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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 inexpensive houses pay almost 50% higher effective tax rates than owners of expensive houses. This pattern appears throughout the United States and is caused by systematic assessment regressivity – inexpensive houses are overassessed relative to expensive houses. I use an instrumental variable approach to show that a large portion of this pattern can be attributed to measurement error in sale prices. Sixty percent of the remaining regressivity can be explained by tax assessors' flawed valuation methods that ignore variation in priced house and neighborhood characteristics and 40% by infrequent reappraisal. A simple valuation method can alleviate assessment regressivity and increase poor homeowners' net worth by more than 10%.

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1 Introduction

It is a well-known feature of property tax data that assessments appear to be regressive – inexpensive houses tend to be overassessed relative to expensive houses (Sirmans et al., 2008). The result of regressive assessments is that owners of inexpensive houses pay higher effective property tax rates than owners of expensive houses. The literature on assessment regressivity has proposed many explanations, which include 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, there is no good estimate of the resulting excess tax payments and their impact on wealth inequality. Assessment regressivity is also an important policy issue because its existence suggests that the realized distribution of property tax burden deviates substantially from the intended distribution under a regime where property tax rate is uniform across all houses located in the same taxing jurisdiction.

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. First, I use an instrumental variable approach to show that, *for the majority of states*, property tax assessments are, on average, regressive. Second, I provide empirical evidence for an untested explanation of assessment regressivity, tax assessors' valuation methods that ignore priced house and neighborhood characteristics. Third, I show that the true aggregate degree of assessment regressivity can be explained by two mechanisms: 60% by flawed valuation methods and 40% by infrequent reappraisal. Lastly, I show that regressive property tax rates increase wealth inequality among homeowners and correcting them could substantially increase poor homeowners' wealth.

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 undertaxation that each homeowner faces because I can compare effective property tax rates across houses while holding fixed the bundle of public goods that each homeowner in the same TCA buys.

Since TCA data are new to the literature, I begin my empirical analysis with summary statistics of this 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, there are many TCAs within a small geographic area. For example, the average zip code contains 10 TCAs. This fact highlights that, even in a small geographic area, the variation in public goods quality that homeowners in the United States have access to can be large. Despite the fact that TCAs tend to cover small land areas, within-TCA variations in house prices and neighborhood characteristics are large. For example, the average home in the top decile of the TCA's house price distribution is more than five times more expensive than the average home in the bottom decile. In addition, expensive homes tend to be located in neighborhoods that are much wealthier and less ethnically diverse.

With the focus of this paper on assessment regressivity, I move on to quantify the degree of assessment regressivity among single-family homes. Simple averages show that, among houses located in the same TCA and year, owners of inexpensive houses pay a 50% higher effective property tax rate than owners of expensive houses.[1] Next, I estimate the degree of assessment regressivity among transacted houses located in the same TCA and year by regressing log valuation ratio, assessed value divided by sale price, onto log sale price with TCA by year fixed effects. The estimated slope coefficent is -0.323, which suggests that assessments are regressive.

However, a negative slope coefficient is to be expected because sale price is, in principle, true market value plus measurement error, which introduces attenuation bias into regression estimates (Kochin and Parks, 1982). To overcome this problem, I use an instrumental variable approach where, for a given house i that was sold in year t, I instrument its log sale price with average log sale prices from other transactions in the same census tract, but leave out transactions in the same census tract block group. The leave-out approach ensures that the instrument is orthogonal to the measurement error embedded in the observed transaction price. The two-staged least squares (2SLS) regression yields a slope coefficient estimate of -0.079, which suggests that assessments are indeed regressive, but approximately 75% of the observed regressivity is caused by attenuation bias. The remaining 25% is the true degree of assessment regressivity.

[1]TCA boundaries do change over time and so it is important to compare houses in the same TCA-year pair.

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

The next part of the paper quantifies the relative importance of three prominent explanations of assessment regressivity. I begin with the infrequent reappraisal explanation, which takes two forms: (1) revaluation cycles that span more than 1 year, and (2) assessment growth limit laws. When assessed values lag market prices, assessments become regressive because houses that experience large price appreciations become relatively undertaxed. I quantify the contribution of this explanation by comparing the estimated degree of assessment regressivity between all transacted homes and transacted homes that are not subjected to stale assessed values or assessment growth limit laws. I find that infrequent reappraisal can explain approximately 40% of the true degree of assessment regressivity.

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

To quantify the proportion of aggregate assessment regressivity that can be explained by flawed valuation methods, I start by constructing synthetic assessed values for single-family houses that I observe repeated sales. Following Bayer et al. (2017), the synthetic assessed value is the product of the house's most recent transaction price in year $t-k$, the innovation in its local house price index between year $t-k$ and year t, and the observed assessment ratio.[3] Intuitively, a house's previous transaction price should capture all of its relevant pricing information in year $t-k$, and innovations 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 transactions, the house's synthetic assessed value should be a good proxy of its market value in year t. Replacing observed assessed values with synthetic assessed values in a linear regression where log valuation ratio is regressed onto log sale price shows that 60% of the true degree of assessment regressivity can be explained by flawed valuation methods.

Lastly, I use appeals data from Cook County, IL, to quantify the amount of assessment regressivity that can be attributed to heterogeneous appeals behavior and outcomes. I find that owners of expensive homes tend to file more appeals, win more often, and receive larger assessed value reductions. However, the differences in appeals probability, win probability, and assessed value reduction percentage between owners of expensive and owners of inexpensive houses are small. I show that the degree of within-TCA-year assessment regressivity in Cook County is essentially unchanged when assessment regressivity is estimated using pre-appeal assessed values instead of post-appeal assessed values. This set of results suggests that heterogeneous appeals behavior and outcomes cannot explain the county's regressive assessments within TCAs.

The final section of the paper explores a potential solution to the regressive assessment problem. I begin by showing that the difference between realized sale prices and imputed market values computed using the procedure from Bayer et al. (2017) are much smaller than the difference between realized sale prices and observed appraised values. This result suggests that county assessors can adopt this method to improve their appraisal accuracy.

Next, I investigate how the adoption of this valuation method would affect the distribution

[3]The assessment ratio is the ratio of the assessed value and the appraised value. The institutional details section provides a more comprehensive discussion of this object.

of tax burden and wealth 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 imputed market value. Within a TCA and year, the counterfactual tax rate is calculated as the ratio of total property tax revenue raised from all houses with imputable market values and total imputed market values. A house's counterfactual tax bill is calculated as the product of the counterfactual tax rate and its imputed market value. The difference between the two objects is the amount of over- or undertaxation 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 median excess property tax payment amount for houses in the bottom decile is \$234 per year, which is equivalent to 28% of the group's median observed tax bill. On the other hand, the median underpayment among houses in the top 1% is \$1,505 or 6% of the group's median observed tax bill. Since poor households sort into inexpensive houses while rich households sort into expensive houses, the property tax system serves as a regressive wealth tax among homeowners. A back-of-the-envelope calculation that assumes that property taxes are fully capitalized into house prices at a discount rate of 4% shows that using this valuation method would increase the median poor homeowners' wealth by more than 10%.

In an independent and contemporaneous work, Berry (2021) uses the same data set to document a national pattern of assessment regressivity and explores potential explanations. It is important to note that this paper moves the literature beyond the results from Berry's (2021) work in several ways. First, Berry (2021) uses a Monte Carlo simulation to argue that it takes an implausibly large amount of measurement error in sale prices to generate the degree of assessment regressivity that we observe in the data. On the other hand, I use the instrumental variable approach to explicitly show that, after accounting for measurement error in sale prices, assessments are indeed regressive. Second, while Berry (2021) suggests that assessors' flawed valuation methods may be causing assessment regressivity, in Section 5.4, I provide concrete empirical evidence for the explanation. Third, Berry (2021) makes no attempt to quantify the relative importance of each potential explanation. I show that 40% of true assessment regressivity can be explained by infrequent reappraisal and the remaining 60% can be explained by flawed valuation methods.

A recent paper by Avenancio-León and Howard (2019) uses a similar data set to document and explain the assessment gap between minority and White homeowners. A key difference between the work by Avenancio-León and Howard (2019) and this paper is that this paper focuses on documenting and explaining assessment regressivity and not the racial assessment gap. In fact, Avenancio-León and Howard (2019) show that assessment regressivity can partly explain the racial assessment gap, which highlights that the two are distinct phenomena. An important result in Avenancio-León and Howard (2019) is that sale prices are more sensitive to neighborhood characteristics than assessments are, which suggests, but does not show, that this difference in sensitivity may cause regressive assessments. The current paper moves beyond this sensitivity result in several ways. First, this paper argues that assessment regressivity is caused by tax assessors' omission of *any* priced characteristics from his or her valuation model, *not just* neighborhood characteristics. Second, I show that there is a clear relationship between assessment regressivity and valuation model misspecification. Lastly, I quantify the proportion of assessment regressivity that can be explained by flawed valuation methods.

I contribute to the literature on assessment regressivity in several ways. First, I use a nationally comprehensive data set and an instrumental variable approach to show that assessment regressivity is pervasive across the United States. This is a new fact because prior works use property tax data from small localities to document and explain this pattern (Black, 1977; Smith et al., 2003; Eom, 2008; Weber and McMillen, 2010; Ross, 2012, 2013; McMillen, 2013; Hodge et al., 2017). Second, I provide empirical evidence that a nontrivial proportion of assessment regressivity can be explained by tax assessors' flawed valuation methods.[4] Third, I quantify the relative importance of infrequent reappraisal, flawed valuation methods, and attenuation bias in explaining the aggregate degree of assessment regressivity. This result moves the literature closer to a consensus on the causes of regressive assessments. Lastly, I use newly available TCA data to quantify the effect that regressive assessments have on wealth inequality among homeowners and propose a simple valuation method that could alleviate assessment regressivity.

This paper also adds to a growing body of works that studies the unintended consequences

[4]Black (1977) was the first to suggest this explanation, but his work did not provide empirical evidence to support his claim.

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 assessors' offices overappraise inexpensive houses and underappraise expensive houses because they ignore variation in priced house and neighborhood characteristics. Since individuals with low levels of wealth sort into inexpensive houses, the property tax system ends up overtaxing economically disadvantaged 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, A_i, and the statutory tax rate τ^s:

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

To compute the house's assessed value, the government 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. The assessment ratio is arbitrarily chosen by a local government entity (Lincoln Institute of Land Policy, 2014).[5] To arrive at each house's final assessed value, relevant exemptions are applied.[6] Taxing entities calculate their tax base by summing up all final assessed values in its jurisdiction and compute the statutory tax rate that is then applied to each house's final assessed value.

[5] 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 a tax code area.

[6] Each local jurisdiction has its own set of idiosyncratic property tax exemptions. 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 primary residences' 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 decided either 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:

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

R is the total revenue that the taxing entity wishes to raise from residential property taxes and $\sum_{j=1}^{n} A_i$ is the entity's 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 tax base and determines with its own revenue target and, hence, its own statutory property tax rate. Each house is assigned to a TCA, which is a geographic region with a unique set of local government entities that serves and taxes 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. Therefore, a house's property tax bill is calculated as follows:

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

k is the index for TCAs, and j is the index for taxing entities within a TCA. Within-TCA effective property tax rates across houses can vary 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. If there is a negative relationship between valuation ratios and true market values, then inexpensive houses are relatively overassessed and effective tax rates are regressive.

Figure 1 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 20 is \$11.225 per \$1,000 of assessed value, while the rate in TCA number 21 is \$11.458. 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.

Figure 2 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. TCA number 03992 contains multiple neighborhoods, represented by separate clusters of parcels, which suggests that there is 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.

3 Data

3.1 Data Sources

The first main data set that this paper uses is the CoreLogic Tax data set, which contains property tax and parcel characteristic data for approximately 150 million property parcels in the United States. The data set covers many types of real estate parcels – residential, commerical, industrial, agricultural, vacant, and tax exempt. This study focuses on single-family homes. For most parcels, the data set contains 10 years of tax data, spanning different year intervals. The main sample that this paper uses covers observations from 2005 to 2019. Tax-related variables include property tax bill, tax year, appraised value, assessed value, assessment year, exemption indicators, and TCAs. Parcel characteristics include land and property information such land area size, living area size, number of bedrooms, number of bathrooms, etc.[7]

A key innovation in this paper is the use of TCA data. In the 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 1.[8] The CoreLogic data set has TCA data for all states, except for Massachusetts, which I exclude from my analysis.[9]

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 TCAs. I clean TCA 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 have the same name and are located in the same county as the same TCA. Figure A1 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-year house price bins. Each house's statutory tax rate is scaled by the TCA-year'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.[10]

The second main data set that this 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 more. I use arm's length transactions in my analyses. The CoreLogic Tax data set can be merged with the CoreLogic Deeds data set via unique county-provided parcel identifiers.

[7] The data set does not provide itemized information on each tax bill's property tax exemption, which prevents me from studying the impact that local exemption programs have on property tax rate regressivity.

[8] 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 each local government entity's taxing boundary. In principle, both data sets should capture the information. CoreLogic's TCA data provide a convenient way for researchers to compare houses in the same taxing jurisdiction, without having to construct them from scratch.

[9] Many parcels in Rhode Island and Michigan are missing TCA data.

[10] In some areas, property tax bills include uniform lump-sum charges that mechanically makes statutory property tax rates and, hence, effective property tax rates regressive. Figure A1 shows that the effect of these lump-sum charges is small.

Five-year estimates of census tract block group characteristics provided by the Census Bureau's American Community Surveys (ACS) are used to construct neighborhood characteristic 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). Lastly, I use the Federal Housing Finance Agency's (FHFA) and Zillow's single-family house price index data to impute market values.

3.2 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 that took place between 2000 and 2019. I exclude nominal sales, interfamily transfers, multiparcel sales, partial parcel sales, and foreclosure sales. To make it into the sample, the home must have a positive property tax bill, appraised value, assessed value, and TCA 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 reduces the probability that mislabeled non-arm's length transactions are included. The upper bound lowers the chance that mislabeled multiple-parcels sales are included.[11] 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. Lastly, because of Proposition 13, I exclude single-family home transactions in California.[12]

3.3 TCA Statistics

This section presents summary statistics on TCA characteristics. I use 2018 data for this exercise because it is the year that the CoreLogic Tax data set covers the largest number of parcels, which means that it should be the year that I could get the most representative snapshot of TCA characteristics and the number of TCAs at different levels of geographic granularity.

Table 1 presents the resulting summary statistics. Massachusetts and Rhode Island are

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

[12] 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.

excluded from the sample because 2018 TCA data are missing 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.[13] 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. The land area that TCAs cover is comparable to that of census tract block groups. Data from the 2018 ACS show that the average and median census tract block group land area are 12 and 0.5 square miles, respectively.

The next set of statistics shows 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.[14] On average, 45% of all parcels within a TCA are residential parcels, while the majority of the remaining parcels are commercial, agricultural, 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 TCAs within states. On average, a state has almost 3,000 TCAs. The average county has 49 TCAs and the average zip code has 10. These summary statistics suggests that the set and the quality of public goods that homeowners who live near each other enjoy may vary significantly.

Since TCAs are, on average, small geographic areas, a natural question that arises is how much do house prices and neighborhood characteristics vary within a TCA? Table 2 presents summary statistics on within-TCA-year house prices and neighborhood characteristics. To construct

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

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

this table, I take all single-family home transactions where I observe TCA and neighborhood characteristics and sort them into price deciles within each TCA-year pair. Next, I compute average house prices and neighborhood characteristics for each price decile. All dollar amounts are converted to 2018 USD. Neighborhood characteristics are computed using census tract block group characteristics from the ACS 5-year estimate data set.

The first key takeaway from Table 2 is that house prices vary substantially within a TCA-year pair. The average single-family house in the 10th decile is more than five times more expensive than the average house in the first decile. Variation in neighborhood characteristics is also large. For example, compared to neighborhoods surrounding the most inexpensive homes, average median household income is almost 50% higher in neighborhoods surrounding the most expensive homes. This gap in average median household income is correlated with differences in other neighborhood characteristics. Expensive houses tend to be located in richer, newer, Whiter, less commercial, and less industrial neighborhoods.

4 Estimating Assessment Regressivity

4.1 Estimation Methodology

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

$$logA_{it} - logM_{it} = \alpha + \beta logM_{it} + TCA \times Year\,FE + \epsilon_{it}. \tag{4}$$

A_{it} denotes assessed value, M_{it} denotes sale price, i indexes houses, and t indexes years.[15] Log valuation ratio is regressed onto log sale price and a negative β coefficient suggests that assessments are regressive. The regression shown in equation 4 is biased toward finding a negative slope coefficient because sale prices are noisy proxies of true market values (Cheng, 1974; Kochin

[15] The regression requires that, for a given house year, I observe a sale price and an assessed value. For house years with multiple sale prices, I use last observed sale prices. All results are unchanged when I use first sale prices.

and Parks, 1982; Kennedy, 1984; Clapp, 1990; Sirmans et al., 1995). Suppose that (1) assessment ratios equal one, (2) assessed values equal true market values, and (3) sale prices equal assessed values times an error term, then a house's sale price M can be written as follows:

$$M = e \times A = e \times M^*. \tag{5}$$

e is an error term that is normally distributed with unit mean and variance σ^2. I assume that errors are proportional to true market values instead of additive because it seems less plausible that the probability that a \$100,000 house has a \$1,000 pricing error should equal the probability that a \$1,000,000 house has a pricing error of the same size. Under this set of assumptions, attenuation bias would cause β to be negative, even though, by assumption, assessments are not regressive.

I interpret the error term e as deviations from true market values caused by bargaining frictions, which is a key feature of the housing market (Mateen et al., 2021). For example, a sophisticated buyer may manage to buy a house for less than its true market value.[16] I assume that pricing errors are correlated among houses in the same neighborhood, defined as a census tract block group, but independent across neighborhoods. This assumption is sensible because a group of sophisticated buyers who decide to buy houses in the same neighborhood could cause sale prices of these houses to move away from their true market values in the same direction.[17] The same intuition applies to cases where wealthy out-of-town buyers make all-cash offers that are significantly higher than listed prices. The appendix provides supporting evidence for this assumption.

With this interpretation of e, I use the instrumental variable approach to address the attenuation bias problem. A valid instrument for house i's log sale price in year t is the average log sale price of other transactions in house i's census tract, leaving out transactions in house i's census tract block group. Leave-out average log sale price should be highly correlated with house i's log sale price, which ensures that the instrument is sufficiently strong. Furthermore, the leave-out

[16]Other reasons why pricing errors may be prevalent in the housing market include forced sale spillover effects (Campbell et al., 2011; Gupta, 2019), experience effects (Giacoletti and Parsons, 2021), information frictions (Giacoletti, 2017), owners' liquidity constraints, market liquidity issues (Campbell et al., 2011), and housing boom-bust cycles (Cheng et al., 2014).

[17]Note that a skilled real estate agent who serves an entire city would not necessarily cause pricing errors to be correlated across neighborhoods because real estate agents represent both buyers and sellers.

approach satisfies the exclusion restriction because, by leaving out transactions in the same census tract block group, the correlation between the instrument and the error term embedded in the transaction's sale price is, by assumption, zero.[18] With this estimation strategy, the true degree of assessment regressivity is captured by β^{IV} in the following two-stage least squares regression:

$$logM_{it} = \alpha' + \beta'\overline{logM_{it}} + TCA \times Year\,FE + \epsilon'_{it}. \tag{6}$$

$$logA_{it} - logM_{it} = \alpha + \beta^{IV}\widehat{logM_{it}} + TCA \times Year\,FE + \epsilon_{it}. \tag{7}$$

$\overline{logM_{it}}$ denotes the leave-out average log sale price of other transactions in house i's census tract. $\widehat{logM_{it}}$ 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.

4.2 Baseline Assessment Regressivity Estimates

This section documents baseline facts about assessments and effective property tax rates regressivity among houses in the same TCA and year. Figure 3 uses data from over 20 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 sort houses in the same TCA-year into 20 price bins. For each house, I calculate its effective tax rate, property tax bill divided by 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, more inexpensive homes are taxed at higher rates than more expensive homes.[19] The disparity in effective tax rates between

[18] One potential advantage that the current instrument has over the one proposed by Clapp (1990) is that it does not rely on the assumption that pricing errors are small enough such that they do not push sale prices across house price bins that houses in the sample are allocated to. It is not clear that the small pricing error assumption holds in today's housing market because Giacoletti (2017) shows that the idiosyncratic component of housing returns can be large.

[19] I get a similar picture when I scale effective tax rates by mean TCA-year effective tax rate and plot mean scaled

inexpensive 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 more inexpensive houses are paying a much higher price than owners of expensive houses.[20]

Section 4.1 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. I use the empirical strategy proposed in Section 4.1 to address this issue. Table 3 presents the regression results. Column 1 reports the ordinary least squares (OLS) regression result where log valuation ratio is regressed onto log sale price with TCA-year fixed effects. The slope coefficient estimated by this regression is -0.32, which suggests that assessments are regressive within TCA-year pairs.

Column 2 presents the first-stage regression result where log sale price is regressed onto the instrumental variable described in Section 4.1. The slope coefficient shows that a one log point increase in leave-out average log sale price is associated with a 0.65 log point increase in log sale price, which implies that house i's sale price is highly correlated with leave-out average sale prices of nearby houses. Column 3 presents the second-stage regression result. The estimated slope coefficient is -0.079, which suggests that assessments are indeed regressive, but approximately 75% of the observed regressivity is caused by attenuation bias.[21] This estimate is likely to be a lower bound of the true degree of regressivity because the sample excludes houses where I do not observe sale prices. These houses are likely to be located in markets with thin transaction volumes, which have been shown to have more regressive assessments (McMillen and Weber, 2008).

Although the true degree of assessment regressivity is much smaller than the observed degree of assessment regressivity, the economic magnitude of this slope coefficient is not small. A homeowner whose house is worth $100,000 faces an effective property tax rate that is approximately

effective tax rates for each price bin.

[20]Due to data limitations, this paper does not deal with the issue of heterogeneous usage of property tax-funded public goods. It could be the case that disadvantaged homeowners use and benefit more from these amenities, which would imply that rich homeowners are overpaying for things that do not benefit them.

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

20% greater than a homeowner whose house is worth $1,000,000, which is a large deviation from the government's goal of charging a uniform within-TCA property tax rate. Columns 4 and 5 present the result for within-census tract and within-county degree of assessment regressivity, respectively. The magnitude of these estimates are similar, which suggests that assessments are regressive at many relevant levels of geographic granularity. The rest of the paper deals with explaining the remaining amount of within TCA assessment regressivity.

5 Flawed Valuation Methods and Assessment Regressivity

This section describes how tax assessors' flawed valuation methods can give rise to assessment regressivity and presents empirical results that support the explanation.

5.1 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 structural attributes (e.g., number of bedrooms, number of bathrooms, and size) 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 located 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 related to the properties' physical structure.

In the rest of the section, I treat neighborhood characteristics as omitted variables because assessors often exclude them from hedonic regression. 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 geographic area can be large (Ananat, 2011), which explains why using fine geographic fixed effects (e.g., census tract block group) would not solve model-induced assessment regressivity. In the following subsection, I explain how a common valuation method used by county assessors tends to produce regressive assessments.

5.2 Hedonic Pricing Method

The hedonic pricing method (HPM) regresses sale prices observed in year t onto measurable house and neighborhood characteristics observed in the same year (Rosen, 1974). Coefficients from this regression model are used to calculate appraised values for all houses. The International Association of Assessing Officers (IAAO) provides a guideline on variables to include (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. Clearly, variables such as construction quality and location amenities are very difficult to quantify and appraisers would likely omit them, and the HPM would yield regressive assessments.[22]

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, the degree of assessment regressivity, can be written as follows:

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

$\hat{m}$ denotes appraised values. $R_{\hat{m}}^2$ denotes the coefficient of determination from the tax assessor's hedonic regression. This derivation of β assumes that $\rho_{\hat{m},m} > 0$ and uses the definition of an OLS regression R^2, which can be expressed as the squared value of the Pearson correlation coefficient between the predicted values and the dependent variable. It is clear from the equation

[22] To provide a concrete example of the list of variables that tax assessors use in their linear regression models, I turn to Cook County, IL, 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.

that β is a positive function of R^2, which implies that, all else equal, assessments are more regressive when tax assessors' hedonic regressions cannot explain variation in sale prices well.[23]

5.3 Testable Predictions

This section outlines testable predictions from the flawed valuation methods explanation. The explanation asserts that assessment regressivity is caused by tax assessors' valuation models' over-reliance 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:*

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

M_{it} denotes the observed sale price for house i in year t and $\mathbf{h}^*_{\mathbf{it}}$ is a vector of house characteristics associated with house i in the same year. $\hat{m}(\mathbf{h}^*)$ denotes predicted log 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 the 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. The prediction is that, across TCA-years, $R^2_{\hat{m}(\mathbf{h}^*),kt}$ should be positively correlated with β_{kt}.

[23]McMillen and Singh (2018) make a similar argument and provide a formal proof, which shows that, under certain conditions, $\beta = R^2 - 1$. Other appraisal methods commonly used by tax assessors and how they produce regressive assessments are discussed in the Online Appendix.

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.[24] A positive correlation between these two quantities 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 predict realized sale prices well.

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 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:

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

[24] Note that a positive correlation between β and $R^2_{\hat{m}(\mathbf{h}^*)}$ is not mechanical because I do not know the exact appraisal models that local tax assessors used to produce assessed values that I observe in the data.

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

$$logM_{it} = \theta + \gamma_1' \mathbf{h}^*_{\mathbf{it}} + \gamma_2' \mathbf{n}^*_{\mathbf{it}} + \delta_{it}. \tag{13}$$

$\mathbf{n}^*_{\mathbf{it}}$ *is a vector of nieghborhood characteristic associated with house* i *in year* t*.* 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 quantities confirms that assessment regressivity is caused by valuation models that omit priced neighborhood characteristics.[25]

5.4 Testing the Predictions

To test Prediction 1, I begin by constructing a data set of transacted houses in which I observe house characteristics, neighborhood characteristics, sale prices, and assessed 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 4.1. Next, I estimate $R^2_{\hat{m}(\mathbf{h}^*)}$ by running the regression from equation 9. House characteristics that I use are log number of bedrooms, log number of bathrooms, log living-area square footage, and log age.[26]

Table 4 presents summary statistics for the estimated parameters. There are approximately 11,000 TCA-years in the sample. The average β_{kt} is -0.44 and the average β^{IV}_{kt} is -0.2, which is consistent with the observation that assessments tend to be regressive. The degree of regressivity varies significantly across TCA-years. β_{kt} ranges from -1 to 0.07, while β^{IV}_{kt} ranges from -2.29 to

[25] Another way to study how valuation methodology affects assessment regressivity is to collect information on each county's valuation method and exploit changes in valuation methods to show the causal relationship between valuation methods and regressive assessments. However, in practice, this is a very difficult task because information on each county's current and past valuation methods is very hard to find.

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

1.65. 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. There is significant variation 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} and $R^2_{\hat{m}(\mathbf{h}^*),kt}$, which lines up well with equation 8. I formally test this relationship by regressing β_{kt} onto $R^2_{\hat{m}(\mathbf{h}^*),kt}$ with county-year fixed effects. Column 1 of Table 5 presents the result. As expected from the plot, there is a positive and statistically significant relationship between β_{kt} and $R^2_{\hat{m}(\mathbf{h}^*),kt}$. Column 2 shows that the conclusion holds when I use β^{IV}_{kt} as the dependent variable.

To show that variation in neighborhood characteristics is the unaccounted component that drives the relationship between β_{kt} and $R^2_{\hat{m}(\mathbf{h}^*),kt}$, I compute $R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt}$ by estimating regression equation 13.[27] Table 4 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 variation in ΔR^2_{kt}, which shows that there are TCA-years where neighborhood characteristics are important to house prices 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 relationship between the two quantities. The third column of Table 5 reports the estimated OLS regression 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

[27] Neighborhood characteristics that I use are minority share, log median household income, unemployment rate, percentage of adults with a college degree, percentage of households that participate in Supplemental Nutrition Assistance Program (SNAP), median gross rent as a percentage of household income, homeownership percentage, home vacancy percentage, percentage of commercial parcels, percentage of industrial parcels, and percentage of agricultural parcels. Neighborhood characteristics are measured at the census tract block group level. I interpret these neighborhood characteristics as proxies for neighborhood quality and not as actual pricing characteristics.

omitted neighborhood characteristics drive the panel variation in assessment regressivity. Column 4 shows that the result holds when I use β_{kt}^{IV} as the dependent variable.[28]

6 Quantifying Sources of Assessment Regressivity

This section quantifies the proportion of assessment regressivity that can be explained by infrequent reappraisal, flawed valuation methods, and appeals.

6.1 Infrequent Reappraisal and Flawed Valuation Methods

Appraised values often lag sale prices because houses do not get reappraised every year (Engle, 1975; Heavey, 1978). Infrequent reappraisal comes in two forms: (1) revaluation cycles that span more than one year, and (2) assessment growth limit laws.[29] Slow-moving appraised values can cause assessment regressivity because, over time, houses that experience large increases in market values become relatively underappraised and undertaxed. I can quantify the proportion of assessment regressivity that can be attributed to infrequent reappraisals by comparing the degree of assessment regressivity among all houses with the degree of assessment regressivity among houses that are not subjected to infrequent reappraisal nor assessment growth limit laws.

This exercise requires me to identify a sample of houses that are subjected to infrequent reappraisal or assessment growth limit laws. I call this sample the stale appraised value sample. Houses that are not subjected to infrequent reappraisal or assessment growth limit laws belong to the fresh appraised value sample. I begin by identifying houses with appraised values that were not updated in the same year that they were sold, i.e., stale appraised values. Empirically, I consider a house to have stale appraised value if its current appraised value equals its one-year lagged appraised value. This procedure decreases the sample size because, for each transaction, I need to

[28] 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.

[29] Assessment growth limit laws cap the annual increase in a home's assessed value, which effectively limits the annual increase in the homeowner's property tax bill. For example, Florida's assessment growth limit law states that "for properties receiving the homestead exemption, the annual increase in assessed values is limited to the lower of the following: either 3% of the assessed value of the property for the prior year; or the percentage change in the Consumer Price Index" (Lincoln Institute of Land Policy, 2014).

be able to observe both the house's current and lagged appraised values. Next, I include newly constructed single-family homes that were finished and sold in the same year into the fresh appraised value sample because, except in the state of Connecticut, new constructions are reappraised upon completion. Lastly, using information from the Lincoln Institute's Property Tax Database and state governments' websites, I identify states that have assessment growth limit laws during the sample period and put all old homes in these states into the stale appraised value sample. Table A2 summarizes this information.

To quantify the proportion of assessment regressivity that can be explained by flawed valuation methods, I begin by constructing synthetic assessed values for all transacted homes. For each transaction associated with a certain house i, I grow house i's most recent previous sale price by the change in its local single-family house price index.[30] To get the synthetic assessed value, I multiply the product by the observed assessment ratio, which is the observed assessed value divided by the observed appraised value:

$$A_{i,t}^{syn} = M_{i,t-k} \times \frac{HPI_t}{HPI_{t-k}} \times \frac{A_{i,t}}{V_{i,t}}. \tag{14}$$

$M_{i,t-k}$ is house i's previous sale price in year $t-k$, $\frac{HPI_t}{HPI_{t-k}}$ is the change in its local house price index between year $t-k$ and year t, and $\frac{A_{i,t}}{V_{i,t}}$ is the observed assessment ratio. This approach makes two implicit assumptions. First, house i's previous sale price captures house i's priced house and neighborhood characteristics in year $t-k$. Stated differently, 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 sales.

The next step is to construct synthetic valuation ratios by taking the log difference between house i's synthetic assessed value and its sale price. I then estimate the degree of assessment regressivity using the instrumental variable approach outlined in Section 4.1. β^{IV} captures the degree of assessment regressivity that is free from attenuation bias. Next, I drop all transactions

[30] This method is similar to the approach taken by Bayer et al. (2017). I use the FHFA's all-transaction single-family house price index. `https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx`. Whenever possible, I use the census tract-level index. When census tract-level data are not available, I supplement with the zip code-level index.

that are associated with house-years with stale appraised values and transactions of old homes in states with assessment growth limit laws to eliminate the effect that infrequent reappraisal has on assessment regressivity. Lastly, I run the 2SLS regression where log synthetic valuation ratio, the difference between log synthetic assessed value and log sale price, is regressed onto the log sale price. The resulting slope coefficient captures the degree of assessment regressivity that is free from attenuation bias, infrequent reappraisal, and some degree of model-induced valuation errors.

The difference between the first and second slope coefficients is an estimate of the proportion of regressivity that can be explained by infrequent reappraisal. The difference between the second and third slope coefficients is the amount of assessment regressivity that can be explained by flawed valuation methods. Any remaining regressivity could come from the fact that equation 14 does not account for renovations that might have occurred between sales. Hence, the difference between the second and third slope coefficients can be interpreted as the lower bound of the proportion of assessment regressivity that can be explained by flawed valuation methods.

Table 6 presents the regression results. For this analysis, I only include transactions where I observe previous transaction prices that are not more than 5 years old. This requirement ensures that the assumption that past transaction prices are good predictors of current transaction prices holds. The first column presents the baseline 2SLS regression result. The slope coefficient is -0.05. Column 2 presents the estimated degree of assessment regressivity that remains after accounting for infrequent reappraisal. The last column presents the 2SLS regression result where log synthetic valuation ratio is regressed onto log sale price. The slope coefficient is 0.007 and is not statistically different from zero. Comparing these three slope coefficients shows that, for this sample of transactions, the true degree of assessment regressivity can be decomposed into the following components: 38% from infrequent reappraisal ($\frac{-0.05+0.031}{-0.05}$) and 62% ($\frac{-0.031}{-0.05}$) from flawed valuation methods.[31]

[31] Results are qualitatively similar when synthetic assessed values are computed using Zillow's zip code-level single-family house price index. The proportion of assessment regressivity that can be explained by infrequent reappraisal is similar when I perform the same analysis on all homes; -0.05 lies just outside of the 90% confidence interval of the slope coefficient estimate presented in column 2.

6.2 Heterogeneous Appeals Behaviors and Outcomes

This subsection evaluates the heterogeneous appeals behaviors and outcomes explanation. Suppose that, relative to individuals who own more expensive homes, individuals who own more inexpensive homes are less likely to appeal their county-proposed assessed values. Furthermore, suppose that owners of more inexpensive 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 appeals data from Cook County, IL.[32] I use unique parcel identifiers to merge Cook County's appeals data with tax, transaction, and TCA data from CoreLogic. The merged data set contains observations from 2007 to 2017. Next, I use the procedure from Section 6.1 to impute market values for house-years with no transaction price. The resulting data set is a panel of more than 3.8 million observations with annual appeals information, assessed values, imputed market values, and, where available, sale prices.[33] Finally, I assign houses to 1 of 20 price bins within their TCA-year to explore how appeals behaviors and outcomes vary across price bins.[34]

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 appeal probability and house price. The plot shows a positive relationship between the two quantities. However, the difference in appeal probability between owners of the most expensive homes and owners of the most inexpensive homes is only approximately 4%. I formally test whether the positive correlation between appeal probability and house price is statistically significant by regressing an appeal indicator variable onto within-TCA-year price decile indicator variables with TCA by year fixed effects. Column 1 of Table 7 presents the results, which agree with the qualitative conclusion.

Next, I investigate the relationship between win probability and house price. Figure 7 plots average win probability against within-TCA-year house price bins. This sample only includes houses

[32] `https://datacatalog.cookcountyil.gov`.

[33] Results are quantitatively and qualitatively similar when I use Zillow's house price index to impute market values.

[34] Since houses are not sold randomly, assigning houses to price bins according to imputed prices and sale prices partly alleviates the concern that the assignment will be biased by the selection process that determines which houses get sold.

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. The plot shows a positive relationship between the two quantities. Column 2 of Table 7 reports regression results that confirm this finding. Similar to the appeal probability plot, the difference in win probability between owners of the most expensive homes and owners of the most inexpensive homes is small.

Despite small differences in appeal and win probabilities, it could be the case that, upon winning, owners of expensive houses receive substantially larger assessed value reductions. Figure 9 plots average assessed value reduction percentage against within-TCA-year house price bins, conditional on appealing. 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. The plot shows a positive relationship between the two quantities. However, the variation in assessed value reduction is small. The average assessed value reduction percentage that owners of the most inexpensive homes receive is only approximately 0.3% lower than the average percentage reduction that owners of the most expensive homes receive. Column 3 of Table 7 reports regression results that confirm this finding.

I can glean the overall effect that appeals have on assessment regressivity by plotting the unconditional average assessed value reduction percentage against within-TCA-year house price bins. Figure 8 presents this plot. First, the correlation between assessed value reduction and house price is positive. This finding is confirmed by regression results presented in column 4 of Table 7. Second, the pattern is similar to that of the appeal probability plot, which is not surprising, given the small differences in win probabilities and assessed value reduction percentages between the top and bottom price deciles. Third, the difference in unconditional assessed value reduction between the top and bottom price deciles is approximately 0.3%, which is small in comparison to the difference in average valuation ratios across the two price deciles (0.78 versus 0.32, respectively).

Although the interprice decile difference in assessed value reduction percentage seems small, it is still unclear how much of Cook County's aggregate degree of assessment regressivity can be explained by heterogeneous appeals behaviors and outcomes. One way to quantify the *cumulative* effect that appeals have on within-TCA-year assessment regressivity is to estimate the degree of assessment regressivity among houses in Cook County if homeowners had *never* filed a single appeal. This analysis is possible because, for each home, I observe pre-appeal assessed values that the county assessor's office proposed during each reassessment cycle. I can use these proposed assessed values to construct counterfactual valuation ratios that would have realized, if homeowners had never filed a single appeal. The difference in degrees of assessment regressivity between the observed and counterfactual valuation ratios captures the amount of assessment regressivity that is caused by appeals.

Table 8 presents regression results where log observed and counterfactual valuation ratios are regressed onto log sale or imputed price and within-TCA-year price decile indicator variables. Column 1 reports results from a regression where log observed valuation ratio is regressed onto log sale or imputed price. The slope coefficient is -0.506, which is the degree of assessment regressivity that resulted from appeals acitivity in the county. Note that the sample size is smaller than in column 1 of Table 7 because, for each home to be included in the sample, I must observe its proposed assessed value, which is observable once every three years. Column 2 of Table 8 presents results from a regression where log counterfactual valuation ratio is regressed onto log sale or imputed price. The estimated slope coefficient is -0.503, which is not statistically different from the slope coefficient estimate in column 1. The comparison implies that the *cumulative* effect that appeals have on within-TCA-year assessment regressivity is small, which is in line with results from the preceding analyses. Columns 3 and 4 repeat the analysis using the instrumental variable approach and find the same qualitative conclusion.

It is clear from Figure 8 that the pattern of assessed value reduction along the house price distribution is not linear. To account for the nonlinearity, columns 5 and 6 of Table 8 presents regression results where log observed and counterfactual valuation ratios are regressed onto within-TCA-year price decile indicator variables. Comparing the regression coefficients in columns 5 and 6 reveals that assessment regressivity is similar across the two regimes, which suggests that the cumulative effect that appeals have on within-TCA-year assessment regressivity is limited.[35]

[35] Results are qualitatively and quantitatively similar when I exclude observations with imputed prices.

The conclusion presented above is not surprising for the following reasons. First, interprice decile differences in appeals probability, win probability, and assessed value reductions are small. Second, since every three years, houses in Cook County are reappraised using the hedonic pricing method, there is not a lot of time for the effects of appeals to accumulate.[36] Lastly, this result agrees with findings from previous works that use Cook County data to study the effect that appeals have on *countywide* assessment regressivity.[37]

It is important to note that the results presented in this section merely *suggest* that appeals do not drive regressive assessments. First, the analysis above uses data from Cook County, which is hardly representative of the whole nation. Second, the analysis ignores game theoretic interactions between assessors and residents. For example, it is possible that assessors know that owners of expensive homes are particularly troublesome. In response, assessors preemptively make proposed assessed values for these homes artificially low to avoid interacting with these individuals. In this scenario, the effect of heterogeneous appeals behaviors would still be included in the counterfactual assessed values that the previous analysis relies on.

7 A Potential Solution

Results from Section 6.1 suggest that imputing market values using the procedure from Bayer et al. (2017) can alleviate assessment regressivity. This section combines data from CoreLogic with data from the 2016 Survey of Consumer Finance (SCF) to study the impact that such a change would have on appraisal accuracy and the distribution of tax burden and wealth among homeowners.[38]

7.1 Valuation Accuracy

A primary concern in the world of property appraisal is appraised value accuracy. Despite the shortcomings of sale prices discussed in Section 4.1, it is the industry's standard to compare model-

[36] `https://www.cookcountyassessor.com/about-cook-county-assessors-office`.

[37] Figure 1 from Ross (2017) and Figure 8 from McMillen (2013) show that appeals do worsen assessment regressivity, but by a small amount. I repeat the same analysis on countywide regressivity and find the same conclusion. Table A3 presents these results.

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

produced appraised values with realized sale prices to gage the valuation methodology's accuracy. To perform this analysis, I begin by using the procedure from Bayer et al. (2017) to impute market values for all house years that I observe sale prices and appraised values in the same year.[39] Since this section is a counterfactual policy analysis, I also include single-family homes in California in the sample.[40] This step yielded more than 15 million observations.

Next, I compare the valuation accuracy of imputed market values against that of observed appraised values, i.e., the local assessors' methodology, by computing the absolute value of the log difference between the method-produced values and observed sale prices.[41] Table A4 presents summary statistics on these absolute values. On average, imputed market values are closer to observed sale prices than tax assessors' appraised values. The average absolute value of log difference decreases by almost 15%, from 0.28 to 0.24. The percentage difference is larger when I compare medians, which show a decrease of more than 25%, from 0.19 to 0.14. The maximum error is also smaller at 1.97 versus 1.53. These results suggest that imputed market values are better proxies of sale prices than existing appraised values.

7.2 Impact on Tax Burden and Wealth Distribution

The second part of this section studies the effect that this change would have on the distribution of property tax burden and wealth across homeowners. For this exercise, I also include single family homes in California into the analysis because the SCF database can only produce national-level summary statistics. Like before, I use the procedure from Bayer et al. (2017) to impute market values for all houses that have 2016 property tax data. This step yielded over 32 million observations. An advantage of using imputed market values is that it allows me to include a large number of single-family homes into the analysis, which makes the sample more comparable to the national-level summary statistics that the SCF provides.

I use data from the SCF to divide homeowners into 11 groups, according to the value of their

[39] Like in previous sections, I use the all-transaction house price index provided by the FHFA. All results are quantitatively similar when I use Zillow's house price index.

[40] Results are similar when I exclude houses in California from the analysis.

[41] I use appraised values and not assessed values because assessed values are calculated as multiples of appraised values, which would mechanically have large deviations from observe sale prices.

primary residences. These groups are, approximately, the 10 deciles of primary residence value and the top 1%. Columns 2 and 3 of panel A of Table 9 show the lower and upper bound values for each group. Using the CoreLogic data set, I calculate excess tax payments (ETP) for each house. ETP is defined as the difference between the observed tax bill and the counterfactual tax bill that would have resulted if houses were taxed according to their imputed market values:

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

Within a TCA k, for all houses that have imputed market values, I compute total tax revenue and total imputed market value. Total tax revenue divided by total imputed market value gives the counterfactual statutory tax rate.[42] The counterfactual tax rate is multiplied by each house's imputed market value to arrive at the counterfactual tax bill. A positive ETP value means that the observed tax bill is too high, relative to the market value-based benchmark. For this exercise, I exclude TCAs that have fewer than 30 transactions in 2016.[43]

Column 4 of panel A reports each group's median excess tax payment. Households that have primary home values in the bottom decile, on average, pay \$234 in excess tax payment per year. This amount is equivalent to 28% of the median property tax bill for this group of homeowners. Not surprisingly, ETP values decrease monotonically with house price and turns negative for homeowners whose primary residences are valued above the 20th percentile. Owners of the very most expensive homes receive a tax break that is equivalent to approximately 6% of his or her property tax bill. In terms of effective tax rates, tax bill divided by imputed market value, homeowners in the bottom decile faces a median effective tax rate of 2.2%, while homeowners in the top 1% faces a median effective tax rate of less than 0.9%. The main takeaway from panel A is that the degree of over- and undertaxation that results from regressive assessments is quite large.

Panel B reports statistics on tax payments and net worth. Column 2 presents median homeowner net worth for each home value group, calculated using data from the SCF. As expected,

[42] 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.

[43] Section A.2 of the Main Appendix discusses important caveats for these calculation.

median net worth increases with house price because less wealthy individuals cannot afford to buy expensive homes. Column 3 shows each group's median property tax bill as a percentage of median net worth, i.e., property tax bills converted to median wealth tax rates. Since ETP decreases with house price, it is not surprising that property tax is equivalent to a form of regressive wealth tax for homeowners.

If county assessor offices use imputed market values to calculate tax burdens, how would the wealth distribution among homeowners change? I answer this question by treating each house's excess tax payment as a perpetuity and, by 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). These changes are the amount of home equity that would accrue to homeowners if houses were taxed according to their imputed market values. Column 4 of panel B reports median changes in home equity for each home value group and column 5 converts them to percentages of median net worth. For homeowners in the bottom decile of the house price distribution, median overtaxation of $234 per year is equivalent to a present value amount of $5,580 or approximately 11.5% of median net worth. The interpretation is that, if county assessors implement this change, then the homeowners who are the most disadvantaged would see their net worth increase by more than 10%.[44]

On the other hand, for homeowners in the top 1% of the house price distribution, a $1,505 property tax break is equal to $37,625 in present value term or 0.34% of their net worth. The interpretation is that this valuation method change would decrease the net worth of the median homeowner in this group by 0.34%. These calculations show that implementing such a change would decrease the wealth gap between owners of inexpensive homes and owners of expensive homes by transferring wealth from the rich to the disadvantaged.[45] The exercise also shows that assessment regressivity distorts the distribution of homeowners' wealth in such a way that hurts the poorest homeowners.[46] Lastly, by using this simple valuation method, county assessors would be

[44]Results are qualitatively and quantitatively similar when I use mean values instead of medians.

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

[46]A frequently asked question is this: Suppose that house prices already reflect excess property tax payments, then, in a sense, is it not the case that regressive property tax rates do not matter? In a multiperiod setting, this question assumes that homebuyers can perfectly forecast changes in true market values of houses and future property tax

able to alleviate assessment regressivity and forgo expensive third-party Computer Assisted Mass Appraisal (CAMA) software (Massachusetts Department of Revenue, 2017).

8 Conclusion

This paper uses a comprehensive data set of single-family home property tax burdens and 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 characteristics, can explain a nontrivial portion of this phenomenon. A simple solution is to calculate appraised values as the product of the houses' previous sale prices and the innovation in their local house price indexes.

Although this paper 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. Assessors calculate average price-to-rent ratio from comparable properties and apply it to the property's gross rent. This approach only uses observable property characteristics to find comparable properties, which, under weak assumptions, also produces regressive assessments.[47]

The results from this paper have several implications for economic inequality in the United States. In line with Levinson (2020), I find that property tax is a regressive wealth tax on homeowners. An important implication from this result is that the property tax system potentially exacerbates wealth inequality among homeowners because it helps richer homeowners accumulate wealth at a faster pace and at the expense of poorer homeowners. Furthermore, since homeowner characteristics such as race and ethnicity are highly correlated with house price, it is also the case that the property tax system is overtaxing minority homeowners (Avenancio-León and Howard, 2019).

bills. These assumptions seem implausible because research has shown that even sophisticated individuals cannot predict changes in house prices well (Cheng et al., 2014) and that homebuyers do not fully account for property taxes (Bengali, 2018).

[47] Refer to the Online Appendix for a detailed discussion.

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Figure 1: 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 (TCAs) in Snohomish County, WA. Statutory tax rates are presented as 1 USD of tax per 1,000 USD of assessed value. The contents of this figure are sourced from the Snohomish County Assessor's Office website.

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 2: Tax Code Area Map from Snohomish County, WA

This figure presents a map of tax code areas (TCAs) in Snohomish County, WA. 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. The contents of this figure are sourced from the Snohomish County Assessor's Office website.

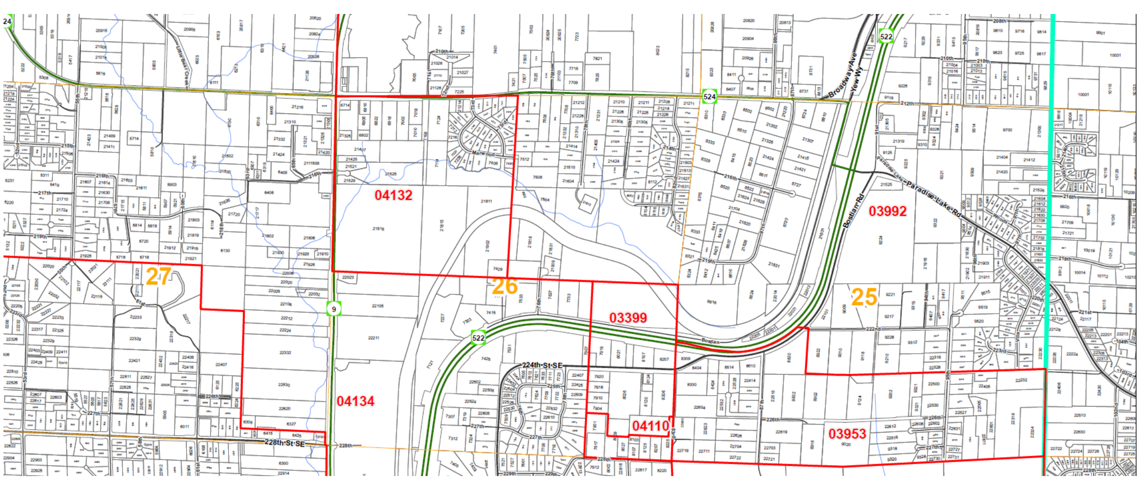


Figure 3: Median Scaled Effective Tax Rate by TCA-Year House Price Bin

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. 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 20 price bins. The most inexpensive houses are in the first bin and the most expensive houses are in the 20th bin. The sample contains single-family houses in 49 states and the District of Columbia that were sold between 2005 and 2019.

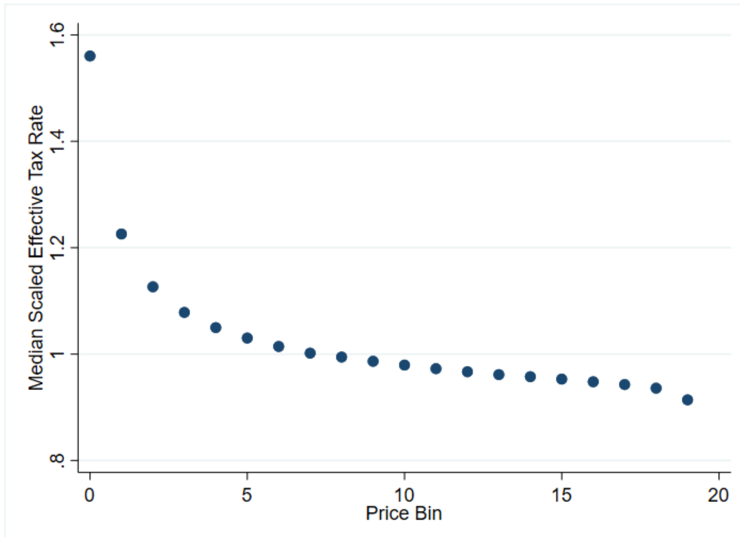


Figure 4: Binnned Scatter Plot of β_{kt} Against $R^2_{\hat{m}(\mathbf{h}^*),kt}$

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 quantities are residualized by county-year indicator variables. The sample contains TCA-years where there are at least 30 transactions.

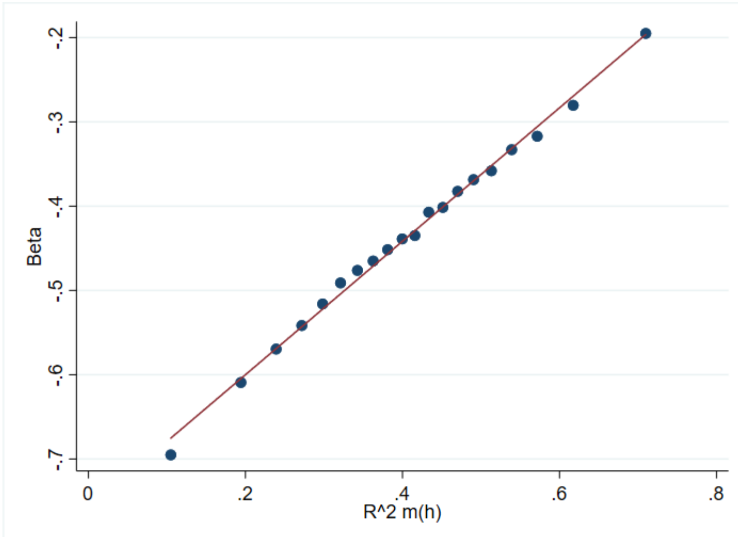


Figure 5: Binnned Scatter Plot of β_{kt} Against ΔR^2_{kt}

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 quantities are residualized by county-year indicator variables. The sample contains TCA-years where there are at least 30 transactions.

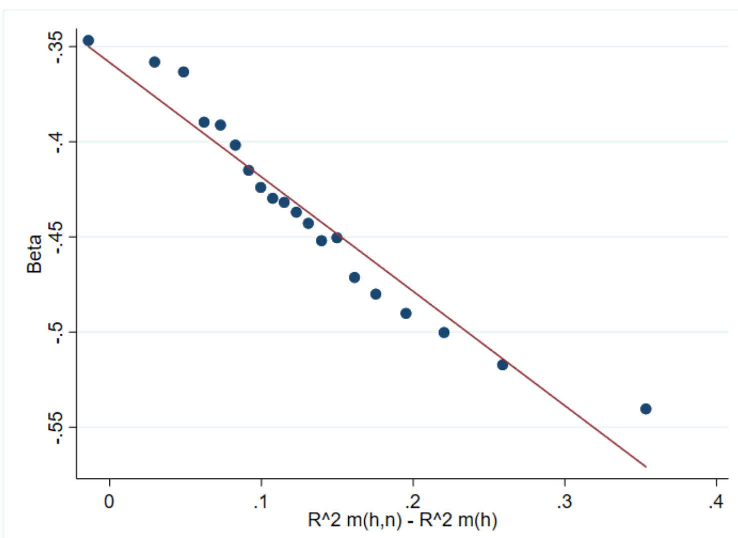


Figure 6: Appeal Probability and House Price

This figure presents a binnned scatter plot of appeal probability against TCA-year house price bins for houses in Cook County, IL. Appeal 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 20 price bins. The most inexpensive houses are in the first bin and the most expensive houses are in the 20th 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).

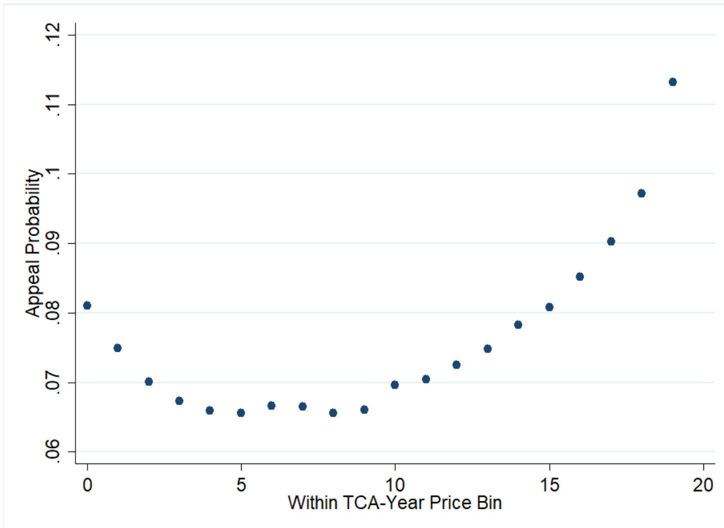


Figure 7: Win Probability and House Price

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 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 20 price bins. The most inexpensive houses are in the first bin and the most expensive houses are in the 20th bin.

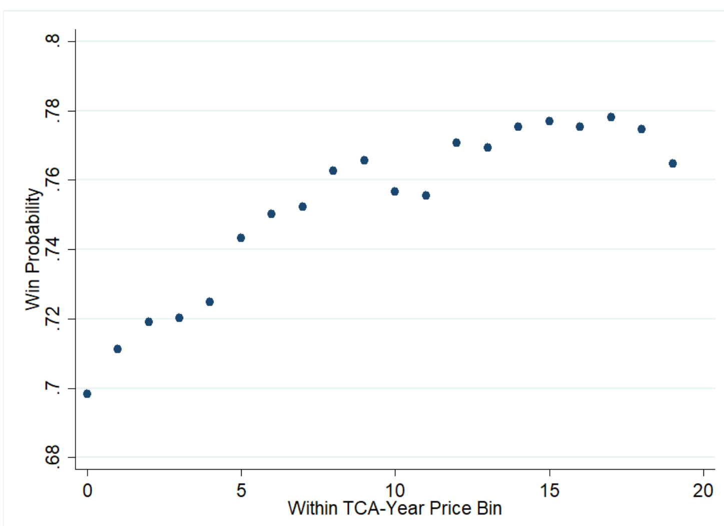


Figure 8: Average Assessed Value Reduction Percentage and House Price – Conditional on Appeal

This figure presents a binnned scatter plot of average assessed value reduction percentage 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 prices can be imputed using the procedure from Bayer et al. (2017). Assessed value reduction percentage is calculated as the amount of assessed value reduction that the homeowner received divided by the proposed assessed value times 100. Houses in each TCA-year are evenly sorted into 20 price bins. The most inexpensive houses are in the first bin and the most expensive houses are in the 20th bin.

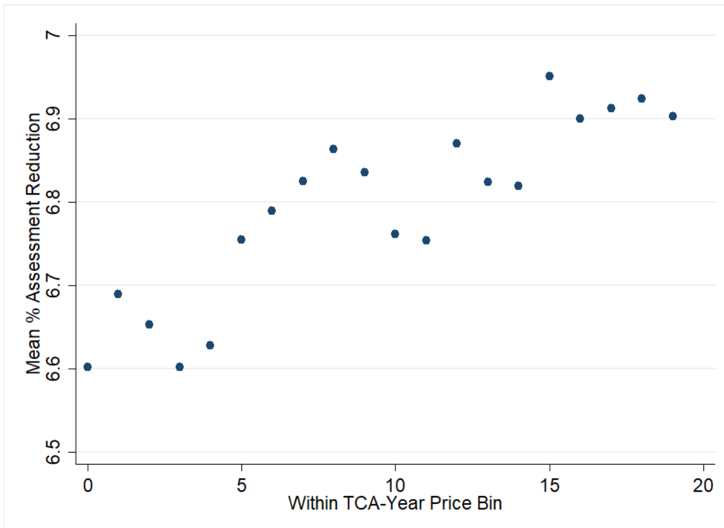


Figure 9: Unconditional Average Assessed Value Reduction Percentage and House Price

This figure presents a binnned scatter plot of average assessed value reduction percentage against TCA-year house price bins for houses in Cook County, IL. The sample includes house-years between 2007 and 2017 where sale prices are observable or where prices can be imputed using the procedure from Bayer et al. (2017). Assessed value reduction percentage is calculated as the amount of assessed value reduction that the homeowner received divided by the proposed assessed value times 100. Houses in each TCA-year are evenly sorted into 20 price bins. The most inexpensive houses are in the first bin and the most expensive houses are in the 20th bin.

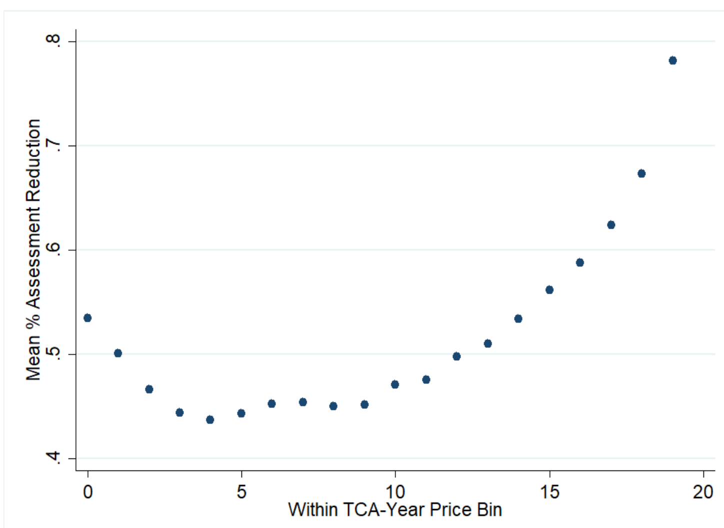


Table 1: Tax Code Area Summary Statistics

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 parcels 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	2,905.33	7,261.16	459.50	1,108.00	2,450.00
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: Within-TCA-year Summary Statistics

This table presents average house price and neighborhood characteristics by TCA-year house price decile. The sample includes single-family home transactions from 2005 to 2019. Column 2 reports average house prices in 2018 USD. Column 3 reports average median household income in 2018 USD. Column 4 reports average house ages. Column 5 reports average minority shares. Minority share is defined as the percentage of the census tract block group's population that is Black, Hispanic, or Native American. Column 6 reports average percentage of residential parcels. Column 7 reports average percentage of commercial parcels. Column 8 reports average percentage of industrial parcels. House prices are calculated using transaction data in CoreLogic. Census tract block group residential parcel percentages, commercial parcel percentages, and industrial parcel percentages are calculated using property classification code from CoreLogic. Other variables are calculated using census tract block group variables from the American Community Survey 5-year estimates.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within TCA-Year Price Decile	House Price	Median Household Income	House Age	Minority Share	Residential Parcel %	Commercial Parcel %	Industrial Parcel %
1	101,028.97	65,121.96	38.12	30.09%	83.41%	6.79%	0.42%
2	144,045.78	68,354.27	36.71	27.20%	84.54%	6.21%	0.39%
3	170,766.79	71,184.56	35.61	25.41%	85.01%	5.85%	0.37%
4	194,033.65	73,810.94	34.65	23.98%	85.35%	5.57%	0.36%
5	216,905.94	76,481.59	33.80	22.64%	85.58%	5.35%	0.35%
6	241,130.73	79,059.24	33.14	21.12%	85.48%	5.18%	0.34%
7	270,821.38	81,972.33	32.46	19.91%	85.53%	5.02%	0.34%
8	308,732.36	85,231.20	31.82	18.70%	85.47%	4.90%	0.33%
9	365,991.72	88,771.63	31.33	17.41%	85.16%	4.81%	0.33%
10	522,445.66	94,542.12	31.29	15.90%	84.87%	4.74%	0.33%

Table 3: Assessment Regressivity Regression Results

This table presents regression results where log valuation ratio is regressed onto log sale price. Log valuation ratio is defined as the difference between log assessed value and log sale price. Column 1 presents OLS regression results. Column 2 presents first stage regression results where log sale price is regressed onto average log sale price of houses in the same census tract as house i, leaving out transactions in the same census tract block group as house i. Column 3 presents 2SLS regression results where log sale price is instrumented with average log sale price described above. All three regressions include TCA by year fixed effects. Column 4 presents 2SLS regression results with census tract by year fixed effects. Column 5 presents 2SLS regression results with county 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)	(5)
Log Sale Price	-0.323***		-0.079***	-0.105***	-0.098***
	[0.006]		[0.015]	[0.009]	[0.009]
Average Log Sale Price		0.648***			
		[0.014]			
Regression	OLS	1st Stage	2SLS	2SLS	2SLS
TCA-Year FE	Y	Y	Y	N	N
Tract-Year FE	N	N	N	Y	N
County-Year FE	N	N	N	N	Y
1st Stage F-stat	-	-	> 16.38	> 16.38	> 16.38
Observations	22,027,801	22,027,801	22,027,801	22,038,830	22,038,816
R-squared	0.789	0.554	0.045	0.057	0.051

Table 4: 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. Log valuation ratio is defined as the difference between log assessed value and log sale price. β^{IV}_{kt} is estimated for each TCA-year by regressing log valuation ratio onto log sale price and log sale price is instrumented with average log sale price of other transactions in the same census tract as house i, leaving out transactions in the same census tract block group as house i. $R^2_{\hat{m}(\mathbf{h}^*),kt}$ 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.

Variable	N	Mean	S.D.	Min	25th	50th	75th	Max
β_{kt}	11,057	-0.44	0.22	-1.00	-0.58	-0.43	-0.28	0.07
β^{IV}_{kt}	11,057	-0.20	0.83	-2.29	-0.49	-0.11	0.08	1.65
$R^2_{\hat{m}(\mathbf{h}^*),kt}$	11,057	0.41	0.18	0.05	0.27	0.40	0.53	0.81
$R^2_{\hat{m}(\mathbf{h}^*,\mathbf{n}^*),kt}$	11,057	0.54	0.16	0.17	0.42	0.54	0.66	0.89
ΔR^2_{kt}	11,057	0.13	0.10	0.01	0.05	0.10	0.18	0.50

Table 5: TCA-Year Panel Regression Results

This table presents OLS regression results where β_{kt} and β^{IV}_{kt} 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. Log valuation ratio is defined as the difference between log assessed value and log sale price. β^{IV}_{kt} is estimated for each TCA-year by regressing log valuation ratio onto log sale price and log sale price is instrumented with average log sale price of other transactions in the same census tract as house i, leaving out transactions in the same census tract block group as house i. $R^2_{\hat{m}(\mathbf{h}^*),kt}$ 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. Standard errors are clustered by TCA. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)	(4)
	β_{kt}	β^{IV}_{kt}	β_{kt}	β^{IV}_{kt}
$R^2_{\hat{m}(\mathbf{h}^*),kt}$	0.792***	0.505***		
	[0.011]	[0.057]		
ΔR^2_{kt}			-0.601***	-0.738***
			[0.026]	[0.100]
County-Year FE	Y	Y	Y	Y
Observations	11,053	11,053	11,053	11,053
R-squared	0.641	0.421	0.204	0.201

Table 6: Observed and Synthetic Valuation Ratios Regression Results

This table presents regression results where log observed valuation ratio and log synthetic valuation ratio are regressed onto log sale price. Log valuation ratio is defined as the difference between log assessed value and log sale price. Column 1 presents 2SLS regression results where log observed valuation ratio is regressed onto log sale price and log sale price is instrumented with average log sale price of other transactions in the same census tract as house i, leaving out transactions in the same census tract block group as house i. Column 2 reports 2SLS regression results where houses with stale appraised values and houses in states that have assessment growth limit laws are excluded. Column 3 presents 2SLS regression results where log synthetic valuation ratio is used as the dependent variable. Synthetic valuation ratios are computed using synthetic assessed values, which are based on imputed market values produced by the method from Bayer et al. (2017). The sample includes all homes that were sold where synthetic valuation ratios can be calculated. 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)
Log Valuation Ratio:	Observed	Observed	Synthetic
Log Sale Price	-0.050***	-0.031**	0.007
	[0.012]	[0.012]	[0.011]
Method	2SLS	2SLS	2SLS
Years Since Reappraisal	Any	Zero	Zero
AGL States Included	Y	N	N
TCA-Year FE	Y	Y	Y
1st Stage F-stat	$>$ 16.38	$>$ 16.38	$>$ 16.38
Observations	4,078,863	2,828,039	2,828,039
R-squared	0.043	0.031	-0.004

Table 7: House Prices, Appeal Behaviors, and Outcomes – Cook County, IL

This table presents OLS regression results where appeal-related variables are regressed onto within-TCA-year price decile indicator variables. Appeal 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, IL that have observable sale prices or where prices can be imputed using the procedure from Bayer et al. (2017). Win 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 observed or can be imputed. Percentage reduction is the reduction in assessed value that the house received from its appeal divided by the county-proposed assessed value times 100. 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:	Appeal	Win	% Reduction	% Reduction
Price Decile 1	-0.029***	-0.053***	-0.192*	-0.222***
	[0.004]	[0.008]	[0.113]	[0.032]
Price Decile 2	-0.037***	-0.041***	-0.267***	-0.275***
	[0.004]	[0.006]	[0.084]	[0.031]
Price Decile 3	-0.040***	-0.033***	-0.272***	-0.290***
	[0.004]	[0.006]	[0.072]	[0.030]
Price Decile 4	-0.039***	-0.021***	-0.204**	-0.276***
	[0.004]	[0.007]	[0.086]	[0.029]
Price Decile 5	-0.040***	-0.010	-0.158**	-0.278***
	[0.003]	[0.006]	[0.072]	[0.028]
Price Decile 6	-0.036***	-0.017***	-0.234***	-0.258***
	[0.003]	[0.005]	[0.068]	[0.025]
Price Decile 7	-0.032***	-0.003	-0.139**	-0.225***
	[0.003]	[0.006]	[0.060]	[0.021]
Price Decile 8	-0.026***	0.002	-0.112**	-0.181***
	[0.002]	[0.005]	[0.050]	[0.017]
Price Decile 9	-0.018***	0.004	-0.085*	-0.124***
	[0.002]	[0.004]	[0.048]	[0.012]
Sample	All	Appealed	Appealed	All
TCA-Year FE	Y	Y	Y	Y
Observations	3,814,966	289,851	289,851	3,814,966
R-squared	0.045	0.042	0.067	0.038

Table 8: Impact of Appeals on Assessment Regressivity – Cook County, IL

This table presents OLS regression results where observed and counterfactual log valuation ratios are regressed onto log sale price or within-TCA-year price decile indicator variables. Log valuation ratio is defined as the difference between log assessed value and log sale price. The dependent variable for columns 1, 3, and 5 is observed log valuation ratio, which is the difference between log observed assessed value and log sale price. The dependent variable for columns 2, 4, and 6 is the counterfactual log valuation ratio, which is the difference between log appeal-adjusted assessed value and log sale price. Appeal adjustment replaces post-appeal assessed values with the county-proposed assessed values. Columns 1 and 2 report OLS regression results where log valuation ratio is regressed onto log sale price. Columns 3 and 4 report two-staged least squares regression results where log sale price is instrumented with average log sale price of other transactions in the same census tract as house i, leaving out transactions in the same census tract block group as house i. Columns 5 and 6 report regression results where log valuation ratio is regressed onto within-TCA-year price decile indicator variables. The sample includes houses that have sufficient appeal history such that assessed values can be adjusted and 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)	(5)	(6)
Log Valuation Ratio:	Observed	Counterfactual	Observed	Counterfactual	Observed	Counterfactual
Log Sale Price	-0.506***	-0.503***	-0.248***	-0.236***		
	[0.019]	[0.019]	[0.017]	[0.018]		
Price Decile 1					0.720***	0.715***
					[0.035]	[0.035]
Price Decile 2					0.441***	0.431***
					[0.022]	[0.022]
Price Decile 3					0.316***	0.305***
					[0.013]	[0.013]
Price Decile 4					0.244***	0.233***
					[0.009]	[0.009]
Price Decile 5					0.198***	0.186***
					[0.008]	[0.008]
Price Decile 6					0.164***	0.153***
					[0.007]	[0.007]
Price Decile 7					0.133***	0.123***
					[0.006]	[0.006]
Price Decile 8					0.104***	0.096***
					[0.005]	[0.005]
Price Decile 9					0.071***	0.065***
					[0.004]	[0.004]
Method	OLS	OLS	2SLS	2SLS	OLS	OLS
TCA-Year FE	Y	Y	Y	Y	Y	Y
1st Stage F-stat	-	-	> 16.38	> 16.38	-	-
Observations	3,431,573	3,431,573	3,431,573	3,431,573	3,431,573	3,431,573
R-squared	0.493	0.488	0.334	0.323	0.416	0.412

Table 9: Assessment Regressivity and 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 and a counterfactual tax bill, which is the tax bill that would have realized if the house were taxed according to its 2016 imputed market value. ETP as Percentage of Tax Bill is median excess tax payment divided by median tax bill. ETP as Percentage of Net Worth is the ratio of median excess tax payment and median net worth. Change in home equity for each house is calculated as its excess tax payment treated as a perpetuity and discounted at 4%. Median percentage change in net worth is calculated as median change in home equity divided by median net worth.

Panel A

(1) Home Value Percentile Group	(2) Minimum Home Value	(3) Maximum Home Value	(4) Median ETP	(5) ETP as % of Tax Bill
< 10th	1	64,000	234	28.30%
10th - 20th	64,000	96,000	55	4.44%
20th - 30th	96,000	132,000	-12	-0.76%
30th - 40th	132,000	160,000	-44	-2.34%
40th - 50th	160,000	197,000	-56	-2.52%
50th - 60th	197,000	245,000	-68	-2.55%
60th - 70th	245,000	319,000	-94	-2.85%
70th - 80th	319,000	425,000	-131	-3.12%
80th - 90th	425,000	638,000	-189	-3.37%
90th - 99th	638,000	2,127,000	-329	-3.62%
$\geq$ 99th	2,127,000	196,136,000	-1,505	-5.93%

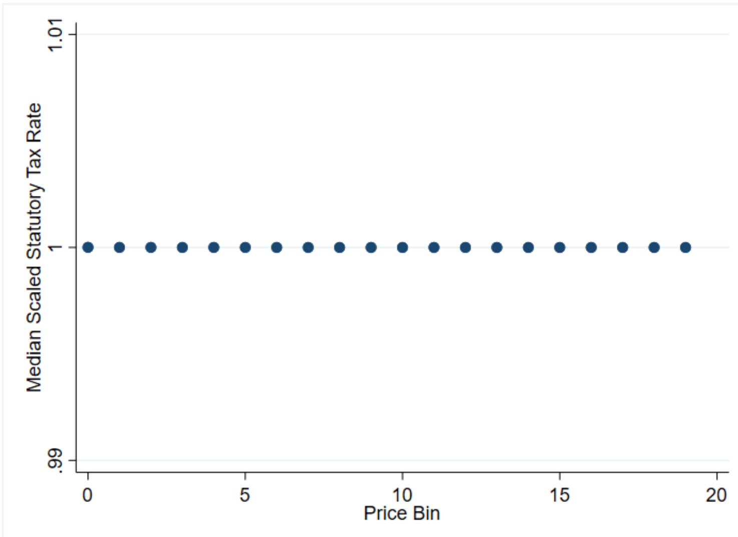
Panel B

(1) Home Value Percentile Group	(2) Median Net Worth	(3) ETP as % of Net Worth	(4) Median Change Home Equity	(5) % Change in Net Worth
< 10th	50,828	0.46%	5,850	11.51%
10th - 20th	97,529	0.06%	1,375	1.41%
20th - 30th	123,927	-0.01%	-300	-0.24%
30th - 40th	188,996	-0.02%	-1,100	-0.58%
40th - 50th	183,636	-0.03%	-1,400	-0.76%
50th - 60th	213,778	-0.03%	-1,700	-0.80%
60th - 70th	338,907	-0.03%	-2,350	-0.69%
70th - 80th	493,710	-0.03%	-3,275	-0.66%
80th - 90th	826,608	-0.02%	-4,725	-0.57%
90th - 99th	1,733,942	-0.02%	-8,225	-0.47%
$\geq$ 99th	10,960,858	-0.01%	-37,625	-0.34%

A Main Appendix

Figure A1: 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 assessed value in year t. 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 20 price bins. The most inexpensive houses are in the first bin and the most expensive houses are in the 20th bin. The sample contains single-family houses in 49 states and the District of Columbia that were sold between 2005 and 2019.



A.1 Instrumental Variable Identifying Assumption

The instrumental variable approach described in Section 4.1 relies on the assumption that, for a given house i that was sold in year t, the pricing error embedded in the sale price is uncorrelated with the proposed instrument, which is the average log sale price of transactions in the same census tract as house i, leaving out transactions in house i's census tract block group. This section provides supporting evidence for this assumption.

I compute pricing error for each single-family home transaction by using the imputation method from Bayer et al. (2017). I define the log pricing error for house i that was sold in year t as the following:

$$e_{it} = logM_{it} - logM_{it}^{imp}.$$

M_{it} is the observed transaction price and M_{it}^{imp} is the imputed market value, which is computed in the following way:

$$M_{it}^{imp} = M_{i,t-k} \times \frac{HPI_t}{HPI_{t-k}}.$$

$M_{i,t-k}$ is house i's previous sale price in year $t-k$, $\frac{HPI_t}{HPI_{t-k}}$ is the change in its local house price index between year $t-k$ and year t. Like before, I use the census tract-level single-family home house price index from the FHFA.

The identifying assumption would be violated if pricing errors are systematically correlated with the proposed instrument. To investigate whether the identifying assumption is violated, I run the following panel regression:

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

$\overline{logM_{it}}$ is the proposed instrument. Table A1 presents the regression results. Column 1 reports the OLS regression results where log pricing error is calculated using the FHFA's all-transaction census tract-level single-family house price index. The sample includes transactions with previous transaction prices that are not more than 5 years old. The filter ensures that previous transaction prices are good proxies of current transaction prices, i.e., older transaction prices are less likely to contain relevant pricing information. The slope coefficient γ is small and not statistically different from zero. This result suggests that the identifying assumption is not violated. For robustness, I use Zillow's zip code-level single-family home price index to calculate pricing errors and repeat the exercise. Column 2 of Table A1 reports the result, which yields the same conclusion and shows that the result reported in column 1 is not driven by index construction methodology.

To give additional evidence that there is no systematic relationship between log pricing error and the proposed instrument, Figure A2 presents a binned scatter plot of log pricing error, calculated using the FHFA's all-transaction census tract-level single-family house price index, against leave-out average log sale price. Both variables are residualized by TCA-year indicator variables. The plot shows no systematic relationship between log pricing error and the proposed instrument. The picture is similar when I use Zillow's zip code-level single-family home price index to calculate pricing errors.

A.2 Caveats for Wealth Inequality Calculations

Due to data limitations, the calculations in Section 7 make several simplifying assumptions. The first assumption is that redistributing tax burdens among houses that have imputable market values is close enough to the tax burden distribution that would have realized if, instead, all houses have imputable market values and the calculations were repeated on the population. Second, I assume 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.

Table A1: Log Pricing Error and Average Log Sale Price

This table reports OLS regression results where log pricing error is regressed onto leave out average log sale price. Log pricing error is defined as the difference between log observed sale price and log imputed price. Prices are imputed using the procedure from Bayer et al. (2017). Leave out average log sale price is calculated as, for a given house i in year t, the average log sale price of other transactions in the same census tract, leaving out transactions in the same census tract block group as house i. The dependent variable in column 1 is log pricing error calculated using the FHFA's all-transaction census tract level single-family home price index. The dependent variable in column 2 is log pricing error calculated using Zillow's zip code level single-family house price index. The sample includes all homes that were sold where market values can be imputed and where previous transaction prices are not more than 5 years old. 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)
Dependent Variable	Log Pricing Error	
Leave Out Average Log Sale Price	0.009	0.001
	[0.006]	[0.007]
SFR Index	FHFA	Zillow
TCA-Year FE	Y	Y
Observations	4,597,963	3,948,611
R-squared	0.071	0.066

Figure A2: Binned Scatter Plot of Log Pricing Error Against Leave Out Average Log Sale Price

This figure presents a binned scatter plot where log pricing error is plotted against leave out average log sale price. Log pricing error is calculated as the log difference between observed transaction prices and imputed price. Prices are imputed using the procedure from Bayer et al. (2017) and the FHFA's all-transaction census tract level single-family home price index. Leave out average log sale price is calculated as the average log sale price of houses in the same census tract as house i, leaving out transactions in the same census tract block group as house i. The sample includes transactions where predicted market prices can be computed and the most recent previous transaction prices used in the calculations are not more than 5 years old. Both quantities are residualized by TCA-year indicator variables.

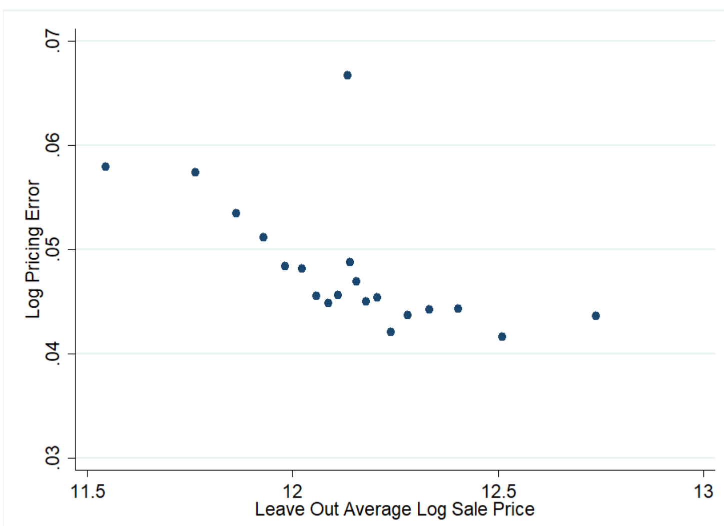


Table A2: Summary of Assessment Growth Limit Laws by State

This table summarizes each state's assessment growth limit (AGL) laws as they apply to old and new homes. AGL equals "Y," if a state has any assessment growth limit law during the sample period. There are exceptions. For example, in Illinois, only Cook County has assessment growth limit laws. In every state, except for Connecticut, new constructions (NC) are reappraised when they are finished and are not subjected to assessment growth limits. NC AGL equals "N" for states that have assessment growth limit laws that do not apply to new constructions. NC AGL equals "N/A" for states with no assessment growth limit law. The District of Columbia (DC) has an assessment growth limit law that applies to tax bills but not assessed values. Homeowners in DC receive a property tax rebate if the annual increase of their property tax bill exceeds 10%. This information is gathered from the Lincoln Institute's Property Tax Database and states' websites.

State	AGL	NC AGL	State	AGL	NC AGL
AL	N	N/A	MO	N	N/A
AK	N	N/A	MT	Y – up to 2015	N
AZ	N	N/A	NE	N	N/A
AR	Y	N	NV	N	N/A
GA	Y	N	NH	N	N/A
CA	Y	N	NJ	N	N/A
CO	N	N/A	NM	Y	N
CT	Y	Y	NY	Y	N
DE	N	N/A	NC	N	N/A
FL	Y	N	ND	N	N/A
HI	Y	N	OH	N	N/A
ID	N	N/A	OK	Y	N
IL	Y – Cook County	N	OR	Y	N
IN	N	N/A	PA	N	N/A
IA	Y	N	RI	N	N/A
WI	N	N/A	SC	Y	N
KS	N	N/A	SD	N	N/A
KY	N	N/A	TN	N	N/A
DC	N	N	TX	Y	N
LA	N	N/A	UT	N	N/A
ME	N	N/A	VT	N	N/A
MD	Y	N	VA	N	N/A
MA	N	N/A	WA	N	N/A
MI	Y	N	WV	N	N/A
MN	Y – up to 2009	N	WY	N	N/A
MS	N	N/A			

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

This table presents OLS regression results where observed and counterfactual log valuation ratios are regressed onto log sale price. Log valuation ratio is defined as the difference between log assessed value and log sale price. The dependent variable for columns 1 and 3 is observed log valuation ratio, which is the difference between log observed assessed value and log sale price. The dependent variable for columns 2 and 4 is the counterfactual log valuation ratio, which is the difference between log appeal-adjusted assessed value and log sale price. Appeal adjustment replaces post-appeal assessed values with the county-proposed assessed values. Columns 1 and 2 report OLS regression results where log valuation ratio is regressed onto log sale price. Columns 3 and 4 report two-staged least squares regression results where log sale price is instrumented with average log sale price of other transactions in the same census tract as house i, leaving out transactions in the same census tract block group as house i. The sample includes houses that have sufficient appeal history such that assessed values can be adjusted and observable sale prices or imputable market values. All regressions include 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)
Log Valuation Ratio:	Observed	Counterfactual	Observed	Counterfactual
Log Sale Price	-0.263***	-0.251***	-0.141***	-0.126***
	[0.014]	[0.015]	[0.008]	[0.008]
Method	OLS	OLS	2SLS	2SLS
Year FE	Y	Y	Y	Y
1st Stage F-stat	-	-	> 16.38	> 16.38
Observations	3,431,637	3,431,637	3,431,637	3,431,637
R-squared	0.348	0.320	0.250	0.221

Table A4: Pricing Accuracy Comparison

This table presents summary statistics of absolute value of log difference in observed sale prices, observed appraised values, and imputed market values. Imputed market values are computed using the procedure from Bayer et al. (2017) and the FHFA local house price index. The sample includes all single-family home transactions where all three values are not missing.

	Mean	S.D.	Min	25th	50th	75th	Max
Observed Appraised Values	0.28	0.32	0.00	0.08	0.19	0.35	1.97
Imputed Market Values	0.24	0.29	0.00	0.06	0.14	0.30	1.53

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 assessor 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 that is being assessed. The definition of a neighborhood or a comparable area is arbitrarily defined by the assessor. In the final step, the assessor calculates the average price per square foot from these comparable sales and use that quantity to assign an assessed value to the house (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 average neighborhood characteristics that are captured in the CSA's average price per square foot calculation gives rise to insufficient covariation between assessed values and sale prices, which causes assessments to be regressive:

$$logA_{it} - logM_{it} = \alpha + \beta logM_{it} + \epsilon_{it} \tag{1}$$

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

Let A denote assessed value and M denote sale price. The two equations above show that low covariance between assessed values and sale prices leads to a negative β coefficient, which means that assessments are regressive.

To see more formally why the CSA's averaging procedure produces low covariance between assessed values and sale prices, consider the argument below. Suppose that sale prices reflect true

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

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 assessor finds several comparable houses and computes the average price per square foot from their observed sale prices. House j's assessed value is as follows:

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

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

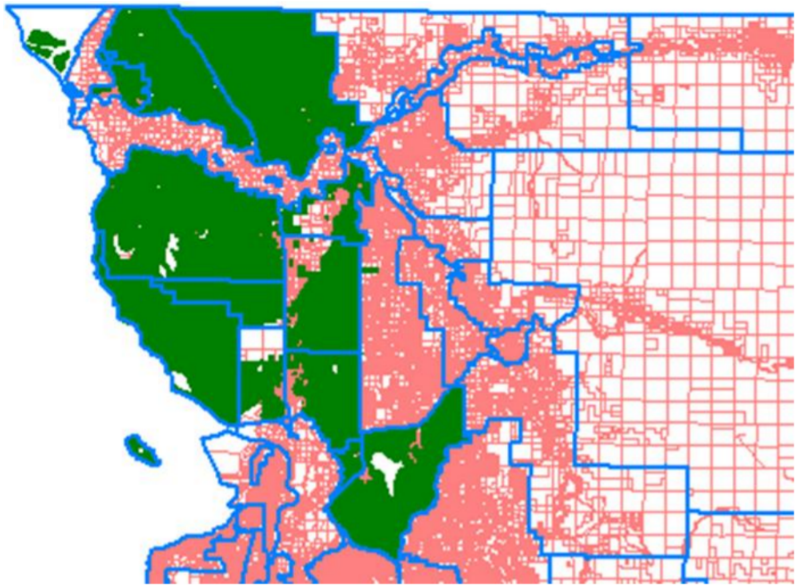
$$a_j = \overline{m_{i\neq j}^{SQ}} + s_j.$$

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 assessed values and sale prices decreases and assessments become more regressive as the appraiser computes average price per square foot across larger geographic areas.

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

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.



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 land price (IAAO, 2014). The cost approach is often implemented in the following steps. First, the assessor 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 assessor applies a location 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 transaction prices. Finally, the appraiser uses the comparable sales approach or the land residual method to assign a market value to the land parcel that the structure sits on (Snohomish County Assessor's Office, 2010).[3] The sum of the cost of the structure and land price gives the property's total assessed 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 assessors define neighborhoods and choose comparable houses. Neighborhoods are defined too coarsely, 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, assessed 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 land price estimated using CSA. Suppose that the true market value of house i can be expressed in a similar way:

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

$$M_i = S_i + P_i.$$

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:

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

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 assessor 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 assessed 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:

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

If draws are not independent, then $\sigma_{\overline{X}}^2 \leq \sigma_X^2$. 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 covariance. 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.

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