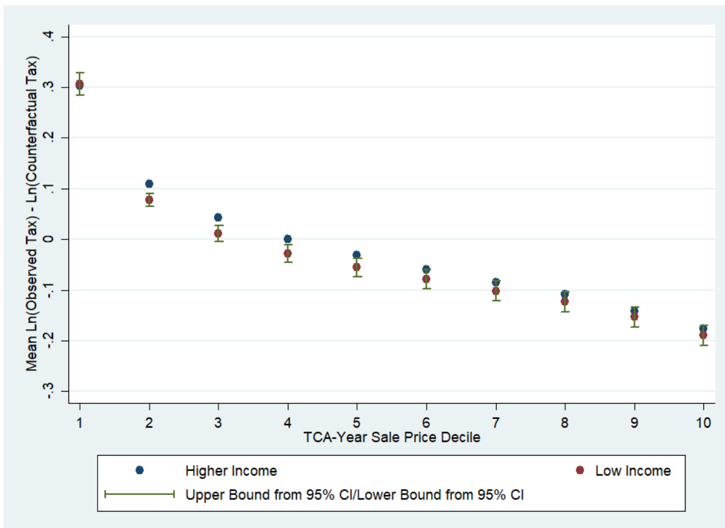


Figure 10: Low College Share Taxation Gap by TCA-Year Price Decile

This plot compares average log taxation gap of houses in census tract block groups with low college share to average log taxation gap of other homes, conditional on TCA-year price decile. Taxation gap is defined as the ratio of the observed tax bill and the counterfactual tax bill, if the home were taxed according to its sale price in that year. A census tract block group is considered to have low college share if its percentage of college-educated adults is lower than the year's median value. Blue dots are average log taxation gap of houses in census tract block groups with low college share in each TCA-year price decile. Red dots are average log taxation gap of other homes in each TCA-year price decile. In each TCA-year price decile, the blue dot is calculated as the sum of the reference group's average log taxation gap and the approriate coefficient from Column 2 of Table 12. The bars are 95% confidence intervals drawn from the same t-tests.

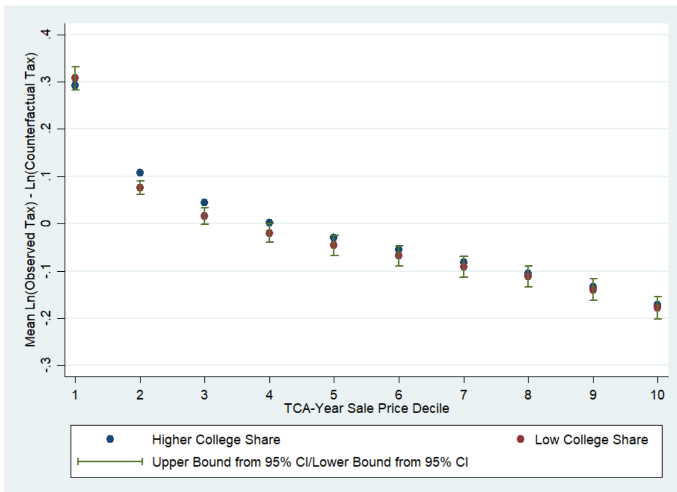


Figure 11: High Minority Share Taxation Gap by TCA-Year Price Decile

This plot compares average log taxation gap of houses in census tract block groups with high minority share to average log taxation gap of other homes, conditional on TCA-year price decile. Taxation gap is defined as the ratio of the observed tax bill and the counterfactual tax bill, if the home were taxed according to its sale price in that year. Minority share is calculated as the sum of black, Hispanic, and Native American population divided by total population. A census tract block group is considered to have high minority share if its percentage of minority individuals is higher than the year's median value. Blue dots are average log taxation gap of houses in census tract block groups with high minority share in each TCA-year price decile. Red dots are average log taxation gap of other homes in each TCA-year price decile. In each TCA-year price decile, the blue dot is calculated as the sum of the reference group's average log taxation gap and the approriate coefficient from Column 3 of Table 12. The bars are 95% confidence intervals drawn from the same t-tests.

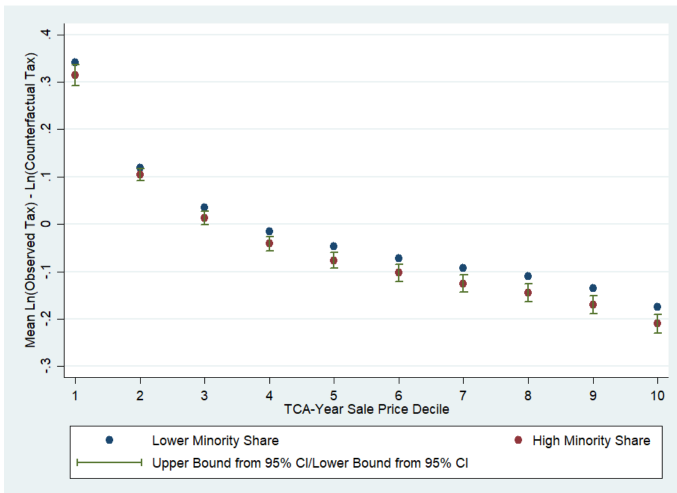


Table 1: Tax Code Area Summary Statistics

This table presents summary statistics of tax code areas that appear in 2018. The top panel presents summary statistics on tax code area characteristics. Number of Parcel is the number of deeded parcels in a given tax code area. Land area is the total land area of a tax code area computed as the sum of the land area of all parcels that belong to the tax code area. Percentage of parcel type is computed as the number of parcels of each type divided by the total number of parcels. The bottom panel presents summary statistics on the number of tax code areas by geographic unit. The sample excludes Massachusetts and Rhode Island because there is no tax code area data for these two states in 2018.

Variable	N	Mean	S.D.	25th	Median	75th
Number of Parcels	138,188	930.08	7,432.64	8.00	65.00	408.00
Land Area in Square Miles	138,188	17.48	149.88	0.05	0.49	5.74
% of Residential Parcels	138,188	0.45	0.38	0.03	0.46	0.82
% of Commercial Parcels	138,188	0.11	0.23	0.00	0.01	0.08
% of Industrial Parcels	138,188	0.03	0.12	0.00	0.00	0.00
% of Agricultural Parcels	138,188	0.20	0.33	0.00	0.00	0.25
% of Vacant Parcels	138,188	0.16	0.26	0.00	0.02	0.20
% of Tax Exempt Parcels	138,188	0.05	0.15	0.00	0.00	0.02

Geographic Unit	N	Mean	S.D.	25th	Median	75th
State	48	2905.33	7261.16	459.50	1108.00	2450.00
County	2,830	49.28	254.41	5.00	13.00	36.00
Zip Code	33,845	9.99	16.15	2.00	5.00	12.00
Census Tract	63,856	7.28	11.74	2.00	3.00	8.00
Census Tract Block Group	208,538	3.94	5.98	1.00	2.00	4.00

Table 2: Assessment Regressivity Regression Results

This table presents regression results where log valuation ratio is regressed onto log sale prices. Column 1 presents OLS regression results. Column 2 presents 2SLS results where log sale price is instrumented with log leave-one-out average sale price of other transactions in the same census tract block group. All specifications include TCA by year fixed effects. Standard errors are clustered by TCA and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)
	Ln(Appraised Value) - Ln(Sale Price)	
Ln(Sale Price)	-0.31***	-0.12***
	[0.01]	[0.01]
Model	OLS	2SLS
TCA-Year FE	Y	Y
Kleibergen-Paap Wald F Statistic	-	> 16.38
Observations	22,269,724	22,269,724
R-squared	0.37	0.06

Table 3: Summary Statistics of Estimated Parameters

Each observation is a TCA-year, indexed by kt. β_{kt} is estimated for each TCA-year by regressing log valuation ratio onto log sale price. β_{kt}^{IV} is estiamted for each TCA-year by regressing log valuation ratio onto log sale price and log sale price is instrumented with log leave-one-out average sale price of other transactions in the same census tract block group. $R^2_{\hat{m}(\mathbf{h}^*),kt}$ is the coefficient of determination from TCA-year regressions where log sale price is regressed onto house characteristics. $R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt}$ is the coefficient of determination from TCA-year regressions where log sale price is regressed onto house and neighborhood characteristics. $\Delta R^2_{kt} = R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt} - R^2_{\hat{m}(\mathbf{h}^*),kt}$. The sample contains TCA-years where there are at least 30 transactions and where, for each transaction, there are at least 30 other transactions to compute leave-one-out average sale price.

Variable	N	Mean	S.D.	Min	25th	50th	75th	Max
β_{kt}	10,974	-0.42	0.23	-1.03	-0.57	-0.42	-0.27	0.19
β_{kt}^{IV}	10,974	-0.21	0.68	-1.91	-0.48	-0.17	0.07	1.35
$R^2_{\hat{m}(\mathbf{h}^*),kt}$	10,974	0.41	0.18	0.05	0.27	0.41	0.54	0.81
$R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt}$	10,974	0.54	0.16	0.17	0.42	0.54	0.66	0.89
ΔR^2_{kt}	10,974	0.13	0.10	0.01	0.05	0.10	0.17	0.50

Table 4: TCA-Year Panel Regression Results

This table presents OLS regression results where β_{kt} and β_{kt}^{IV} are regressed onto $R^2_{\hat{m}(\mathbf{h}^*),kt}$ and ΔR^2_{kt}, separately, with county by year fixed effects. Each observation is a TCA-year, indexed by kt. β_{kt} is estimated for each TCA-year by regressing log valuation ratio onto log sale price. β_{kt}^{IV} is estiamted for each TCA-year by regressing log valuation ratio onto log sale price and log sale price is instrumented with log leave-one-out average sale price of other transactions in the same census tract block group. $R^2_{\hat{m}(\mathbf{h}^*),kt}$ is the coefficient of determination from TCA-year regressions where log sale price is regressed onto house characteristics. $R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt}$ is the coefficient of determination from TCA-year regressions where log sale price is regressed onto house and neighborhood characteristics. $\Delta R^2_{kt} = R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt} - R^2_{\hat{m}(\mathbf{h}^*),kt}$. The sample contains TCA-years where there are at least 30 transactions and where, for each transaction, there are at least 30 other transactions to compute leave-one-out average sale price. Standard errors are clustered by TCA. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)	(4)
	β_{kt}	β_{kt}^{IV}	β_{kt}	β_{kt}^{IV}
$R^2_{\hat{m}(\mathbf{h}^*),kt}$	0.77***	0.46***		
	[0.01]	[0.05]		
ΔR^2_{kt}			-0.60***	-0.91***
			[0.03]	[0.09]
County-Year FE	Y	Y	Y	Y
Observations	10,974	10,974	10,974	10,974
R-squared	0.57	0.21	0.37	0.21

Table 5: Synthetic Valuation Ratio Regression Results

This table presents regression results where log observed valuation ratio and log synthetic valuation ratio are regressed onto log sale price. Column 1 presents OLS regression results where the dependent variable is log observed valuation ratio. Column 2 presents 2SLS results where log sale price is instrumented with log leave-one-out average sale price of other transactions in the same census tract block group. Column 3 presents 2SLS results where log sale price is instrumented with the same variable as in Column 2. Synthetic valuation ratios are computed using synthetic appraised values, which are imputed market values produced by the procedure from Bayer et al. (2017). The sample includes all homes that were sold in year t and in one of the preceding 5 years. All specifications include TCA by year fixed effects. Standard errors are clustered by TCA and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)
	Ln(Appraised Value) - Ln(Sale Price)		
	Observed	Observed	Synthetic
Ln(Sale Price)	-0.24***	-0.07***	-0.01
	[0.01]	[0.01]	[0.01]
Model	OLS	2SLS	2SLS
TCA-Year FE	Y	Y	Y
Kleibergen-Paap Wald F Statistic	-	> 16.38	> 16.38
Observations	4,971,035	4,971,035	4,971,035
R-squared	0.49	0.06	0.01

Table 6: Infrequent Reappraisal Regression Results

This table presents regression results where log valuation ratio is regressed onto log sale price. Column 1 shows OLS regression result for all houses sold. Column 2 shows 2SLS regression result for the same sample of houses but log sale price is instrumented with log leave-one-out average sale price of other transactions in the same census tract block group. Column 3 shows 2SLS regression results for houses that were sold and reappraised in the same year. All specifications include TCA by year fixed effects. Standard errors are clustered by TCA and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)
	Ln(Appraised Value) - Ln(Sale Price)		
Ln(Sale Price)	-0.28***	-0.06***	-0.04***
	[0.01]	[0.01]	[0.01]
Years Since Re-appraisal	≥ 0	≥ 0	0
Model	OLS	2SLS	2SLS
TCA-Year FE	Y	Y	Y
Kleibergen-Paap Wald F Statistic	-	> 16.38	> 16.38
Observations	19,355,842	19,355,842	13,090,496
R-squared	0.43	0.05	0.03

Table 7: Property Tax Burden, Income, and Wealth

This table presents summary statistics on household net worth and property tax bill by primary residence value group. Distribution of households' primary residence values and average net worth are collected from the 2016 Survey of Consumer Finance. Mean property tax bill are calculated from CoreLogic. Percentile group upper and lower bounds are rounded to the nearest thousand. Numbers not shown as percentages are in 2019 USD. Tax as % of Net Worth is calculated as the ratio of mean tax bill and mean net worth.

Home Value Percentile Group	Minimum Home Value	Maximum Home Value	Mean Net Worth	Mean Tax Bill	Tax % of Net Worth
$<$ 10th	1	64,000	101,052	1,320	1.31%
10th - 20th	64,000	96,000	166,526	1,615	0.97%
20th - 30th	96,000	132,000	214,855	1,928	0.90%
30th - 40th	132,000	160,000	316,823	2,220	0.70%
40th - 50th	160,000	197,000	319,683	2,550	0.80%
50th - 60th	197,000	245,000	409,073	3,006	0.73%
60th - 70th	245,000	319,000	587,328	3,617	0.62%
70th - 80th	319,000	425,000	938,840	4,613	0.49%
80th - 90th	425,000	638,000	1,668,463	6,252	0.37%
90th - 99th	638,000	2,127,000	4,065,906	10,241	0.25%
$\geq$ 99th	2,127,000	196,136,000	22,419,290	27,452	0.12%

Table 8: Assessment Regressivity's Impact on Wealth Inequality

This table presents summary statistics on excess tax payments by primary residence value group. Distribution of households' home values are collected from the 2016 Survey of Consumer Finance. Numbers not shown as percentages are in 2019 USD. Excess tax payment (ETP) for each house is calculated as the difference between the observed 2016 tax bill, which is calculated from the house's 2016 appraised value, and a counterfactual tax bill. The counterfactual tax bill is the tax bill that would have realized if the house were taxed according to its 2016 sale price. Change in home equity for each house is calculated as its excess tax payment treated as a perpetuity and discounted at 4%. ETP as Percentage of Tax Bill is the ratio of mean excess tax payment and mean tax bill. ETP as Percentage of Net Worth is the ratio of mean excess tax payment and mean net worth. Mean percentage change in net worth is calculated as mean change in home equity divided by mean net worth.

Home Value Percentile Group	Mean Excess Tax Payment	ETP as % of Tax Bill	ETP as % of Net Worth	Mean Change Home Equity	% Change in Net Worth
$<$ 10th	590	44.70%	0.58%	14,756	14.60%
10th - 20th	337	20.87%	0.20%	8,433	5.06%
20th - 30th	179	9.28%	0.08%	4,485	2.09%
30th - 40th	95	4.28%	0.03%	2,365	0.75%
40th - 50th	53	2.08%	0.02%	1,330	0.42%
50th - 60th	12	0.40%	0.00%	297	0.07%
60th - 70th	-62	-1.71%	-0.01%	-1,559	-0.27%
70th - 80th	-139	-3.01%	-0.01%	-3,485	-0.37%
80th - 90th	-219	-3.50%	-0.01%	-5,466	-0.33%
90th - 99th	-475	-4.64%	-0.01%	-11,881	-0.29%
$\geq$ 99th	-3,904	-14.22%	-0.02%	-97,608	-0.44%

Table 9: Baseline Taxation Gap Results

This table presents OLS regression results where the log difference of observed tax bill and counterfactual tax bill is regressed onto demographic indicator variables. The counterfactual tax bill is the tax bill that would have realized if the house were taxed according to its sale price. Low Income equals 1 if the home is located in a census tract block group where its median household income is lower than the sample's median value in that year. Low College Share equals 1 if the home is located in a census tract block group where its share of college-educated adults is lower than the sample's median value in that year. High Minority Share equals 1 if the home is located in a census tract block group where its minority share is higher than the sample's median value in that year. Minority share is defined as the percentage of the census tract block group's population that is black, Hispanic, or Native American. Standard errors are clustered by TCA and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	Ln(Observed Tax) - Ln(Counterfactual Tax)		
Low Income	0.014***		
	[0.004]		
Low College Share		0.018***	
		[0.004]	
High Minority Share			0.017***
			[0.003]
TCA-Year FE	Y	Y	Y
Observations	18,765,539	18,765,539	18,765,539
R-squared	0.022	0.022	0.022

Table 10: Demographics and House Price Sorting

All numbers are averages, except for within-TCA-year price deciles. Observed tax as a percentage of counterfactual tax is the ratio of the house's observed property tax bill to its counterfactual tax bill. The counterfactual tax bill is the tax bill that would have realized if the house were taxed according to its sale price. Average sale price and median household income are reported in thousands of nominal USD. All demographic variables are constrcuted from each home's census tract block group characteristics. Minority share is defined as the percentage of the census tract block group's population that is black, Hispanic, or Native American.

Within-TCA-Year Price Decile	House Price	Observed Tax as % of Counterfactual Tax	Median HH Income	% of Adults with College Degree	Minority Share
1	97.74	167%	61.87	26%	30%
2	138.83	125%	65.06	28%	28%
3	164.48	112%	67.93	30%	26%
4	186.74	106%	70.61	32%	24%
5	208.78	102%	73.27	33%	23%
6	232.74	99%	76.03	35%	21%
7	261.77	97%	79.01	37%	20%
8	299.39	95%	82.32	39%	19%
9	358.52	93%	86.10	41%	17%
10	535.39	91%	92.02	44%	16%

Table 11: Taxation Gaps Conditional on Price Decile Regression Results

This table presents OLS regression results where the log difference of observed tax bill and counterfactual tax bill is regressed onto demographic indicator variable, TCA-year price decile indicator, and their interaction terms. The counterfactual tax bill is the tax bill that would have realized if the house were taxed according to its sale price. "Demographic Indicator" is a placeholder for the demographic characteristic listed at the head of each column. Low Income equals 1 if the home is located in a census tract block group where its median household income is lower than the sample's median value in that year. Low College Share equals 1 if the home is located in a census tract block group where its share of college-educated adults is lower than the sample's median value in that year. High Minority Share equals 1 if the home is located in a census tract block group where its minority share is higher than the sample's median value in that year. Minority share is the percentage of the census tract block group's population that is black, Hispanic, or Native American. Each regression includes TCA by year fixed effects. Standard errors are clustered by TCA and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

Dependent Variable	Ln(Observed Tax) - Ln(Counterfactual Tax)		
Demographic Variable	Low Income	Low College Share	High Minority Share
Demographic Indicator	0.003	0.014	-0.028**
	[0.011]	[0.013]	[0.011]
Price Decile 2	-0.194***	-0.187***	-0.224***
	[0.003]	[0.003]	[0.003]
Price Decile 3	-0.131***	-0.125***	-0.155***
	[0.002]	[0.002]	[0.002]
Price Decile 4	-0.102***	-0.098***	-0.120***
	[0.001]	[0.002]	[0.001]
Price Decile 5	-0.085***	-0.082***	-0.098***
	[0.001]	[0.001]	[0.001]
Price Decile 6	-0.074***	-0.071***	-0.084***
	[0.001]	[0.001]	[0.001]
Price Decile 7	-0.066***	-0.064***	-0.073***
	[0.001]	[0.001]	[0.001]
Price Decile 8	-0.060***	-0.058***	-0.065***
	[0.001]	[0.001]	[0.001]
Price Decile 9	-0.057***	-0.055***	-0.060***
	[0.001]	[0.001]	[0.001]
Price Decile 10	-0.055***	-0.053***	-0.058***
	[0.001]	[0.001]	[0.001]
Price Decile 2 × Demographic Indicator	-0.036***	-0.045***	0.013*
	[0.006]	[0.007]	[0.007]
Price Decile 3 × Demographic Indicator	-0.035***	-0.042***	0.006
	[0.004]	[0.004]	[0.005]
Price Decile 4 × Demographic Indicator	-0.031***	-0.036***	0.001
	[0.003]	[0.003]	[0.004]
Price Decile 5 × Demographic Indicator	-0.026***	-0.031***	-0.002
	[0.002]	[0.002]	[0.003]
Price Decile 6 × Demographic Indicator	-0.023***	-0.028***	-0.003
	[0.002]	[0.002]	[0.002]
Price Decile 7 × Demographic Indicator	-0.020***	-0.024***	-0.005**
	[0.002]	[0.002]	[0.002]
Price Decile 8 × Demographic Indicator	-0.018***	-0.022***	-0.006***
	[0.001]	[0.002]	[0.002]
Price Decile 9 × Demographic Indicator	-0.015***	-0.020***	-0.007***
	[0.001]	[0.001]	[0.002]
Price Decile 10 × Demographic Indicator	-0.016***	-0.021***	-0.008***
	[0.001]	[0.001]	[0.001]
TCA-Year FE	Y	Y	Y
Observations	18,765,539	18,765,539	18,765,539
R-squared	0.120	0.122	0.116

Table 12: Significance Test Results for Taxation Gaps Conditional on Price Decile

This table presents statistical significance test results on regression coefficients presented in Table 11. For each t-test, asterisks denote statistical significance at the 10% level or below. Column 1 compares the amount of over-taxation between homes in low-income census tract block groups and other homes in the same TCA-year price decile. Column 2 compares the amount of over-taxation between homes in low-college-share census tract block groups and other homes in the same TCA-year price decile. Column 3 compares the amount of over-taxation between homes in high-minority-share census tract block groups and other homes in the same TCA-year price decile. The last row reports p-values from a joint test against the null hypothesis that coefficients in each column are jointly equal to zero.

	Demographic Indicator		
	Low Income	Low College Share	High Minority Share
Demographic Indicator	0.003	0.014	-0.028*
Dem Ind + Dem Ind × Price Decile 2	-0.033*	-0.031*	-0.015*
Dem Ind + Dem Ind × Price Decile 3	-0.032*	-0.028*	-0.022*
Dem Ind + Dem Ind × Price Decile 4	-0.028*	-0.022	-0.026*
Dem Ind + Dem Ind × Price Decile 5	-0.023*	-0.017	-0.029*
Dem Ind + Dem Ind × Price Decile 6	-0.020*	-0.013	-0.031*
Dem Ind + Dem Ind × Price Decile 7	-0.017*	-0.009	-0.032*
Dem Ind + Dem Ind × Price Decile 8	-0.014	-0.007	-0.033*
Dem Ind + Dem Ind × Price Decile 9	-0.012	-0.006	-0.034*
Dem Ind + Dem Ind × Price Decile 10	-0.013	-0.006	-0.035*
Joint Test p-value	0.000	0.000	0.000

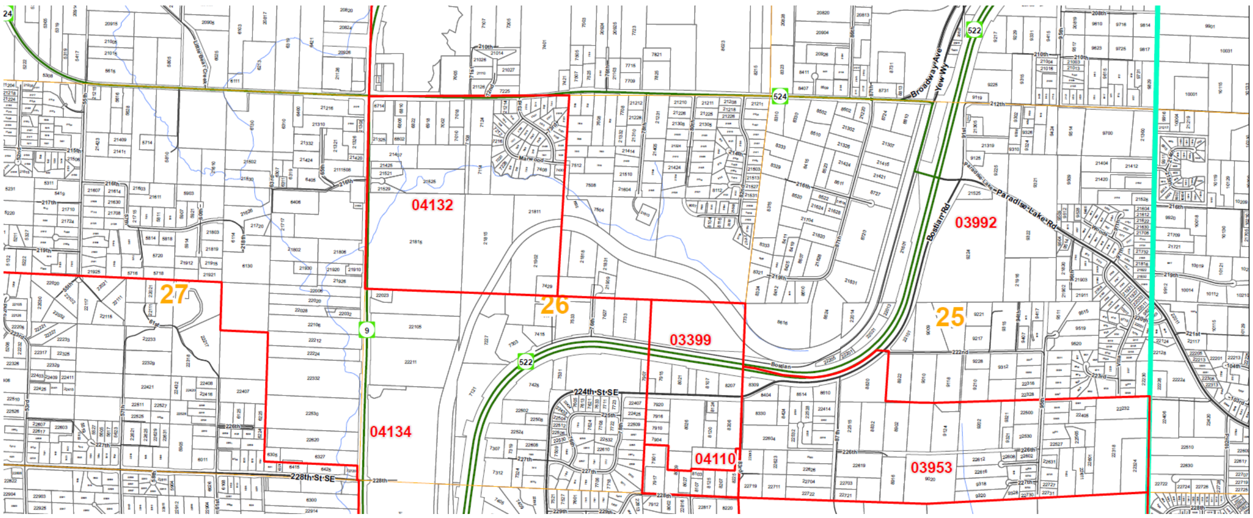
A Appendix

A.1 Tax Code Area Map

Figure A1 presents a map of several TCAs in Snohomish County, WA. TCA numbers and boundaries are shown in red. The map contains several TCAs with varying sizes and shapes. For example, TCA number 04110 is small, while TCA number 03992 is large. In particular, TCA number 03992 contains multiple neighborhoods, represented by separate clusters of parcels, which suggests significant variation in neighborhood characteristics within the same TCA. TCA shape and size vary because they are formed as geographic regions where a unique set of local governments' service boundaries overlap. Intuitively, the number of TCAs within a certain geographic area increases with the number of servicing local governments and the degree in which their boundaries overlap.

Figure A1: Tax Code Area Map from Snohomish County, WA

This figure presents a map of tax code areas (TCA) in Snohomish County, WA. Tax code areas (TCA) are small geographical areas where every house has access to the same set of property-tax funded government services and pay the same statutory tax rate. TCA numbers are printed in red. TCA boundaries are drawn with red lines. There are six TCAs in this map: 03992, 03953, 04132, 04134, 04110, and 03399. Blocks numbered and drawn with thin black lines are parcels. The land area covered by this map is approximately 3.2 by 1.4 miles.



A.2 Additional Synthetic Appraised Value Results

Table A1 presents a summary of results from similar regressions to the ones shown in Table 5. The difference here is that I include transactions with less recent previous sale prices. Not surprisingly, synthetic appraised values's ability to reduce assessment regressivity decreases as time between repeated sales increases. Including transactions with synthetic appraised values calculated from previous sale prices that are up to 10 years old decreases the proportion of assessment regressivity that is explained by flawed valuation methods to 8%. Synthetic appraised values actually yield more regressive assessments when I use previous sale prices that are up to 20 years old.

The reason behind is pattern is the validity of the assumptions made in the synthetic appraised value calculation. First, as more time passes between transactions, it is more likely for major renovations to take place. Therefore, the calculation procedure would introduce more bias as past transaction prices become worse predictors of current transaction prices. Second, it is likely to be the case that census tract is not the appropriate definition of a neighborhood because it covers too much land area. Using an overly coarse definition of neighborhoods is essentially equivalent to using average neighborhood characteristics to price houses from very different neighborhoods, which introduces assessment regressivity.

Table A1: Synthetic Valuation Ratio Regression Results by Time Between Transactions

This table presents regression results where log observed valuation ratio and log synthetic valuation ratio are regressed onto log sale prices, using different samples. Each row reports results from three regressions. β is the slope coefficient estimated form a regression where log oberved valuation ratio is regressed onto log sale price. β^{IV} is the slope coefficient estimated form a 2SLS regression where log valuation ratio is regressed onto log sale price and log sale price is instrumented with log leave-one-out average sale price from other transactions in the same census tract block group. β^{IV}_{syn} is the slope coefficient estimated form a 2SLS regression where log synthetic valuation ratio is regressed onto log sale price and log sale price is instrumented with the same variable as before. Log synthetic valuation ratio is the difference between log synthetic appraised value and log sale price. Synthetic appraised values are computed by using the procedure from Bayer et al. (2017). The first column describes the sample of transactions that is used for each regression. For example, $\leq$ 5 years indicates that all transactions included in the regression have previous transaction prices that are not more than 5 years old. The second column reports the number of observations in each regression. Columns 3 to 5 reports regression coefficients. All regressions include TCA by year fixed effects. Standard errors are clustered by TCA and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

Time Between Sales	N	β	β^{IV}	β^{IV}_{syn}
$\leq$ 5 years	4,971,035	-0.24***	-0.07***	-0.01
		[0.01]	[0.01]	[0.01]
$\leq$ 10 years	9,349,244	-0.25***	-0.08***	-0.06***
		[0.01]	[0.01]	[0.01]
$\leq$ 15 years	11,986,126	-0.25***	-0.07***	-0.07***
		[0.01]	[0.01]	[0.00]
$\leq$ 20 years	13,004,128	-0.25***	-0.06***	-0.08***
		[0.01]	[0.01]	[0.00]
Full sample	13,327,170	-0.25***	-0.06***	-0.08***
		[0.01]	[0.01]	[0.00]

A.3 Additional Heterogeneous Appeals Behavior Results

I formally test for correlation between appeals behavior, outcomes, and house prices by running various versions of the following panel regression.

$$Y_{it} = \alpha + \gamma logM_{it} + TCA \times Year\, FE + \epsilon_{it}$$

Y_{it} is the placeholder for appeal-related outcome variables – appeals indicator, win indicator, and percentage reduction in appraised value. Table A2 presents the results. The slope coefficients are positive for appeals and win probability, but flat for appraisal reduction percentage.

The merged Cook County data set contains both county-proposed appraised values and post-appeals appraised values, which allow me to estimate the degree of assessment regressivity that would have resulted had homeowners never filed an appeal. By comparing the counterfactual degree of regressivity with the observed degree of regressivity, I can quantify the amount of assessment regressivity that is caused by heterogeneous appeals behavior and outcome. Every home in Cook County is reappraised once every three years, i.e., it receives a proposed appraised value once every three years. For each home, I keep the first home-year observation that lands on a reappraisal year. From there, I replace post-appeals appraised values with county-proposed appraised values and estimate the counterfactual degree of assessment regressivity.

Table A3 reports OLS and 2SLS regression results. Column 1 reports OLS regression result where log valuation ratios are computed from post-appealed appraised values and regressed onto log sale price. The estimated slope coefficient is -0.5, which is the observed degree of assessment regressivity with effects of appeals included. Column 2 reports OLS regression result where log valuation ratios are computed from county-proposed appraised values and regressed onto log sale price. Comparing the two slope coefficients shows that there is essentially no difference in the degree of assessment regressivity, which means that heterogeneous appeals behavior and outcome cannot explain the negative relationship between valuation ratio and house price. Columns 3 and 4 repeat the same exercise with 2SLS regressions and find the same result.

Table A2: House Price, Appeal Behavior, and Outcomes - Cook County, IL

This table presents OLS regression results where appeal-related variables are regressed onto log sale price. Appeal indicator equals 1 if the homeowner filed an appeal in a given year. The sample for the regression shown in Column 1 includes all house-years in Cook County Illinois that have observable sale prices or where prices can be imputed, using the procedure from Bayer et al. (2017). Win indicator equals 1 if the homeowner won the appeal that he or she filed and zero otherwise. The sample for the regression shown in Column 2 includes all house-years where the owner filed an appeal and prices are observable or can be imputed. Percentage appraisal reduction is the reduction in appraised value that the house received from its appeal divided by the county-proposed appraised value. The sample for the regression shown in Column 3 includes all house-years where the owner filed an appeal and prices are observable or can be imputed. All regressions include TCA by year fixed effects. Standard errors are clustered by TCA and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	Appeal	Win	% Appraisal Reduction
Ln(Sale Price)	0.01***	0.02***	-0.00
	[0.00]	[0.01]	[0.00]
Sample	All	Appealed	Appealed
TCA-Year FE	Y	Y	Y
Observations	3,803,467	289,791	289,791
R-squared	0.04	0.07	0.04

Table A3: Impact of Appeals on Assessment Regressivity - Cook County, IL

This table presents regression results where observed and counterfactual log valuation ratio are regressed onto log sale price. The dependent variable for Columns 1 and 3 is observed log valuation ratio, which is the difference between log observed appraised value log sale price. The dependent variable for Columns 2 and 4 is counterfactual log valuation ratio, which is the difference between log appeal-adjusted appraised value and log sale price. Appeal adjustment replaces post-appeal appraised values with the county-proposed appraised values. Columns 1 and 2 show OLS regression results. Columns 3 and 4 show 2SLS regression results where log sale price is instrumented with log leave-one-out average sale price of other transactions in the same census tract block group. The sample includes houses that have sufficient appeal history such that appraised values can be adjusted, observable sale prices, or imputable market values. All regressions include TCA by year fixed effects. Standard errors are clustered by TCA and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)	(4)
Dependent Variable	Log Val Ratio	CTF Log Val Ratio	Log Val Ratio	CTF Log Val Ratio
Ln(Sale Price)	-0.50***	-0.50***	-0.20***	-0.19***
	[0.02]	[0.02]	[0.02]	[0.02]
Model	OLS	OLS	2SLS	2SLS
TCA-Year FE	Y	Y	Y	Y
Kleibergen-Paap Wald F Statistic	-	-	> 16.38	> 16.38
Observations	2,839,809	2,839,809	2,839,809	2,839,809
R-squared	0.47	0.46	0.27	0.26

A.4 Homeowners' Asset Portfolio Composition

Table A4: Homeowners' Wealth Composition

This table presents summary statistics on homeowners' wealth composition by primary residence value group. Distribution of households' home values are collected from the 2016 Survey of Consumer Finance. Numbers not shown as percentages are in 2019 USD. Mean Primary Residence Debt is the average mortgage amount tied to the homeowner's primary residence. Mean Primary Residence Value is the average price of homeowners' primary residence. Mean Equity in Primary Residence is the difference between mean primary residence value and mean primary residence debt. Primary Residence Equity as Percentage of Net Worth is the ratio of average equity in primary residence to average net worth.

Home Value Percentile Group	Mean Net Worth	Mean Primary Res Debt	Mean Primary Res Value	Mean Primary Res Equity	Equity as % of Net Worth
$<$ 10th	101,052	9,105	37,295	28,190	27.9%
10th - 20th	166,526	29,430	83,425	53,995	32.4%
20th - 30th	214,855	44,128	113,822	69,694	32.4%
30th - 40th	316,823	57,262	147,286	90,024	28.4%
40th - 50th	319,683	82,509	180,891	98,382	30.8%
50th - 60th	409,073	105,975	221,557	115,582	28.3%
60th - 70th	587,328	112,669	276,390	163,721	27.9%
70th - 80th	938,840	135,501	355,579	220,078	23.4%
80th - 90th	1,668,463	185,577	499,392	313,815	18.8%
90th - 99th	4,065,906	283,053	957,508	674,455	16.6%
$\geq$ 99th	22,419,290	759,708	3,761,840	3,002,132	13.4%

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Online Appendix
Why Are Residential Property Tax Rates Regressive?

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A Regressive Assessments Under the Comparable Sales Approach

This section outlines how assessments can be regressive when tax assessors use the comparable sales approach (CSA) to value houses. Under this approach, the appraiser begins by finding recently transacted houses that have similar characteristics to the house under consideration. These comparable houses should be located in the same neighborhood as the house in question. The definition of a neighborhood or a comparable area is arbitrarily defined by the appraiser. In the final step, the appraiser calculates the average price per square foot from these comparable sales and use that quantity to assign an appraised value to the house under consideration (FNMA, 2020).

The reason that CSA produces assessment regressivity is the coarseness of comparable areas. For example, Figure A1 shows the map of Snohomish County with 2019 benchmark areas drawn with blue boundaries (Snohomish County Assessor's Office, 2019b). Houses in the same benchmark area are considered to be geographically and economically comparable to each other.[1] Notice that these benchmark areas are much larger than a TCA. Therefore, the mean neighborhood characteristics that are captured in the CSA's average price calculation gives rise to insufficient variation in appraised values within a TCA and, thus, insufficient covariation with realized sale prices.

To see this assertion formally, suppose that sale prices reflect true market values and let house i's price per square foot be defined as follows.

$$\frac{M_i}{S_i} := M_i^{SQ}$$

M_i is house i's sale price and S_i is house i's square footage. To price a certain house j, the appraiser finds several comparable houses and computes the average price per square foot from their observed sale prices. House j's appraised value is as follows.

$$A_j = \overline{M_{i \neq j}^{SQ}} \times S_j$$

[1] http://gis.snoco.org/maps/property2/

$\overline{M_{i \neq j}^{SQ}}$ is the sample mean of price per square foot calculated from chosen comparable houses. House j's log appraised value is as follows.

$$a_j = \overline{m_{i \neq j}^{SQ}} + s_j$$

Let X be a random variable and $\overline{X}$ be its sample mean. By the result that $Cov(\overline{X}, X) < Cov(X, X)$, it follows that $Cov(a, m) < Cov(m, m) = Var(m)$ because $\overline{m_{i \neq j}^{SQ}}$ are sample means of m.[2] Intuitively, suppose that neighborhood quality varies across census tract block groups, then the CSA would reasonably capture this variation if appraisers compute price per square foot from comparable houses drawn from the same census tract block group. The covariance between appraised values and sale prices decreases and assessments become more regressive as the appraiser computes average price per square foot across larger geographic areas.

B Regressive Assessments Under the Cost Approach

This section outlines how assessments can be regressive when tax assessors use the cost approach to value houses. The cost approach operates on the premise that, when a buyer purchases a home, he is paying for the cost of the structure less depreciation plus the land price (IAAO, 2014). The cost approach is often implemented in the following steps. First, the appraiser needs to assign a cost to the structure that sits on the land parcel. The most common approach is to use the average construction cost of similar structures in the same area (e.g., state or county) (Pickens County Assessor's Office, 2018). To adjust this construction cost for the property's location (e.g., city or zip code), the appraiser applies a local multiplier to the average construction cost. The multiplier is the average sale price to cost ratio of a group of similar properties in a comparable neighborhood. The idea is that, if neighborhoods are defined correctly, then these multipliers should capture the neighborhood's quality that is impounded into the cost of the structure. Finally, the appraiser uses the comparable sales approach or the land residual method to assign a market value to the land

[2] Consult Sections D and E for additional details on this claim.

parcel that the structure sits on (Snohomish County Assessor's Office, 2010).[3] The sum of the cost of the structure and the land price gives the property's total appraised value (Snohomish County Assessor's Office, 2019a; Thurston County Assessor's Office, 2015).

Similarly to the comparable sales approach (CSA), the flaw of the cost approach lies in how appraisers define neighborhoods and choose comparable houses. Neighborhoods are defined too broadly, i.e., covering too large of an area. Comparable houses are chosen based on observable characteristics, which ignores latent house characteristics that may differ across houses. Formally, appraised values under the cost approach can be expressed as follows.

$$A_i^{Cost} = S_i^{Cost} + P_i^{CSA}$$

S^{Cost} denotes the construction cost of the structure and P^{CSA} denotes the price of the land parcel estimated using CSA. Suppose that the true market value of house i can be expressed in a similar way.

$$M_i = S_i + P_i$$

S is now the true market value of the structure and P is the true market value of the land parcel. Since S^{Cost} and P^{CSA} are sample means, the same arguments made for the CSA apply and it follows that $Cov(A, M) < Cov(M, M) = Var(M)$. Assuming that $\mathbb{E}(A)\mathbb{E}(M)$ is sufficiently large and using the following approximation, it follows that $Cov(a, m) < Cov(m, m) = Var(m)$. With low $Cov(a, m)$, assessments are regressive.

$$Cov(A, M) \approx \mathbb{E}(A)\mathbb{E}(M) \times (e^{Cov(a,m)} - 1)$$

[3] The residual method finds transacted houses in the same neighborhood as the house that is being appraised, subtracts their estimated construction costs from their sale prices, and calculates the land price for the house that is being appraised by averaging these residuals (Town of Lenox, 2018).

C Regressive Assessments Under the Income Approach

This section outlines how assessments can be regressive when tax assessors use the income approach to value houses. Under the income approach, the appraiser collects gross rent and sale price data. To price a certain house i, the appraiser multiplies the house's gross annual rental income with a sales multiplier, which is the average price-to-rent ratio from a sample of recently sold houses located in the same area as house i (IAAO, 2014). Formally, log appraised values from the income approach can be expressed in the following way.

$$a_i^{Income} = \overline{q}_i + r_i$$

$\overline{q}_i$ is the average price-to-rent ratio that appraisers apply to house i's gross rent, r_i. Under the Gordon Growth Model, log market values can be expressed in a similar way (Gordon, 1962).

$$m_i = q_i + r_i$$

q_i is the inverse of house i's discount rate under the Gordon Growth Model. Since $\overline{q}_i$ is a sample mean and assuming that its correlation with r is weakly positive, the same arguments made for the CSA apply and it follows that $Cov(a, m) < Cov(m, m) = Var(m)$. With low $Cov(a, m)$, assessments are regressive.

D Variance of Sample Means

Let X be a random variable with variance σ_X^2. With n independent draws, $X_1, X_2, ..., X_n$, the variance of the sample mean $\overline{X}$ is as follows.

$$
\begin{aligned}
Var(\overline{X}) = \sigma^2_{\overline{X}} &= Var\left(\frac{X_1 + X_2 + ... + X_n}{n}\right) \\
&= \frac{1}{n^2} Var(X_1 + X_2 + ... + X_n) \\
&= \frac{1}{n^2} n\sigma^2_X \\
&= \frac{\sigma^2_X}{n} \\
&< \sigma^2_X
\end{aligned}
$$

If draws are not independent, then $\sigma^2_{\overline{X}} \leq \sigma^2_X$. The two quantities are equal to each other in the case where draws are perfectly correlated.

E Covariance of Sample Means

Let X and Y be random variables with positive covariances. With n independent paired samples (X_i, Y_i), the covariance of the sample means is as follows.

$$
\begin{aligned}
Cov(\overline{X}, \overline{Y}) &= Cov\left(\frac{1}{n}\sum_{i=1}^{n} X_i, \frac{1}{n}\sum_{j=1}^{n} Y_j\right) \\
&= \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} Cov(X_i, Y_j) \\
&= \frac{1}{n^2}\sum_{i=1}^{n} Cov(X_i, Y_i) \\
&= \frac{1}{n} Cov(X, Y) \\
&< Cov(X, Y)
\end{aligned}
$$

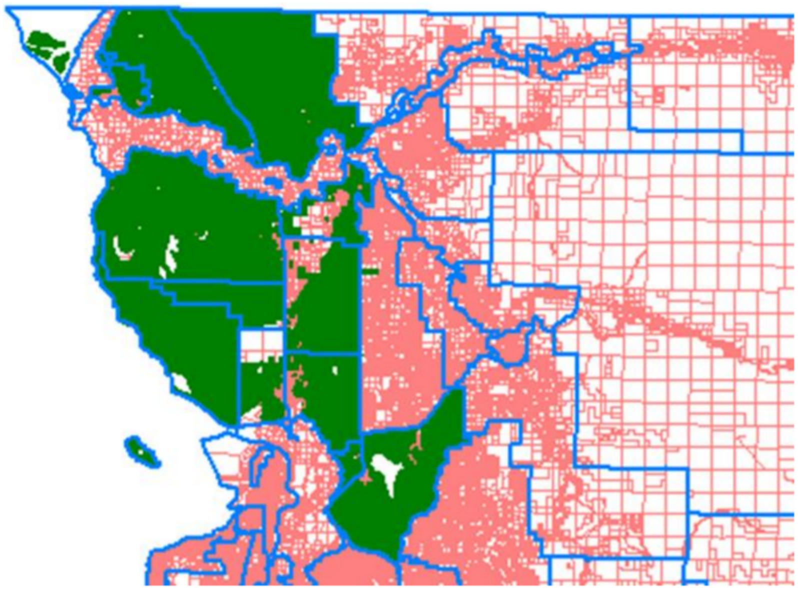
Similarly, the covariance of X and $\overline{Y}$ is as follows.

$$
\begin{aligned}
Cov(X,\overline{Y}) &= Cov\left(X_i, \frac{1}{n}\sum_{j=1}^{n} Y_j\right) \\
&= \frac{1}{n}\sum_{j=1}^{n} Cov(X_i, Y_j) \\
&= \frac{1}{n} Cov(X, Y) \\
&< Cov(X, Y)
\end{aligned}
$$

If draws are not independent, then $Cov(X,\overline{Y}) \leq Cov(X,Y)$ and $Cov(\overline{X},\overline{Y}) \leq Cov(X,Y)$. The quantities are equal to each other in the case where draws are perfectly correlated.

Figure A1: Benchmark Areas in Snohomish County, WA

This figure presents a map of benchmark areas used in Snohomish County's appraisal model. Benchmark areas are drawn with blue boundaries. Individual parcels are drawn with pink lines. This image was taken from Snohomish County's 2019 Region 2 Mass Appraisal Report. The green area represents the county's region number 2.



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