The Assessment Gap: Racial Inequalities in Property Taxation*

Carlos F. Avenancio-León† Troup Howard‡

December 2021

Abstract

We document a nationwide "assessment gap" which leads local governments to place a disproportionate fiscal burden on racial and ethnic minorities. We show that holding taxing jurisdictions and property tax rates fixed, Black and Hispanic residents face a 10–13 percent higher tax burden for the same bundle of public services. We decompose this inequality into between- and within-neighborhood components and find just over half of the inequality arises between neighborhoods. We then present evidence on mechanisms. Property assessments are less sensitive to neighborhood attributes than market prices are. This generates spatial variation in tax burden within jurisdiction, and leads to over-taxation of highly minority communities. We also find appeals behavior and appeals outcomes differ by race. Inequality does not arise from either (i) racial differences in transaction prices or (ii) differences in features of the housing stock.

*We would like to thank Nathan Anderson, Abhay Aneja, Steve Cicala, Hilary Hoynes, Paulo Issler, Maris Jensen, Andrew Kahrl, Pat Kline, Ross Levine, Deborah Lucas, Ulrike Malmendier, Conrad Miller, Enrico Moretti, Adair Morse, Holger Mueller, Hoai-Luu Nguyen, Christine Parlour, Sarah Resnick, Justin Ross, Rob Ross, Emmanuel Saez, Nick Sander, Allison Shertzer, Nancy Wallace, Randy Walsh, Danny Yagan, and Gabriel Zucman; as well as seminar participants at Berkeley, BYU Law, Chicago Booth, Chicago Law, Dartmouth, Duke Fuqua, Duke Sanford, the Federal Reserve Bank of Minneapolis, the Federal Reserve Board of Governors, Florida-Michigan-Virginia Law & Economics Workshop, Georgetown McDonough, George Washington University, Indiana University Kelley, Madison La Follette, MIT Sloan, NAACP LDF, Northwestern Kellogg, NYU Stern, Syracuse Maxwell, UCSD Rady, UNC Kenan-Flagler, Utah Eccles, Vanderbilt Law, Yale School of Environment, Yale SOM, and four anonymous referees for their helpful comments. Particular thanks are due to David Sraer for his advice and guidance. Financial support is gratefully acknowledged from the Fisher Center for Real Estate and Urban Economics at Berkeley-Haas. All remaining errors are our own.

†University of California—San Diego. Email: cavenancioleon@ucsd.edu.

‡University of Utah. Email: troup.howard@eccles.utah.edu.

1 Introduction

In the United States, the core structure of the residential property tax is proportional to home value. Property tax bills, however, are generated by applying the locally determined rate of taxation to an assessed value, which is a local official's projection of market price. Equitable property tax administration requires the ratio of assessed value to market value to be the same for all residents within any particular taxing jurisdiction. This paper documents the existence of a widespread and large racial assessment gap: relative to market value, assessed values are significantly higher for minority residents. This assessment gap places a disproportionate fiscal burden on minority residents: within the same tax jurisdiction, Black and Hispanic residents bear a higher property tax burden than White residents.

We obtain a property-level dataset spanning most properties in the US, along with a comprehensive record of property transactions and tax assessments assembled from administrative data. We associate each property with the race and ethnicity of the home seller using Home Mortgage Disclosure Act records. In addition, we exploit a set of shapefiles that provide geographic delineation for the universe of local governments and other taxing entities in the U.S. to identify unique taxing jurisdictions. Properties belonging to the same jurisdiction face the same level of intended taxation, the same set of entities providing public services, and the same assessment practices.

Our main empirical exercise compares assessment ratios within these tax jurisdictions. The average assessment ratio for a Black resident in our sample is 12.7 percent higher than for a white resident. For Black or Hispanic residents in aggregate, the average assessment gap is 9.8 percent. We show that the assessment gap cannot be explained by racial or ethnic differences in property features, nor is it simply a byproduct of racial income differences and the previously documented propensity for assessment ratios to be regressive with respect to home price (Paglin and Fogarty 1972, Engle 1975, Black 1977, Baar 1981, Clapp 1990, Sirmans et al. 2008, McMillen and Weber 2008). As a result of the assessment gap, minority residents are therefore paying a significantly larger effective property tax rate for the same bundle of public services. For the median minority homeowner, the differential burden is an extra \$300–390 annually. This finding is strongly robust across most states in the U.S. We also produce county-level estimates to characterize the distribution of this assessment gap. The average Black homeowner in a county at the 90th percentile of the assessment gap distribution has a 27 percent higher assessment ratio and pays an extra \$790 annually in property tax.

We explore several channels that drive these assessment gaps in the data. The first channel for which we find support is spatial, and it concerns assessment misvaluations that occur at the neighborhood level. We show that assessed values and market prices align well on home-level characteristics but diverge on tract-level attributes. In other words, market prices capitalize highly local factors, but assessments are much less responsive. This generates spatial variation in the assessment ratio within jurisdiction. The fact that spatial inequality lands disproportionately on minority residents is a function of residential segregation – Black and Hispanic residents face, on average, different neighborhood characteristics than White residents (Ananat 2011, Cutler et al. 1999, Massey and Denton 1993). Such segregation has long been a defining feature of U.S. housing markets, and it was driven during the 20th century by both explicit public policies as well as collective action by White homeowners (Cook et al. 2021, Rothstein 2017, Loewen 2005, King 1995, Drake and Cayton 1970, Wolgemuth 1959). Therefore, our findings show that the legacy of historical racial discrimination can generate disparate taxation within today's minority communities, regardless of whether those misvaluations arise from any intent to actively discriminate.

The second channel concerns a racial differential that persists even after conditioning away spatial factors. Within U.S. Census block groups, which represent regions of approximately 1,200 people, an average minority homeowner has an assessment 5–6 percent higher relative to market price than their nonminority neighbor. This latter finding – which we also show is consistent across the distribution of individual income – is particularly surprising given that most assessors likely neither know, nor observe, individual homeowner race. We show that homeowner interactions with the bureaucracy of property tax administration can increase inequality, and provide supporting evidence by documenting racial differentials in assessment appeals. We use administrative records from Cook County, the second largest county in the U.S., to show that minority homeowners: (i) are less likely to appeal their assessment, (ii) conditional on appealing, are also less likely to win, and (iii) conditional on success, typically receive a smaller reduction than nonminority residents.

We rule out a third explanation which is unrelated to property tax administration: inequality arising from racial differences in transaction prices. An assessment gap might plausibly result from Black or Hispanic sellers realizing lower prices than White homeowners for similar homes, even if assessments reflect the true value of a home. We rule out this possibility by showing that Black and Hispanic sellers actually receive a price *premium* of 2–3 percent. This is consistent with the findings of (Bayer et al. 2017). If anything, racial differences in transaction prices suggest that our main findings are understated and constitute a lower bound.

Lastly, we connect our findings of inequality with the well-documented pattern of regressive assessment ratios established by the literature – starting with Paglin and Fogarty (1972), and most recently in national studies by Berry (2021) and Amornsiripanitch (2021). Although evidence on mechanisms is scarce, one foundational assumption has been that patterns of price regressivity arise from differences in home-level attributes – i.e., that more unique, larger, and therefore more expensive homes are more difficult to assess (Paglin and Fogarty 1972). To evaluate this mechanism, we implement a design that controls for observable property features directly by augmenting our baseline specification with fixed effects for every unique combination of home attributes in the data. Differences stemming from features of the housing stock do not explain our findings of inequality at any level: controlling for property attributes across jurisdiction, within jurisdiction, or within neighborhood has a minimal impact on the racial assessment gap.

We next explore how location relates to racial inequality and price regressivity. The average Black or Hispanic homeowner lives in a less expensive home than the average White homeowner – an unsurprising outcome given large racial wealth gaps. Thus, our evidence showing the critical role of neighborhood-level misvaluation in generating racial and ethnic inequality also demonstrates one potential explanation for overall regressivity in assessment ratios. However, neighborhood traits are not only reflective of historical patterns of residential segregation, but also an important driver of home prices. Therefore, if spatial errors led all communities with low home values to be similarly over-assessed, this would also generate racial and ethnic inequality. However, we show that misvaluations land more heavily on highly-minority communities regardless of neighborhood values. Comparing tracts of similarly valued homes, the racial assessment gap is monotonically increasing in minority share, and this pattern holds across all quintiles of neighborhood-level home prices.

The main contribution of this paper is to the literature on racial disparities in property taxation. Kahrl (2016) describes property tax rates as central to African American political mobilization during the Reconstruction era, and also provides examples of homeowners in the 1920s and 1930s suing local governments for relief from discriminatory assessments. Rothstein (2017) details similar developments in the 1960s and 1970s. Baar (1981) summarizes legal challenges to assessment practices throughout the 1970s, and notes a pattern of over-assessment in low-income and highly minority communities. Atuahene and Berry (2019) estimate a causal link between inflated assessments and tax foreclosures within one county in Michigan between 2009 and 2015.[1] We build upon this research by: (i) documenting the extent of racial and ethnic assessment gaps with comprehensive national data; (ii) partitioning the county into taxing jurisdictions so that our estimates provide an accurate measure differences in tax burden, while holding policy rates and public goods fixed; (iii) using administrative data to link individual properties with homeowner race and ethnicity rather than relying on regional demographic aggregates; and (iv) evaluating mechanisms through which the assessment gap arises.

Several papers within the broader literature focusing on administrative-inequality in property taxes have explored the role of racial and ethnic demographics in appeals outcomes. Weber and McMillen (2010), Doerner and Ihlanfeldt (2014), and Ross (2017) all show that neighborhood-level minority population share correlates with reduced propensity to appeal, lessened likelihood of success, and/or smaller reductions. McMillen (2013) shows that the total effect of appeals in Cook County increases uniformity with respect to the target assessment ratio, but also that the entire distribution becomes more regressive, in large part due to a lack of appeals originating from properties with the highest ex-ante assessment ratios. Our study is the first linking appeals records to individual homeowner race and ethnicity, permitting a within-neighborhood analysis and direct evidence on racial and ethnic differences, both in overall tax burden and in appeals outcomes.

The paper proceeds as follows. Section 2 describes the typical structure of local property taxation, highlights important institutional details, and outlines our empirical strategy. Section 3 categorizes possible sources of racial and ethnic variation in assessment ratios. Section 4 details the data sets we use. Section 5 presents the results. Section 6 concludes.

2 Setting and Empirical Strategy

2.1 Local Property Taxes

In the United States, the vast majority of local governments levy an annual residential property tax. Each home is subject to some politically established level of intended taxation, often representing tax levies across multiple independent governments. For instance, one home might be subject to property taxes imposed by a county, a city, and an independent school district. Tax bills are generated

[1] In a related article Atuahene (2017) argues that present-day assessment practices in the city of Detroit should be considered federally illegal under the Fair Housing Act.

by applying the local policy rate of taxation to the home's assessment: an administrative valuation assigned to each property annually for tax purposes.[2] The local policy rate may be explicitly set (by direct voter approval or through authority delegated to elected officials), or it may be indirectly defined: a certain level of spending will be approved, and then this amount will be divided by the total value of local property, yielding an implicit rate. Assessments are typically generated at the county level, which means potentially more than 3,000 different processes employed.[3]

This structure of property tax administration motivates our empirical test of property tax equity: assessment ratios must be identical for all homes facing the same level of intended taxation. This relationship must hold exactly for a pure ad valorem tax on the market value of property – a baseline that is regularly outlined in state legislation authorizing the property tax. From this starting point of a purely proportional tax on market value, however, most localities provide for deliberate deviation in the form of property tax exemptions. Based on certain eligibility criteria, a homeowner is shielded from having to pay taxes on some portion of the home's value. In Florida, for example, homeowners are exempt from property taxation on the first $25,000 of home value, but only for their primary residence.[4] Another common exemption applies to senior citizens. Because eligibility varies by resident within a region, property tax exemptions on the whole will induce variation in effective tax rates within a region where intended tax burden is held constant. Our focus on assessment ratios allows us to measure inequality without any confounding effects of exemption policies.

We hold intended taxation fixed by conducting our analysis within regions where every home faces the same set of overlapping governments. In Section 4, we describe the process of partitioning the U.S. into such regions, which we call taxing jurisdictions. Estimating inequality within taxing jurisdiction not only ensures that we hold fixed the (aggregate) policy rate, along with all relevant assessment practices (most critically the local target for assessment ratios), but also ensures that we compare homeowners receiving public goods and services from the same set of public entities. This also means that any inequality we find cannot arise from differing choices about the level of public goods provision. Although it is certainly possible that, for instance, the quality of educational services provided by an

[2] While there are examples of localities imposing flat, per-parcel property taxes, these tend to be specific levies approved to fund a particular project (or to cover debt service for a given bond issuance). We do not have any way of providing an aggregate breakdown of tax dollars raised by ad valorem taxation versus per-parcel taxes; in every region we have looked at specifically, the latter is a very small portion of overall proceeds.

[3] In some regions, the authority devolves to the township level. This appears to be relatively more common in the New England states.

[4] 2019 Florida Statutes 196.031.1(a).

independent school district varies from school building to school building in ways that correlate with race, tax levels are determined by district rather than by school building, and therefore, all homeowners of the same district have implicitly entered into the same taxation-for-services compact.

2.2 Assessment Algorithms

Automated Valuation Models or Computer Assisted Mass Appraisal are the standard for larger jurisdictions, as there are too many properties to make in-person inspection feasible. Some districts will cycle between more frequent mass appraisal and less frequent physical inspection; this latter component often involves only external inspection. An assessment is assigned to every property for each tax year, but in many locations, assessments are updated less than annually and therefore are reused for several years.

The International Association of Assessing Officers (IAAO) is the preeminent professional organization in this space, and it publishes professional standard guidelines for mass appraisal. The IAAO's standards essentially outline hedonic pricing models using a relatively small vector of property-level characteristics. Most districts have access to home-attribute information as part of property tax rolls.[5]

A standard general approach values homes as a function of housing stock characteristics, local characteristics, and a geographic fixed effect. In this approach, assessors would estimate and then attach hedonic prices to each home attribute, including physical characteristics, as well as neighborhood characteristics. Presumably due to the challenge of observing and quantifying relevant neighborhood characteristics, it seems common to allow a geographic fixed effect to drive a portion of the price, rather than including a large vector of geographic covariates. Some assessors allow hedonic prices to vary by location as well.

Our sense is that rule-of-thumb approaches are also not uncommon: assessors increase the value of homes by X percent in a given year, within a given region. While many locations have access to historical sales prices from transaction data, in some localities this information is not systematically collected. Professional capacity within assessing offices also varies widely. Smaller regions often hire consultants; larger regions are more likely to have dedicated in-house assessment staff.

[5] We have, however, heard from multiple county officials that sometimes this information is missing or unreliable.

2.3 Empirical Strategy

Our central estimating equation is:

$$ln(A_{ijt}) - ln(M_{ijt}) := ar_{ijt} = \gamma_{jt} + \beta^r race_{ijt} + \epsilon_{ijt}. \tag{1}$$

where A and M are assessed and market values respectively, ar is the log assessment ratio for property i, located in taxing jurisdiction j, transacting in year t; $race$ is a vector of indicator variables for racial and ethnic groups; and γ_{jt} is a jurisdiction-year fixed effect. In Section A of our Online Appendix, we show that this estimating equation arises directly from the null of an equitably administered proportional tax. The jurisdiction-year fixed effect is essential for two reasons. First, it ensures we compare homeowners taxed and served by the same set of governments, thereby ensuring that our estimates are interpretable as differences in tax burden while holding intended tax rates fixed. Second, these fixed effects control for different local choices of target assessment ratio.[6]

In Equation 1, $race$ is a categorical variable, making β^r a vector of estimated group-level deviations from the average realized assessment ratio. If β^W, the average assessment ratio for White residents, is statistically different from β^M, the average assessment ratio for any grouping of minority residents, this would be evidence of inequality in tax burden. The Online Appendix shows that this framework easily nests property tax exemptions, which are prevalent in most jurisdictions.

Our benchmark test for racial and ethnic inequality is closely linked to the legal notion of disparate impact. Department of Housing and Urban Development regulations state: "[A] practice has a discriminatory effect where it actually or predictably results in a disparate impact on a group of persons[...] because of race, color, religion, sex, handicap, familial status, or national origin."[7] Courts interpreting disparate impact claims have relied on exactly this type of test of group means.[8]

[6] Along with local policy rates, intended tax burden is also characterized by the target assessment ratio, which is a local choice. For example, in a locality where a target assessment ratio is 0.4, a \$200,000 home would receive an assessment of \$80,000. Although one might expect the natural benchmark to be a target assessment ratio of 1.0 (a \$200,000 home would receive an assessment of \$200,000), a practical quirk of property tax administration is wide regional heterogeneity in target ratio. The state of Georgia, for instance, mandates that assessments be 40 percent of market value; Illinois selects a statewide ratio of 33.3 percent, but the largest county in the state chooses 10 percent instead; and Colorado's target, 7.15 percent as of 2021, evolves annually as a function of aggregate relative value between residential and nonresidential real estate.

[7] 24 CFR 100.500(a).

[8] *Texas Dept. of Housing and Community Affairs v. Inclusive Communities Project, Inc.*, 576 U.S. 519 (2015).

3 Potential Explanations for Assessment Ratio Variation

Within-jurisdiction variation in assessment ratios is a sufficient statistic for property tax inequality, regardless of what generates the variation. That said, after documenting magnitudes, this paper focuses on categorizing how this inequality arises. A range of plausible drivers could generate variation in assessment ratios, with sharply different policy implications.

3.1 Denominator, Not Numerator

Racial differences in transaction prices arising from any feature of housing market microstructure would induce variation in assessment ratios through the denominator (market values) even if the numerator (assessed values) were correct relative to a "true" latent home value. We rule out this explanation by using repeat sales to test for racial differences in transacted prices and showing that the evidence supports minority home sellers receiving a price premium.[9] This is consistent with other findings from the literature (Bayer et al. 2017), and means that to the extent that racial differences in transacted prices exist, they lower our estimates of inequality.

Therefore, variation in *assessments* generates the inequality we find. Our analysis seeks to document and understand patterns in the aggregate outcomes of these local processes, but given the number of assessing districts nationwide, it does not delve into the specific model employed by any locality.

3.2 Biased Assessors

We do not provide evidence of biased assessors exercising overt racial animus. Our findings are consistent with structural inequality: disparities that can arise from entrenched systems independently of any latent discriminatory intention or attitudes. In fact, assessors are unlikely to observe homeowner race or ethnicity in the majority of cases. In larger jurisdictions, in-person valuation tends to be unfeasible, and assessments are generated using automated valuation models without a site visit. Even when site visits do occur, they are often restricted to external examination of the property. We document inequality in the outcomes of such modeling, but cannot distinguish between model mistakes and deliberate distortion.

Though we do not have data on the race of assessing officers, or the public official ultimately

[9] Note that this is an average of within- and across-race transactions; the former is by far the largest proportion of sales. Therefore, this means that the average minority home buyer also pays a premium.

responsible for property tax administration, we show that inequality is so broadly present in the majority of states and counties that it almost surely encompasses regions where those producing assessments are themselves members of racial and ethnic minorities. In addition, we use a measure of racial animus from Stephens-Davidowitz (2014) to show that inequality is economically and statistically significant within both high and low animus regions. Although our results certainly do not rule out overt racial discrimination, such discrimination is neither a necessary element nor a central implication of the inequality we document.

3.3 Spatial Factors

Location, location, location.

–Classic real estate maxim[10]

Perfectly accurate assessments would value local amenities in exact lockstep with housing markets. Any misvaluation of spatial attributes will definitionally create spatial tax inequality. Residential racial segregation could then lead such inequality to land along racial and ethnic lines. The average Black or Hispanic homeowner in the U.S. faces a different set of neighborhood attributes than the average White homeowner. Specifically, the average Black or Hispanic homeowner lives in a neighborhood where local amenities push prices lower (after absorbing property characteristics) (Menendian et al. 2021, Perry et al. 2018, Reardon et al. 2015, Ananat 2011, Massey and Denton 1993). If assessments are insufficiently responsive to spatial features, this would lead to undervaluation in neighborhoods exposed to highly valued amenities and relative overvaluation in neighborhoods exposed to negatively valued amenities.

To explore whether misvaluation of local attributes generates a wedge between market values and assessments, we use a hedonic modeling framework to extract implied attribute prices from home values. We then compare the magnitude of market-implied attribute prices with assessment-implied prices. For any given attribute, a small mismatch implies that misvaluation of this characteristic does not induce large erroneous variation in assessment ratios, and a large mismatch would denote an important source of misvaluation.

Beyond misspecification of the assessment valuation model, we also explore the impact of common

[10] Earliest known usage, *Chicago Tribune*, 1926.

administrative policies that potentially interact with housing market features to create spatial variation in assessments. This includes assessment caps (a restriction on year-to-year growth in assessments) and frequency of assessment reevaluation.

3.4 Individual Drivers

Spatial factors cannot explain all of the inequality we find. We establish this by showing that inequality persists within small regions – an approximation to the ideal experiment of comparing two adjacent properties with homeowners of differing race or ethnicity.

We hypothesize that inequality within neighborhoods results from homeowner engagement with property tax bureaucracy. We test this hypothesis in Section 5.3.3 by focusing on assessment appeals. Other scholars have raised this possibility in a property tax setting. Existing work shows a correlation between neighborhood-level demographics and appeal outcomes. Weber and McMillen (2010) and Ross (2017) also use data from Cook County, along with tract-level demographic data, and find that high minority share census tracts correlate with fewer appeal applications and lower success rates. Doerner and Ihlanfeldt (2014) report similar findings in 2005–2009 data from Florida, using a between-block group analysis. To the best of our knowledge, we are the first to use property-level data on individual homeowner race and ethnicity to conduct a within-neighborhood analysis.

3.5 Sorting into Different Homes and Price-Regressive Assessment Ratios

Beginning with Paglin and Fogarty (1972), the property tax literature has documented a correlation between low-priced homes and high assessment ratios, a finding generally referred to as regressivity in assessment ratios. While early literature debated whether this pattern was an artifact of statistical bias (Kochin and Parks 1982, Clapp 1990, Black 1977), this pattern now is well established in the literature (McMillen and Singh 2020, Ross 2017, McMillen 2013, Weber and McMillen 2010, McMillen and Weber 2008), and within the last year two new studies have carefully documented the breadth of this finding nationally (Berry 2021, Amornsiripanitch 2021).

We will explore how our findings of racial inequality relate to patterns of price regressivity. These two outcomes will be closely linked because racial wealth gaps lead the average Black or Hispanic homeowner to live in a lower-priced home than the average White homeowner. Therefore, a mechanism that generates inequality purely as a function of race would also tend to generate price regressive assessment ratios; and a mechanism that generates regressivity purely as a function of price would tend to generate racial and ethnic inequality.

One natural econometric instinct for establishing this distinction would be to simply measure racial differences in assessment ratios after controlling for home price. In this setting, however, this is importantly an inappropriate choice, because home prices – especially that portion of home price shaped by location – is potentially a function of race, meaning that neighborhood-level patterns of price-regressive assessment ratios might be reflective of fundamentally racial inequities.[11]

We address this concern by separately considering mechanisms related to property attributes and to home location – a distinction grounded in the literature on assessment regressivity. While there is not yet consensus on any set of underlying mechanisms,[12] most early studies alluded to a central role for property attributes, positing that more expensive homes are harder to value – and thus are assessed too low – because they tend to be larger, more idiosyncratic, and less standardized.[13] We will use data on home attributes to explore whether racial inequality persists between physically similar homes; and data on census tracts to see whether it persists between homes in similar neighborhoods.

Of course it is stylized to treat location and property attributes as two separable drivers of home price. However, the stylized distinction will provide a framework for exploring how the patterns we document could be a consequence of some race-neutral mechanism that generates price-regressivity, or whether assessment errors linked to race and ethnicity might instead be a mechanism generating observed patterns of price-regressivity.

In Sections 5.1 – 5.4, we evaluate each of the channels outlined in this section and find that racial gaps in assessment ratios are substantial across neighborhoods, but also persist within neighborhoods; and are not driven by racial differences in sales. Approximately half of the assessment gap is highly

[11] A wide range of public policies spanning much of the 20th century created high levels of residential segregation in the United States. Institutional and social choices – including, but certainly not limited to, widespread redlining until the 1960s, "white flight" patterns, restrictive zoning policies, persistent public disinvestment in "underserved communities", and the design and siting of public housing – have exerted strong and persistent impacts on market prices in many predominantly minority communities, both directly and indirectly (Aaronson et al. 2020, Perry et al. 2018, Bruhn 2018, Rothstein 2017). Accordingly, there is no justification for viewing home prices as a primitive, exogenous factor driving variation in assessment ratios, leaving only residualized variation to be explained by other factors such as race or ethnicity.

[12] McMillen and Singh (2020): "One of the stylized facts of the literature on property assessments is that assessment rates – the ratio of assessed value to the sale price of a property – tend to be higher for low-priced properties. The source of this form of regressivity is unclear."

[13] As in, e.g., pp. 559–560 of Paglin and Fogarty (1972): "High priced houses tend to be more individual in terms of design, decorative details, etc. – matters which are not easily plugged into existing appraisal formulae and which consequently tend to be undervalued when using mass-appraisal techniques."

invariant to conditioning on location, housing stock attributes, differences in individual income, or average levels of income by neighborhood. The other half is fundamentally spatial, arising from neighborhood-level misvaluation. Regardless of race, this spatial inequality is highest within the set of lowest-priced regions and properties; however, racial inequality is also largest comparing homes within the lowest-value census tracts, and is also starkly increasing in minority demographic share.

4 Data

The core research design of this paper rests on combining data from three sources. We obtain property-level records of assessments and transactions from ATTOM, a comprehensive dataset with annual observations on 118 million properties in the U.S. from 2003–2016. Assessment and transaction records are sourced from county assessor and recorder offices, respectively. We restrict our attention to residential properties of up to four units (92M properties total). Commercial property is generally assessed differently from residential properties, so we cannot draw inference from jurisdiction average assessment ratios without restricting our analysis to residential properties only. Further, multifamily homes (e.g. large apartment buildings) are sometimes subject to different assessment rules. The restriction to residential properties of one to four units gives us a set of properties that should always be assessed in the same way within jurisdiction. To avoid having to impute any market values, our baseline dataset includes only homes for which we observe the sale price in an arm's-length, full consideration transaction.[14] Importantly, each home is identified with a latitude and longitude for the parcel. These are used to geolocate the home within government borders. We form assessment ratios using assessments and transactions observed in the same period (year).

We obtain shapefiles for government boundaries from Atlas Investment Research's Atlas Muni Data. These 75,000 shapefiles are intended to span the universe of local governments in the U.S. The core set of shapefiles covers counties, cities, towns, schools, and special districts as defined by the U.S. Census. In addition, Atlas Muni Data developed proprietary shapefiles for any entity which has ever accessed public debt markets, as compiled from Municipal Securities Rulemaking Board filings. As debt issuance is very often paired with either broad authority to tax (in the case of general obligation bonds) or a voter-approved one-off tax levy (more common for revenue bonds), we consider each of

[14] The recorder portion of the ATTOM dataset has several indicator flags for arm's-length transactions and partial interest sales, which collectively can be used to isolate transactions that reflect an accurate signal of market value.

these entities as a potential taxing entity. Collectively, in addition to all 50 states, the Atlas data covers 3,142 counties, 46,660 cities or towns, 13,709 independent school districts, and 11,924 special purpose districts. We use standard GIS techniques to associate each home with its encompassing network of overlapping governments. A taxing jurisdiction then is defined as a set of homes which all face the same set of governments. This definition ensures that we hold constant assessment practices, the aggregate level of intended property taxation, and also the set of entities providing public goods and services.

The Home Mortgage Disclosure Act (HMDA) mandates that financial institutions disclose certain information about mortgage applications and mortgage origination at an individual loan level, including applicant race and ethnicity. We merge HMDA records to the ATTOM dataset following the standard procedure in the literature (see, e.g. Bayer et al. 2017 or Bartlett et al. 2018), which relies on matching year, census tract, lender name, and dollar amount (rounded to thousands). We provide additional details of the merge in the Online Appendix.

The initial merge establishes race and ethnicity of the home buyer.[15] We care about the race and ethnicity of the *seller*, because the seller is the owner at the time when the assessment is generated. Therefore, we exploit the dynamic structure of the transactions dataset to build a panel of homes for which we know the declared race and ethnicity of the homeowner at each year. There are two relevant cases: (i) sales and (ii) refinance transactions. For sales, the transaction pins down the race/ethnicity of the buyer, which is then associated with that property in each subsequent year until the next observed transaction. For refinance transactions, we carry race and ethnicity not only forward in time but also backward, as the home does not change ownership.

One salient choice we make is to remove all California properties from the final dataset. We present estimates of racial and ethnic inequality in California in our Online Appendix. We remove California from the national sample due to the stringent limitations on assessment practices authorized by Proposition 13 in 1978. While jurisdictions have enacted property tax caps, because of higher cap limits or relatively lower home appreciation (as compared to California), these caps are less likely to bind than Proposition 13.[16] We do find similar patterns of inequality in California; however our subsequent analysis of mechanisms in this paper is less relevant for California, simply because assessments

[15] HMDA records also include information on coapplicants. We use race and ethnicity of the primary applicant only.

[16] We include analysis of property tax caps in Section 5.3.2.

there are so mechanically driven by the restrictions of Proposition 13.

Figure 1 provides a visual overview of each major step in constructing our core dataset. Further detail on each step also appears in our Online Appendix. Table 1 analyzes balance along the two major dimensions of sample selection: i) whether a sale is observed, and ii) whether an assessment ratio can be associated with race and ethnicity in the HMDA data. For each margin of selection, we compare balance on tract- and property-level attributes by regressing the attribute on an indicator for sample inclusion and the jurisdiction-year fixed effect used in all specifications throughout the paper. Column (1) compares the entire set of observed transactions (the leftmost bar in Figure 1) against a 20% random-sample of all unsold homes, selected by state-year.[17] Imbalance on racial demographics is, of course, an important potential selection bias. We do not observe this. Relative to homes which do not transact, observed transactions are in census tracts with 38-50bps fewer Black or Hispanic population share, the homes are 29 square-feet smaller on average, and are built 1 year later. All coefficients are statistically significant (reflecting the large sample), but economically very small.

Column 2 examines the margin of the HMDA merge. We see similarly small differences. Homes associated with race/ethnicity in HMDA are in regions with 64–66bps lower minority population share. Matched homes are in regions with a population that is slightly larger (by 1.5 percent) and slightly older (by approximately 2 months). Features of the housing stock are very similar: matched homes are smaller by 10 square feet on average, and are built more recently by 1.7 years. The largest mismatch is on individual home prices: matched homes have transaction prices close to 4 percent higher than unmatched homes. The major exclusion from HMDA is all-cash transactions, so a difference on price is not surprising. The sample's overall balance on racial demographics shows that the increased likelihood of matching higher-valued homes does not generate over- or under-matching within highly minority communities. Assessment ratios for matched homes are 1 percent higher. Again, in light of the balanced neighborhood racial demographics, no clear prediction about potential bias arises from this margin of selection, and relative to the magnitude of our findings, this 1 percent imbalance is small.

The final baseline dataset is a panel of 6.9M homes spanning 49 states. For each observation, we have an assessment ratio, know the associated taxing jurisdiction, and have the reported race and ethnicity of the homeowner. The data are anonymized: each home is characterized by a unique ID

[17] The 20% sample is for computational feasibility, and delivers a set of homes roughly equal in size to the total set of transactions observed (approx. 75M).

variable. Each home is associated with a census tract and a census block group, permitting us to merge in tract-level variables from the American Community Survey five-year estimates.

5 Results

5.1 Baseline Findings: Assessment Gap

Our core specification follows Equation 1. Assessment ratios are regressed directly on a categorical variable for racial and ethnic groups, along with a jurisdiction-year fixed effect to hold intended taxation fixed and to absorb variation arising from regional choices of assessment ratio target. By design, we focus on *unconditional* assessment ratio variation within taxing jurisdiction. For purposes of understanding inequality in tax burden, this is the meaningful statistic. This is an important distinction relative to other settings. For instance, in analyzing the Black–White wage gap, proxies for productivity and skill are desirable controls. No natural benchmark holds that people should earn the same wage regardless of skill. For property taxation, however, our taxing jurisdictions characterize regions where every homeowner is subject to the same policy tax rate. From the standpoint of tax equity, no conditioning variables should be relevant: our equitable tax null must hold for every homeowner regardless of factors like wealth, education, home value, age, and race/ethnicity.

Across all our results, we consider two groupings of minority residents. The first is mortgage holders whose racial identification in HMDA is "black or African American." The second adds mortgage holders whose ethnic identification is "Hispanic or Latino" and thus combines the two largest racial and ethnic minorities in the country.[18] In all cases, the comparison group is non-Hispanic White residents.

Table 2 presents our baseline finding of a racial/ethnic assessment gap. Within jurisdiction, assessment ratios are 12.7 percent higher for Black homeowners and 9.8 percent higher for Black or Hispanic homeowners. Given a national median effective property tax rate of approximately 1.4 percent, and a median home value of approximately $207,000, this translates to an additional tax burden of $300–$390 per year for Black and Hispanic homeowners.[19]

[18] In our Online Appendix, we show results for a third grouping: all mortgage holders identified in HMDA as having any race other than White or Black, and not of Hispanic or Latino ethnicity. This last grouping is not a natural division and masks a large amount of underlying racial heterogeneity. The data is not sufficient to conduct a more precise racial breakdown or a county-of-origin breakdown. We include these results for the sake of completeness.

[19] Averaging over White, non-Hispanic residents, the median jurisdiction in our data realizes an effective tax rate of 1.4 percent. Other methods of computing a national median property tax rate return similar figures. We obtain a median home value of $207,000 for minority homeowners by taking Zillow's national 2019 estimate of $231,000, and reducing

We show two results characterizing the distribution of the assessment gap. First, Figure 2 shows the assessment gap by state for Black residents and for Black and Hispanic residents. We present results only from states with at least 500 observations, which excludes seven states.[20] In the remaining set, the assessment gap is positive and strongly statistically significant in most states. For Black homeowners, the state-level estimates range from 33 percent to -3 percent. Estimates are positive and significant in 34 states, positive and insignificant in five, and negative and insignificant in three. For Black or Hispanic homeowners, the pattern is very similar.

Second, we estimate the assessment gap at a county level. The results for Black residents are shown in Figure 3. The distribution for Black and Hispanic residents grouped together has a very similar shape.[21] We again restrict attention to counties with at least 500 observed assessment ratios. This reduces our sample to 671 counties. Our estimates range from 54 percent to -49 percent. The interquartile range is 14.8 percent to 4.7 percent. Point estimates are positive and significant at the 5 percent level in 391 counties, positive and insignificant in 219 counties, negative and insignificant in 53 counties, and negative and significant at the 5 percent level in eight counties. For a Black homeowner at the 90th percentile of this distribution, the assessment gap would be 27 percent. For a $207,000 home subject to a 1.4 percent tax rate, this would translate into an additional tax burden of $790 annually.

Finally, we link the assessment gap distortion with actual higher taxation. Thus far, our focus on assessment ratios has been very deliberate. Assessed values and market prices are observable by the econometrician with little ambiguity. Taxes are more complicated, chiefly due to exemptions. Every state provides for a variety of property tax exemptions in state legislative codes, and most localities have further autonomy to create exemptions. Exemption policies, by design, create inequality by lowering tax burden for a subset of residents within a locality. An exemption that correlates with race or racial demographics – a senior citizen exemption, for instance, in a region with a population divided between elderly White residents and young Black residents – would create something that looks like a distortion in the tax burden, but which would be entirely consistent with the legislative intent and

it by 10 percent, which reflects the ratio of Black or Hispanic-owned home value to median home value in our baseline dataset for the latest available year (2016).

[20] These seven states are "nondisclosure" states, meaning that no law or administrative policy mandates the reporting of sales price. We are able to produce estimates for another set of seven nondisclosure states, as a sufficient volume of transactions are reported nonetheless. In these states, selection into reporting is a possibility. The remaining 34 states mandate disclosure (Dornfest et al. 2019).

[21] Results are available from the authors upon request.

public administration of the tax system.[22] We are unable to observe, and thus control for, age of the homeowner – let alone any other individual-level drivers of more complicated exemption policies. The strength of focusing the assessment ratio is these potentially confounding factors are irrelevant. However, if tax exemptions were to significantly unwind the impact of erroneous assessments, then distortions in the assessment ratio might be less consequential.

Tax bills, along with exemption amounts, are reported for approximately 80 percent of the homes in our sample. Table 3 directly estimates racial differentials in effective tax rate within this sample. We compute effective tax rate both before and after exemptions. For Black homeowners, the assessment gap is 12.9 percent in this subsample. Effective tax rate is 15 percent higher using the actual tax bill, and 14.7 percent higher with exemptions added back. Considering Black or Hispanic residents together, the estimated assessment gap is 9.7 percent. We find a 11.4 percent higher effective tax rate from tax bills and an 11.1 percent increase with observed exemptions added back. Inequality appears slightly larger in effective tax rates than in assessment ratios. It is possible that flat per-parcel fees, in conjunction with racial differnces in average home price, explain a portion of this effect. Inequality is also slightly larger after exemptions than before; which matches other findings in the literature that exemption policies can widen racial and ethnic inequality (Ihlanfeldt and Rodgers 2021). Tables A12 – A15 in the Online Appendix provide additional robustness regarding the timing of the tax bill and the direct pass-through of assessment ratios to effective tax rates.

5.1.1 Just Over Half of Inequality is Spatial

A large portion of inequality arises from home location. We establish this through a spatial decomposition that separates inequality within neighborhood from inequality between neighborhoods. The ideal experiment would compare two contiguous properties on the same street. Any distortion in assessment ratios arising from neighborhood factors would most plausibly be equivalent for these two homes. We approximate this experiment by conditioning on successively smaller geographies and show that the estimates are stable.

Columns (2) and (3) of Table 2 list the results. Within census tracts, which are regions of 4,000 people on average, we find inequality of 6.4 percent for Black homeowners and 5.3 percent for Black

[22] Scholars have shown that racial differences in exemption take-up may also contribute to racial inequality in tax burden (Ihlanfeldt and Rodgers 2021).

or Hispanic homeowners (Column 2).[23] According to the U.S. Census Geographic Areas Reference Manual, census tracts are initially drawn with the goal of being "as homogeneous as possible with respect to population characteristics, economic status, and living conditions." This criterion provides additional support for our strategy of attempting to hold neighborhood composition fixed by looking within tract. However, tracts may be large enough that home prices are not identically affected by local factors. Column (3) shows inequality estimated within census block groups – regions of 600–3,000 people. The estimates are approximately 50bps lower relative to the tract-level analysis (though not statistically different): the point estimates are 5.9 percent and 4.85 percent for Black and Black or Hispanic homeowners respectively.

For both groupings of minority homeowners, then, a bit more than 50 percent of the average inequality arises between neighborhoods, and is conditioned away within census block group. In Section 5.3, we explore mechanisms generating both spatial and nonspatial inequality.

5.2 What Does Not Explain the Assessment Gap?

5.2.1 Property Attributes

As discussed in Section 3.5, if assessment ratios are regressive for reasons having nothing to do with race or ethnicity, the result would still be inequality in property taxes along racial and ethnic lines. We cannot distinguish between race-related misvaluation and price-related misvaluation by controlling for transaction price, because this is overcontrolling if race itself affects market prices: $M_{ijt} = f(race, \Theta_{ijt})$, where Θ_{ijt} is a vector including without loss of generality all factors other than race affecting prices.[24] Assuming log-additive separability for expositional purposes only, augmenting our baseline specification with a price control would yield:

$$ar_{ijt} = \gamma_{jt} + \beta_1^r race_{ijt} + \Gamma(\beta_2^r race_{ijt} + \psi\Theta_{ijt}) + \epsilon_{ijt}. \quad (2)$$

In Equation 2, estimated racial inequality for Black homeowners would be β^B. However, the total racial effect is what we want to measure: $\beta_1^B + \Gamma\beta_2^B$. In positing that race is an input to market prices,

[23] As always, our analysis is within jurisdiction. Tracts are sometimes split between jurisdictions. Thus, to be precise, we use jurisdiction-tract-year fixed effects.

[24] The regressivity literature has also emphasized statistical bias that arises from including price as a regressor. This is a secondary concern here; the primary issue is avoiding a "bad control" problem.

we do not have in mind racial differences in transaction prices (addressed in Section 5.2.2) but rather the widely-documented stylized fact of lower home prices in highly minority communities.[25]

We address this ambiguity by separately exploring the two main drivers of home price: property attributes and home location. Our data allows us to control directly for home attributes, which we implement using two approaches. The first controls for property features directly in a high-dimensional, nonparametric manner. We augment our baseline specification with a fixed effect for every unique combination of major home attributes in the data:

$$ar_{ijt} = \alpha_{attr(i)} + \gamma_{jt} + \beta^r race_{ijt} + \epsilon_{ijt}. \tag{3}$$

Here $\alpha_{attr(i)}$ is a home-specific tupple of categorical variables capturing: size, number of bathrooms, and home vintage, along with indicators for fireplaces, patios, and/or swimming pools.

In addition to fixed effects for attribute bundles, we also use home characteristics to construct a continuous measure of home prices based only on features of the property stock. Year by year, for every home i in state s, we estimate implied hedonic attribute prices for all characteristics, using data from every state *except* s. This leave-state-out estimation yields national characteristic valuations that are disconnected from any local, spatial drivers of price. We then construct the attribute-implied price for any home as the inner product of its property attribute vector, and the associated location-neutral hedonic price estimates. Section B.iv of the Online Appendix includes full details on how we establish categorical variables in the attribute-bundle approach, along with the exact estimation strategy for the location-neutral price approach. Our results are not sensitive to these choices at all.

Table 5 shows the results of augmenting our baseline specification with these attribute-price measures. We have data on home attributes for approximately two-thirds of the homes in our sample. Column (1) repeats our baseline estimation of the assessment gap in this smaller subsample of homes, and shows that inequality is very similar to the full sample: 12.03 percent and 9.33 percent respectively. Column (2) adds fixed effects for each unique combination of attributes. This specification estimates

[25] Previous literature has explored whether low prices in highly minority communities is related to preferences for segregation or differences in local amenities like school quality (Bayer et al. 2007). In addition, amenities are a partial function of public investment, which also may be a function of race. It is beyond the scope of this paper to disentangle the role of race in home price formation. Equitable assessments mirror variation in market prices, regardless of their cause.

inequality by residualizing assessment ratios on jurisdiction-year (to absorb local target ratio, as always), and thereafter comparing over- or under-assessment within homes of similar size, vintage, and features.

Column (3) uses fixed effects for each of 200 quantiles of the constructed attribute-implied price. Column (4) uses fixed effects for 500 quantiles. Across each of these three specifications, our estimates of inequality are virtually unaltered by controlling for physical attributes of the housing stock.

We can also intersect our attribute fixed effects with locations. The resulting estimates of inequality will compare physically similar homes with other similar homes in the same geographic region. Mirroring the spatial decomposition above, we do this at three levels: taxing jurisdictions, tracts, and block groups. It is important to realize that intersecting attribute bins with geographies is already potentially beginning to control for neighborhood differences. To illustrate, imagine that a taxing jurisdiction has one neighborhood with large single-family homes, and another with predominantly small duplexes (certainly not an uncommon pattern nationwide). Intersecting large- and small-home fixed effects with the jurisdiction fixed effect will estimate inequality as a weighted average of inequality *only* within each of these two neighborhoods – conditioning away the spatial variation between neighborhoods.

Columns (1)–(2) of Panels B–D show the results of intersecting attribute bins with, in turn, jurisdictions, tracts, and block groups. After controlling for attributes and allowing prices to vary between jurisdictions (Panel B), assessment ratios for Black homeowners are 10.92 percent higher. For Black or Hispanic homeowners, the figure is 8.52 percent, a reduction of 1.3pp. In both cases, this very high-dimensional control for attributes explains less than 14 percent of our baseline estimates. As noted, it seems very likely that some portion of that reduction relates to spatial dispersion of home type across neighborhoods.

In panels C and D, we estimate inequality within census tract and census block group respectively, while also intersecting attribute fixed effects with geography. This measures inequality within neighborhood by comparing only physically similar homes within that neighborhood. For Black homeowners, estimated equality is 5.6 and 4.8 percent, respectively – compared to unconditional estimates of 6.4 and 5.9 percent, respectively. For Black or Hispanic homeowners: 4.6 and 4.1 percent, respectively, again relative to unconditional estimates of 5.3 and 4.9 percent, respectively.

The results in Table 5 show that price-regressivity operating through housing stock attributes has a minimal ability to explain the inequality we document. The direct comparison between physically similar homes has virtually no effect on our estimates. In specifications that allow for varying attribute price by neighborhood – effectively comparing extremely similar physical homes within tract or block group – we find a reduction of approximately 1pp, relative to our baseline estimates of 5–6 percentage points.

In Section 5.3.1, we consider the other possible channel through which price regressivity in assessment ratios might relate to racial inequality: home location.

5.2.2 Racial Differences in Transaction Prices

Differences in transaction prices do not generate the inequality that we document. That is, Black or Hispanic homeowners do not systematically realize lower sales prices, thereby pushing observed assessment ratios upwards.

Bayer et al. (2017) uses very similar housing microdata to the ATTOM dataset used in this paper and finds that Black and Hispanic *buyers* pay a premium of around 2 percent. This effect is positive across virtually all racial and ethnic combinations of buyers and sellers, and is largest for within-race transactions (Black seller and Black buyer; or Hispanic seller and Hispanic buyer). In U.S. housing markets, the majority of transactions occur within-race. Therefore, the Bayer et al. (2017) finding would suggest that minority assessment ratios in our sample (which are associated with the race and ethnicity of the home *seller*) may be understated by 2 percent.[26] In turn, this would imply that racial or ethnic differences in transacted prices *lower* our estimates of inequality by 2 percent.

Bayer et al. (2017) uses a within-property analysis and restricts attention to four large metropolitan areas to obtain sufficient transaction density. One embedded assumption is that home characteristics stay constant (and are therefore absorbed by the property-level fixed effect). We add additional evidence using a slightly different methodology that relaxes this assumption.

For the set of homes which sell more than once, we define P_0 as the first transaction price. We use ZIP code-level home price indexes to form a predicted selling price:

$$\hat{P_{it}} = P_{i0} * \frac{HPI_{zt}}{HPI_{z0}} \tag{4}$$

[26] We construct assessment ratios using realized market prices as the denominator. Thus, if realized market prices are higher than "true" value, this would increase the denominator, and reduce the assessment ratio.

where HPI_{zt} is a ZIP code HPI for time t.[27] We then run the following regression:

$$ln(P_{it}) - ln(\hat{P_{it}}) = \gamma_{bg,t} + \beta^{r} seller\ race_i + \epsilon_{izt} \tag{5}$$

where $\gamma_{bg,t}$ is a census block group-year fixed effect. The left hand side is an unexpected component of transaction prices: the difference between realized and predicted prices. We include a fixed effect at the block-group level to absorb spatial imprecision arising from the ZIP code HPI.[28] Coefficients on the categorical *seller race* variable are estimates of racial and ethnic differences in transacted prices which are not explained by local housing market conditions.

Table 4 shows the results, which are largely consistent with Bayer et al. (2017). We estimate that Black sellers receive 2.2 percent more than White sellers within the same census block group and year. Considering Black or Hispanic sellers together, the estimated premium is 3.3 percent. The difference in transacted prices could arise from differential propensity to improve or maintain property, differences in how properties are "staged" for sale, or from a range of other housing market frictions. No matter the reason, these results suggest that, to the extent that a racial differential in market prices exists, realized market prices are slightly higher for minority sellers. This would lead to a *lower* assessment ratio for minority sellers, which means that our estimates of inequality are, if anything, biased downwards on the order of 2–3 percent.

By necessity, this test of transaction prices is based on a set of homes which sell at least twice within the span of our dataset (1–2 decades). However, repeat sales are potentially a selected sample. Appendix Table A8 compares the homes used for the test in Table 4 with other homes that enter our core dataset. These two sets of properties do not differ meaningfully on tract-level racial demographics. In addition, the assessment gap is slightly smaller in the set of homes which do not inform this test, which is the opposite of what would be predicted if the patterns of Table 4 were reversed out-of-sample.

5.3 What Does Explain the Assessment Gap?

[27] We obtain ZIP code HPI measures from Zillow.

[28] By population, the average ZIP code is 7–8 times as large as a block group.

5.3.1 Neighborhood Misvaluation

Spatial variation in assessment ratios is strongly correlated with racial demographics. This effect holds above and beyond inequality generated by individual homeowner race. Table 6, shows the national results of augmenting our baseline analysis with tract-level demographics:

$$ar_{injt} = \gamma_{jt} + \beta race_{injt} + \theta share_{c,jt} + \epsilon_{injt} \tag{6}$$

where ar is the log assessment ratio, and i indexes house, j jurisdiction, n census tract, and t year. $share$ is the tract-level population share for a given racial or ethnic group. Fixed effects are again at the jurisdiction-year level. The coefficients on demographic shares are all strongly significant, showing that assessment gaps are substantially larger in highly minority communities.

In this section, we show that market prices are much more responsive to neighborhood-level attributes than assessments are. This generates spatial inequality in tax burden. In turn, residential sorting leads this spatial inequality to be correlated with race and ethnicity. In 2017, the average Black resident in the U.S. lived in a tract with 43.5 percent Black share, while the average White resident in the U.S. lived in a tract with 7.2 percent Black share.[29] For Black or Hispanic residents, the same figures are 56.6 percent and 17.2 percent, respectively.

To fix ideas, suppose that assessors impute values as a simple function of home size alone: $A_{injt} = f(X_{injt})$, where X is a vector of property attributes, including size, number of rooms, etc. It is well established in the housing literature that local amenities are also capitalized into home prices (Roback 1982, Gyourko and Tracy 1991, Cellini et al. 2010). Thus, suppose $M_{injt} = g(X_{injt}, W_{njt})$, where W is a vector of tract-level amenities including, for instance, local unemployment measures. If the market places a nonzero price on local unemployment, then tract-level variation in unemployment will generate spatial variation in the assessment ratio. Further, if the market hedonic price for unemployment is negative, and if unemployment is correlated with minority demographic share (within jurisdiction), then the mismatch will generate an assessment ratio increasing in minority share.

The data is consistent with this very simple framework. We establish this by presenting evidence from two hedonic regressions: one with market values as the dependent variable and the other with assessed valuations as the dependent variable. Specifically, we specify regressions of the form:

[29] Authors' calculations using American Community Survey data.

$$\ln(y_{injt}) = \gamma_{jt} + \beta^y_{att} X_{injt} + \beta^y_{neigh} W_{njt} + \epsilon_{injt} \tag{7}$$

where $y \in \{A, M\}$, and i indexes home, j taxing jurisdiction, n census tract, and t year. X_{injt} is a (potentially time-varying) vector of home characteristics including square footage, bathrooms, and flags for various amenities; and W_{njt} is a vector of tract-level characteristics. We are interested in comparing $\hat{\beta}^M_{att}$ with $\hat{\beta}^A_{att}$, and $\hat{\beta}^M_{neigh}$ with $\hat{\beta}^A_{neigh}$. That is, we are interested in knowing whether hedonic characteristics appear to be *differently* capitalized into market valuations and assessed valuations.

Figure 4 conveys the results of this analysis. Each bar represents the sensitivity of the (log) assessment ratio with respect to a one standard-deviation change of the given variable. At zero, the assessment hedonic model matches the market hedonics. Above (below) zero, the market hedonic prices are larger (smaller) in magnitude than the corresponding assessment hedonic prices. Finally, bars in Black are property-level attributes, and bars in red are tract-level attributes. Figure 4 shows that within the context of this hedonic estimation, assessments line up well with market prices on home-level characteristics but match much less well on neighborhood characteristics. The property-attribute bars are all less than 1 percent: this means that a one standard-deviation shift on any of these dimensions induces less than a 1 percent shift in the assessment ratio. By contrast, misalignment on tract-level attributes between the assessment and market models is up to an order of magnitude larger. Further, the one variable which receives a greater loading in the assessment model than in the market model is square feet. Appendix Table A5 shows the estimated hedonic prices from both models. From columns (2) and (4), we can see that assessors clearly do pay attention to neighborhood characteristics in some manner, but don't place *enough* emphasis thereupon. As a whole, the evidence in Figure 4 suggests that assessors: (i) overweight the size of the home; (ii) value other home characteristics fairly precisely; and (iii) underweight local neighborhood composition characteristics.

At a technical level, this underweighting could arise from flawed valuation methods in several ways. Assessors commonly allow a geographic fixed effect to drive spatial variation in prices. In this case, if the geographic fixed effect is for too broad a region (an entire city or a quadrant of a city, for example), assessments would be insufficiently high in subregions the market values highly, and insufficiently low in subregions where market prices are low. A similar pattern would result if assessors generate assessments by applying local growth rates to the prior year's assessment, and the areas to which they assign a given rate are excessively large (if one growth rate were picked for an entire city, for example).

Residential Segregation Leads Spatial Misvaluation to Land Along Racial Lines. Insufficient responsiveness to neighborhood features is what generates spatial inequality in assessments, but the fact that minorities live in neighborhoods with different average characteristics is what causes inequality to land along racial and ethnic lines. This fact suggests increasing inequality in highly segregated areas. We test this prediction using a standard measure of residential segregation, an index of dissimilarity:

$$dis_C = \frac{1}{2} \sum_{n \in C} | \frac{b_n}{B_C} - \frac{w_n}{W_C} | \tag{8}$$

The summation is over tracts, n, in county C. b_n and w_n respectively denote the tract-level number of Black and White residents. B and W are the total regional population of each race. The measure represents the share of the racial population that would need to move in order to reach zero segregation. Because most assessments are produced by county officials, we form this measure at the county level. We also base the measure on the 2000 Decennial Census. This predetermined measure of segregation mitigates a story of exogenous mismeasurement that itself causes racial sorting in response. We then estimate inequality within decile of segregation. It is important to note that we form deciles on counties, and that large counties are more segregated on average. Therefore, the most segregated deciles have 5–10 times as many observations in the data as the least segregated.[30] Figure 5 shows the results. Inequality is almost steadily increasing in segregation for Black homeowners. Considering Hispanic homeowners as well, inequality is relatively static until the highest two deciles. For both groupings of minority homeowners, inequality in the most segregated decile is sharply higher than in other regions.

Revisiting Price Regressivity in Assessment Ratios. When assessments are insufficiently sensitive to neighborhood characteristics, homes in regions with relatively lower quality amenities will be over-assessed (market prices are lower due to amenities; assessments are not low enough) and homes exposed to higher quality amenities will be under-assessed (market prices are higher due to amenities; assessments are not high enough). Therefore, as long as home prices correlate with amenity quality, neighborhood misvaluation will result in price-regressive assessment ratios.

[30] Full regression output is available in Table A7 of our Online Appendix.

Accordingly, while our focus in this paper is on racial and ethnic inequality, our findings show one channel through which price regressivity in assessment ratios can arise. Although the property tax literature has documented patterns of regressivity in many settings, there is not yet any consensus on mechanism. In related work, Amornsiripanitch (2021) builds on the analysis in this paper to argue more directly that neighborhood misvaluation explains a large portion of observed price regressivity.

Given the prior literature on regressivity, it is very natural to wonder how the gradient with respect to racial demographics relates to the gradient with respect to home prices. To cleanly separate these two channels, we would need a model of home price formation that could decouple race-related drivers of price from all others. We could then compare assessment gaps in neighborhoods where home prices are low due to racially-linked factors with assessment gaps in neighborhoods where home prices are low for reasons unrelated to race. However, the model of home prices required for such an analysis would be exceptionally complex. Neighborhood home prices are a function of many lags of school quality, transportation infrastructure, nature of the housing stock, investment in public goods, policing outcomes, and demographic flows – all of which have been intricately influenced by racial considerations over the past decades or more. It is beyond the scope of this paper to take such a stand on home price formation.

Instead, we provide several pieces of suggestive evidence to support the idea that spatial misvaluation lands more heavily on minority communities and minority homeowners, even relative to similar nonminority regions and homeowners. In the first, we split our sample into vigintiles by tract-level median home price. Figure 6 shows that tracts with above-median home prices show relatively stable levels of inequality; however, as we move down the lower half of the spatial home price distribution, inequality monotonically increases, exceeding 15 percent at the lowest vigintile.

Next, we use a double-portfolio sort on census tracts to show that this pattern is stronger for neighborhoods with a higher share of minority homeowners. We first split neighborhoods into quantiles based on median home value using tract-level measures from the ACS. Then, within each quantile, we split homes by neighborhood demographic share. To highlight interesting heterogeneity across the entire distribution of minority share, we use cutpoints of 1%, 10%, 25% and 80% Black share.[31]

In a pooled regression, we then estimate "excess" assessment for each bin (assessment ratio deviation from taxing jurisdiction-year average). Figure 7 shows the results where, for visual convenience,

[31] The patterns we show are not in any way sensitive to this choice of cutpoints.

we've scaled the most under-assessed bin to zero. In this figure, price regressivity is the left-to-right pattern – and regardless of demographic share, lower-valued neighborhoods do have higher assessment ratios. The gradient with respect to demographic share is the front-to-back pattern. In all neighborhood value quintiles, assessment is sharply increasing in minority share.

Another potential link between price regressive assessment ratios and racial inequality relates to sorting. Perhaps assessment ratios are always higher in communities with low-priced homes, and as a consequence of lower average wealth and or incomes, Black and Hispanic homeowners sort into these communities. This implies that, if we could control for neighborhood wealth levels, we would expect to see inequality disappear. While we cannot observe and control for wealth directly, we can control for both spatial and personal measures of income.

Figure 8 shows the results of splitting our sample into vigintiles by tract-level median income. Tracts with above-median average income evince relatively stable inequality on the order of approximately 5 percent. This figure closely mirrors the magnitude of within-neighborhood inequality. Moving down the lower half of the spatial income distribution, inequality is monotonically increasing, which shows two things. First, inequality arising from neighborhood misvaluations is concentrated in areas of below median incomes. Second, assessment ratios for Black residents in low-income neighborhoods are also much higher than assessment ratios for White residents in equally low-income neighborhoods, which strongly suggests that the racial assessment gap is something more than a simple reflection of racial income disparities. This is unsurprising: we know that conditional on income, Black and Hispanic homeowners live in sharply different neighborhoods from White homeowners (Aliprantis et al. 2019).

In total, this evidence strongly suggests that spatial misvaluations disproportionately affect minority communities even after conditioning on measures of economic status. However, it is important to note that we are not ruling out the possibility that nonracial patterns of price regressivity induce or amplify racial inequality: home prices are low in some region for exogenous reasons, minority homeowners are more likely to buy these low-priced homes, and all low-priced homes continue to receive erroneously high valuations. Another possibility that we do not explore in this paper is that capitalization of over-assessment (and the associated higher flow of tax payments), further depresses prices and also amplifies racially correlated sorting into regions with high assessment ratios. Capitalization is complicated to address as well: in many places, transaction prices are explicitly an important input into future assessments, implying potential feedback into bidding behavior, and possibly lessening the import of any historical observed assessment patterns. In addition, as we show in Section 5.3.3, the evidence supports individual racial differences in engagement with tax bureaucracy. This suggests a segmented market, where the degree of anticipated capitalization might be a function of bidder race.

The role of capitalization and sorting are both valuable areas for future research. We believe it is important to bear in mind that any model of residential segregation that rests on frictionless sorting based on home prices may abstract rather substantially away from an important set of historical public policies and ongoing social dynamics that have generated and preserved both residential segregation and racial differences in neighborhood prices.

5.3.2 Reassessment Frequency and Assessment Growth Caps

Another potential explanation for spatial inequality is that assessments are correct when they are generated, but diverge over time. Market prices change continuously, but assessments are updated discretely. Although an assessment is formally assigned each year, localities may not update their valuations annually. State law often outlines a minimum reassessment frequency. We collect data on these state policies from the Lincoln Institute.[32] Mandated reassessment cycles range from 1 year to 9 years. Panels A and B of Table 7 show estimated inequality for each frequency. The absence of any reevaluation constraint (column 9) is clearly associated with higher inequality. Across regions with some policy governing reassessment, there is no clear association between frequency and inequality. Inequality is statistically equivalent at frequencies of 4, 8, and 9 years. Inequality in regions with 1- or 2-year cycles is 1–2 percentage points lower than the longest cycles; however, this difference is also not statistically significant. Inequality is substantially higher within 3-year and 6-year subsamples, but in both cases, the magnitude is driven by one locality. Excluding those locations, the estimate for each of the two frequencies would be slightly lower than inequality under annual reassessment (column 1).

A range of deliberate administrative policies could also generate spatial inequality. The deep unpopularity of the property tax, along with concerns about homeowner dislocation as a result of taxing an illiquid asset, has led to legislative constraints on taxation in many states (Wong 2020, Paquin 2015). Many limiting policies apply to aggregate revenues or tax-rate levels. These policies

[32] Similar to assessment cap policies, we observe both statewide policies and state policies affecting certain large counties.

bind in ways that are orthogonal to our equitable tax null and are therefore not relevant for analyzing within-jurisdiction equity. Assessment caps, however – a constraint on the maximum year-over-year growth of an assessment – can potentially generate a mechanical wedge between market values and assessments.

From the Lincoln Institute of Land Policy, we obtain a record of assessment cap policies by year along with the cap rate of growth. We use these to perform three subanalyses regarding areas where: (i) there is no known cap policy, (ii) a cap exists, (iii) a cap exists and binds.[33] We determine whether the cap constraint binds within each year at the ZIP code level using HPIs from Zillow and the Federal Housing Finance Agency. Table A18 of our Online Appendix shows inequality estimated within each of these three subsamples. For Black homeowners, observed inequality is 13.8 percent in regions without any known assessment gap and 13.6 percent in regions subject to a cap (values are not statistically different). However, within ZIP codes where the cap would have bound, inequality is 8.6 percent, suggesting the impact of assessment caps is to *reduce* racial and ethnic inequality.[34] Our interpretation is that in regions where caps bind, policy constrains assessors to disregard valuation models, preventing a portion of the misvaluation that we document.[35]

5.3.3 Homeowner Behavior Within Neighborhoods

Our baseline results shows that 5–6 percentage points of inequality persists between homeowners of different race or ethnicity within a census tract or block group. Within these small geographies, neighborhood amenities are presumably quite consistent, and we have also shown that property-level attributes do not explain these findings.

This inequality is also consistent across the distribution of personal income. Using homeowner reported income from the HMDA records, we estimate within-block group inequality by income vigintile. Figure 9 shows the results. Baseline inequality within tract or block group is on the order of 5–6 percentage points. Conditioning on income, inequality is still present and relatively consistent across all vigintiles. Interestingly, for both groupings of minority homeowners, the largest inequality comes within the highest income quintile.

[33] The Lincoln Institute database covers state policies, including those targeting specific subset counties.

[34] It is important to notice that caps possibly create inequality along other margins. In California, for instance, caps have led to large inequality with respect to homeowner tenure.

[35] We find support for this explanation in related work that conducts a more detailed exploration of how assessment caps affect racial inequality (Avenancio-León and Howard 2022).

We explore whether individual homeowner engagement with the bureaucratic structure of tax administration can generate within-neighborhood inequality. In every jurisdiction of which we are aware, some process for appealing an assessment exists.[36] Therefore, one mechanism we hypothesize and test is racial differentials in propensity to appeal, likelihood of successful appeals, and degree of reduction conditional on appeal.

We are unaware of any compiled dataset of appeals at a national level. We obtain a comprehensive record of appeals submitted to the Cook County Assessors Office between 2002 and 2015, courtesy of Robert Ross (Ross 2017). Covering 1.9M homes and a population of 5.2M (including the city of Chicago), Cook County is the second most populous county in the United States. The Cook County records contain the same anonymized property-ID variable as the ATTOM dataset and therefore are able to be merged directly with our baseline dataset. This yields three additional pieces of information for each property in Cook County: (i) if an appeal was filed in a given tax-year, (ii) whether the appeal was successful, and (iii) if successful, the amount of the reduction. Our Online Appendix contains further administrative details about appeals in Cook County.

We conduct our analysis within block-group-year, thereby comparing appeal propensity, success, and (conditional) magnitude of reduction between two homeowners from the same block group in the same year. Table 8 shows the results of this analysis. The estimates in column (1) show that within-block group inequality in Cook County is approximately 5 percent. Although overall inequality in Cook County is quite high, Column (1) shows that within-neighborhood inequality closely parallels the national average. Column (2) shows propensity to appeal. Column (3) shows success probability conditional on appeal. Column (4) shows the reduction conditional on success. The baseline rate of appeals in Cook County ranges from 10 percent to 21 percent annually during this period, with a mean of 14.6 percent. The estimate in column (2) shows that Black homeowners are 1.1 percent less likely to appeal. The baseline success rate for assessment appeals in Cook County ranges from 52 percent to 80 percent during this period. The mean is 67.4 percent. The estimate in column (3) shows that Black homeowners are 2.2 percentage points less likely to win, conditional on appealing. The mean reduction granted to a successful appeal in this sample is 12.0 percent. The estimate in column (4) shows that conditional on a successful appeal, Black homeowners receive a reduction smaller by 0.48

[36] Our review of state legal codes suggests that two examples are most common: in one case appeals are made directly to a county assessor's office, and in the other case the state empowers some upstream board of review which has authority to adjust the local assessment.

percentage points. Results are broadly similar when considering Black or Hispanic residents together.

Finally, column (5) in each panel shows the total impact of appeals on inequality in Cook County. We can measure the change in assessment ratios that results from appeals without observing transactions (because the market prices difference out):

$$\Delta \log(A_{it}) = \gamma_b t + \beta^r race_{it} + \epsilon_{it}. \tag{9}$$

Here, $\Delta log(A)$ is the (positive) reduction in assessment from appeals, so that a negative coefficient reflects increased inequality. For Black homeowners, one annual appeals cycle increases the assessment gap by 20bps on average. Homeowners can potentially appeal their assessment every year.[37] Our empirical design measures within-neighborhood inequality upon sale – i.e., at the end of a given homeowner's tenure. Median tenure in Cook County is approximately 14 years.[38] A homeowner reducing tax burden by 20bps per year would accumulate a 2.8% reduction in tax burden during that period of time. This combination suggests that appeal disparity would explain approximately 50 percent of within neighborhood-level inequality for the median Black homeowner – although this back-of-the envelope calculation abstracts away from any repeated-game dynamics in the homeowner's decision-making about appealing. A similar proportion is suggested by 16bps of annual appeals-driven inequality for Black or Hispanic homeowners.

A long line of literature in the social sciences suggests a racial component in the extent to which individuals have confidence that public institutions are designed to serve them (extensively surveyed in Nunnally 2012). This belief may be accurate, or it may be inaccurate but lead to disengagement nonetheless. The evidence in Cook County with this hypothesis: White homeowners appear to be more effective at reducing assessment growth by navigating the appeals process. Over the long run, this would imply that assessments would grow more slowly for White homeowners than Black homeowners. In our Online Appendix, we test this hypothesis directly by building a panel of assessments (including the years in which a home does not sell) and exploiting changes in racial ownership. Our findings in Table A11 are very consistent with the evidence in this section: after absorbing time variation at the block-group level, assessments still grow more quickly when a given home has a Black or Hispanic

[37] In Cook County in particular, the county reassesses 1/3 of properties each year; meaning practically that most homeowners would appeal no more frequently than every three years. Our estimation is county-wide, however, meaning that coefficients in column (5) still have the interpretation of an annual impact.

[38] Authors' calculations using American Community Survey data.

owner, relative to when the same home has a White owner.

5.4 Additional Heterogeneities and Discussion

It is natural to wonder how the assessment gap relates to racial attitudes. For each mechanism explored above, no active expression of bias is necessary, but neither can we rule it out. We use two measures of racial animus developed in Stephens-Davidowitz (2014) to split our sample into regions of high and low racial prejudice. In each subsample, we estimate the overall assessment gap and nonspatial component. The racial animus measures are derived from the regional intensity of Google searches containing the most offensive epithet used to refer to African-Americans. One measure is produced at the state level and the other at the media-market level. For the latter, we use a Nielsen crosswalk to assign the media-market measure to counties. We then split our sample along the median of each measure and estimate the assessment gap in a pooled regression. As the measure is designed to capture prejudice towards African-Americans, we estimate the assessment gap only for Black homeowners and not for other groupings of minority residents.

Table 9 shows the results. Using either measure, the assessment gap is significantly larger in high-animus regions. This holds both in the overall estimates shown in columns (2) and (4) and in the homeowner-effect estimates in columns (3) and (5). In regions of below-median prejudice, the assessment gap is still economically and statistically significant. Several plausible mechanisms could lead the assessment gap to be increasing in racial animus. In higher animus regions, minority residents may be more hesitant to engage with property tax bureaucracy, thereby lowering propensity to appeal assessments. Active discrimination could also lead to lower success rates. On the spatial margin, high-animus regions may lead to increased racial residential segregation along with a larger market-price capitalization of racially correlated factors, exacerbating neighborhood-level misvaluations.

Our data sample spans 2005–2016, and thus includes the final years of the housing boom that preceded the Great Recession, along with years following the crash. A range of research has shown racial and ethnic heterogeneities in exposure to housing markets during this period (Bayer et al. 2016, Rugh and Massey 2010). We produce estimates by year to explore how the assessment gap varies over the boom and bust cycle. Table 10 shows the results. Inequality is present in all years, except in 2005 for the grouping of Black and Hispanic homeowners. There is an upward trend during 2005-2007, and then a sharp jump upwards in 2008. It seems highly plausible that this reflects larger price declines in minority neighborhoods, combined with sticky assessments. However, the pattern does not reverse quickly – showing that this cannot be solely a story about short-term frictions in updating assessments. Inequality remains near the 2008 peak through 2014 for both groupings of minority homeowners. In the last two years of the sample, inequality declines somewhat but is still higher than it was in 2007, nearly a decade after the Great Recession.

6 Conclusion

We document widespread racial and ethnic inequalities in property tax burdens in the U.S. Using shapefiles for a comprehensive set of local governments along with other quasi-governmental entities that levy taxes, we define taxing jurisdictions as regions with a unique set of overlapping taxing entities. Within each jurisdiction, an equitable tax benchmark requires the assessment ratio to be constant. Our first major finding is to document a nationwide assessment gap: assessment ratios are on average higher for minority homeowners. Holding jurisdiction – and thereby public services, intended taxation, and local assessment practices – fixed, the average assessment gap between Black or Hispanic residents and non-Hispanic Whites is 10–13 percent.

This inequality does not arise from racial differences in transaction prices – Black or Hispanic homeowners selling their homes for lower prices. Property features, like home size or age, also cannot explain this inequality. Nor can administrative policies related to reassessment frequency, or common legislative constraints on property tax growth in the form of assessment caps.

We show that neighborhood demographics are an important predictor of the assessment gap. Spatial inequality arises because assessments are less responsive to neighborhood characteristics than market prices are. This generates inequality between neighborhoods. As a consequence of residential racial sorting, Black and Hispanic residents face a different average set of neighborhood characteristics, and therefore the misvaluation of these characteristics generates the spatial component of the assessment gap. We show that the assessment gap is largest in the most segregated regions. We show also that the assessment gap cannot be explained by average neighborhood home prices. Low-income Black communities have sharply higher assessment ratios than low-income White communities.

Just under half of the assessment gap persists within neighborhoods. Using one large county as a case study, we show that individual homeowner interactions with bureaucratic systems of property tax administration can generate within-neighborhood inequality. We show that Black and Hispanic homeowners are less likely to appeal their assessment; conditional on appealing are less likely to succeed; and conditional on a successful appeal, receive smaller reductions. We quantify the total impact across this region, and find one annual appeals cycle generates 20bps of inequality between Black and White homeowners within the same census block group.

Our baseline findings establish that minority residents in the U.S. face a higher property tax burden than their nonminority neighbors. Although the professional standards for the appraisal industry emphasize that equity in property taxation demands jurisdictionally constant assessment ratios, the reality of property tax administration in the U.S. is that more jurisdictions fail to achieve this equity than not. In our Online Appendix, we present a proof-of-concept exercise showing that estimating equitable assessments is not an intractable problem: using publicly available zip-code level price indices, a simple framework for producing assessments can reduce inequality by up to 70 percent.

We conclude with a last word on how our work relates to systemic inequality. While many historians and social scientists have well documented the historical prevalence of discriminatory practices in property tax administration, past or contemporaneous intent to build discrimination into the system is not necessary for the existence of systemic discrimination today. Our work shows that seemingly race-neutral, but imperfect, practices such as home assessments can generate inequality when assessment errors or misvaluations disproportionately land along racial lines. Moreover, individual or collective racism from private actors is not necessary for misvaluations to take place. As such, this paper shows how structural inequities can persist through systems that mirror, export, and sometimes amplify inequities already ingrained in the fabric of U.S. society, regardless of intent.

References

Aaronson, D., Hartley, D. A., and Mazumder, B. (2020). The effects of the 1930s holc'redlining'maps.

Aliprantis, D., Carroll, D., and Young, E. R. (2019). What explains neighborhood sorting by income and race?

Amornsiripanitch, N. (2021). Why are residential property tax rates regressive? *Available at SSRN 3729072*.

Ananat, E. O. (2011). The wrong side(s) of the tracks: The causal effects of racial segregation on urban poverty and inequality. *American Economic Journal: Applied Economics*, 3(2):34–66.

Atuahene, B. (2017). Our taxes are too damn high: Institutional racism, property tax assessments, and the Fair Housing Act. *Nw. UL Rev.*, 112:1501.

Atuahene, B. and Berry, C. (2019). Taxed out: Illegal property tax assessments and the epidemic of tax foreclosures in Detroit. *UC Irvine Law Review*, 9(4):847.

Avenancio-León, C. and Howard, T. (2022). Assessment caps and the racial assessment gap. *National Tax Journal*, Forthcoming.

Baar, K. K. (1981). Property tax assessment discrimination against low-income neighborhoods. *The Urban Lawyer*, pages 333–406.

Bartlett, R., Morse, A., Stanton, R., and Wallace, N. (2018). Consumer-lending discrimination in the era of FinTech. *Unpublished working paper. University of California, Berkeley*.

Bayer, P., Casey, M., Ferreira, F., and McMillan, R. (2017). Racial and ethnic price differentials in the housing market. *Journal of Urban Economics*, 102:91–105.

Bayer, P., Ferreira, F., and McMillan, R. (2007). A unified framework for measuring preferences for schools and neighborhoods. *Journal of political economy*, 115(4):588–638.

Bayer, P., Ferreira, F., and Ross, S. L. (2016). The vulnerability of minority homeowners in the housing boom and bust. *American Economic Journal: Economic Policy*, 8(1):1–27.

Berry, C. R. (2021). Reassessing the property tax. *Available at SSRN 3800536*.

Black, D. E. (1977). Property tax incidence: The excise-tax effect and assessment practices. *National Tax Journal*, pages 429–434.

Bruhn, J. (2018). Crime and public housing: A general equilibrium analysis. *Available at SSRN 3064909*.

Cellini, S. R., Ferreira, F., and Rothstein, J. (2010). The value of school facility investments: Evidence from a dynamic regression discontinuity design. *The Quarterly Journal of Economics*, 125(1):215–261.

Clapp, J. M. (1990). A new test for equitable real estate tax assessment. *The Journal of Real Estate Finance and Economics*, 3(3):233–249.

Cook, L., Logan, T. D., and Parman, J. M. (2021). Racial segregation and southern lynching.

Cutler, D. M., Glaeser, E. L., and Vigdor, J. L. (1999). The rise and decline of the American ghetto. *Journal of political economy*, 107(3):455–506.

Doerner, W. M. and Ihlanfeldt, K. R. (2014). An empirical analysis of the property tax appeals process. *Journal of Property Tax Assessment & Administration*, 11(4):5–34.

Dornfest, A. S., Rearich, J., Brydon III, T. D., and Almy, R. (2019). State and provincial property tax policies and administrative practices (ptapp): 2017 findings and report. *Journal of Property Tax Assessment & Administration*, 16(1):43–130.

Drake, S. C. and Cayton, H. R. (1970). *Black metropolis: A study of Negro life in a northern city*. University of Chicago Press.

Engle, R. F. (1975). De facto discrimination in residential assessments: Boston. *National Tax Journal*, pages 445–451.

Gyourko, J. and Tracy, J. (1991). The structure of local public finance and the quality of life. *Journal of Political Economy*, 99(4):774–806.

Ihlanfeldt, K. and Rodgers, L. P. (2021). Explaining racial gaps in property assessment and property taxation.

Kahrl, A. W. (2016). The power to destroy: Discriminatory property assessments and the struggle for tax justice in Mississippi. *Journal of Southern History*, 82(3):579–616.

King, D. (1995). *Separate and Unequal: Black Americans and the U.S. Federal Government.* Oxford: Clarendon Press.

Kochin, L. A. and Parks, R. W. (1982). Vertical equity in real estate assessment: A fair appraisal. *Economic Inquiry*, 20(4):511–532.

Loewen, J. (2005). *Sundown Towns.* New York: Simon and Schuster.

Massey, D. S. and Denton, N. A. (1993). *American apartheid: Segregation and the making of the underclass.* Harvard University Press.

McMillen, D. and Singh, R. (2020). Assessment regressivity and property taxation. *The Journal of Real Estate Finance and Economics*, 60(1):155–169.

McMillen, D. P. (2013). The effect of appeals on assessment ratio distributions: Some nonparametric approaches. *Real Estate Economics*, 41(1):165–191.

McMillen, D. P. and Weber, R. N. (2008). Thin markets and property tax inequities: A multinomial logit approach. *National Tax Journal*, pages 653–671.

Menendian, S., Gailes, A., and Gambhir, S. (2021). Twenty-first century racial residential segregation in the united states. *The Roots of Structural Racism Project, UC Berkeley.*

Nunnally, S. C. (2012). *Trust in Black America: Race, Discrimination, and Politics.* NYU Press.

Paglin, M. and Fogarty, M. (1972). Equity and the property tax: A new conceptual focus. *National Tax Journal*, pages 557–565.

Paquin, B. P. (2015). *Chronicle of the 161-year history of state-imposed property tax limitations.* Lincoln Institute of Land Policy Cambridge.

Perry, A., Rothwell, J., and Harshbarger, D. (2018). The devaluation of assets in black neighborhoods. *Library Catalog: www. brookings. edu.*

Reardon, S. F., Fox, L., and Townsend, J. (2015). Neighborhood income composition by household race and income, 1990–2009. *The Annals of the American Academy of Political and Social Science*, 660(1):78–97.

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy*, 90(6):1257–1278.

Ross, R. (2017). The impact of property tax appeals on vertical equity in Cook County, IL. *Univerity of Chicago, Harris School of Public Policy Working Paper.*

Rothstein, R. (2017). *The Color of Law: A Forgotten History of How Our Government Segregated America.* Liveright Publishing.

Rugh, J. S. and Massey, D. S. (2010). Racial segregation and the american foreclosure crisis. *American sociological review*, 75(5):629–651.

Sirmans, S., Gatzlaff, D., and Macpherson, D. (2008). Horizontal and vertical inequity in real property taxation. *Journal of Real Estate Literature*, 16(2):167–180.

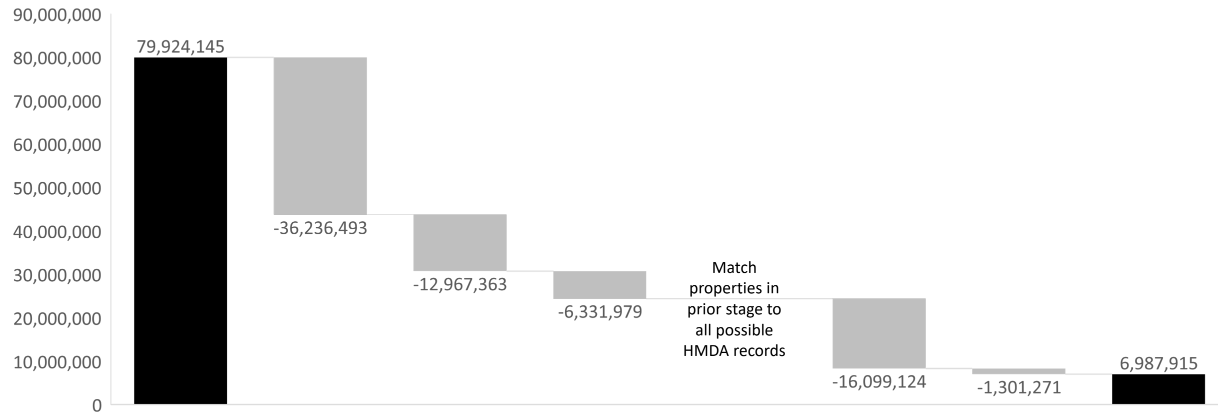
Stephens-Davidowitz, S. (2014). The cost of racial animus on a black candidate: Evidence using google search data. *Journal of Public Economics*, 118:26–40.

Weber, R. N. and McMillen, D. P. (2010). Ask and ye shall receive? predicting the successful appeal of property tax assessments. *Public Finance Review*, 38(1):74–101.

Wolgemuth, K. L. (1959). Woodrow wilson and federal segregation. *Journal of Negro History*, 44(2):158–173.

Wong, F. (2020). Mad as hell: Property taxes and financial distress. *Available at SSRN 3645481.*

Figure 1: Overview of Data Construction

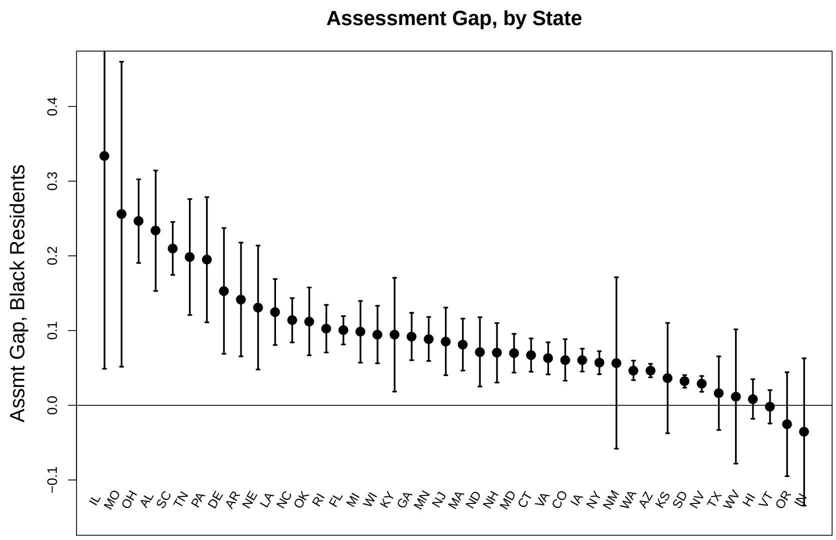


Start: (ungraphed) Annual assessments for 92M residential properties of 1-4 units	Arms-length, residential resale transactions occurring since 2005	Remove obs with missing or conflicting transaction values	Remove obs with missing assessment or conflicting info	• Clean sample • Remove California	*(Pins down race and ethnicity of buyer)*	• Restrict to obs where buyer subsequently becomes a seller • Remove obs with undeclared race/ethnicity	• Remove observations with transaction in prior year • Remove observations in tracts without ACS data	**End**: Core dataset
# of Unique Properties In Sample:	46,302,417	30,337,193	23,035,312	18,581,756	14,735,048	7,033,306	6,113,152	6,113,152

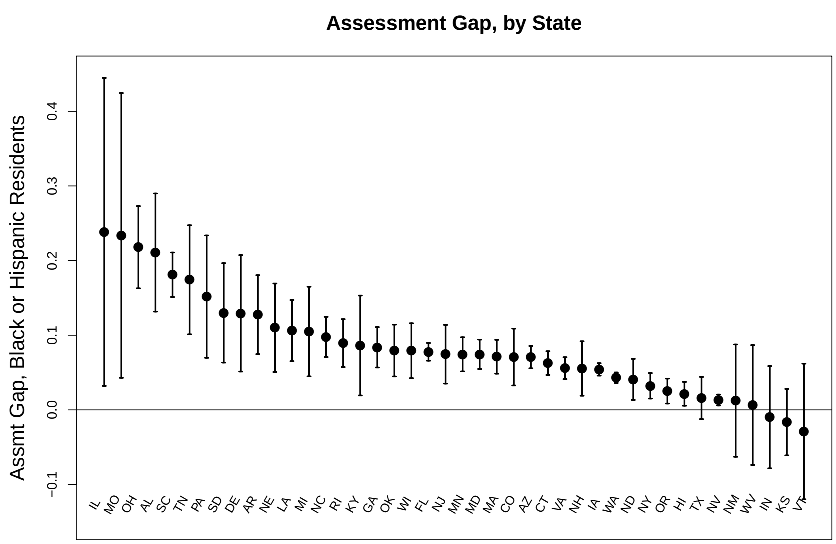
Note: This figure provides an overview of each step in the data construction process. Additional detail on each step is available in Section B of the Online Appendix.

Figure 2: State-Level Estimates of Assessment Gap

Panel A: Black Homeowners

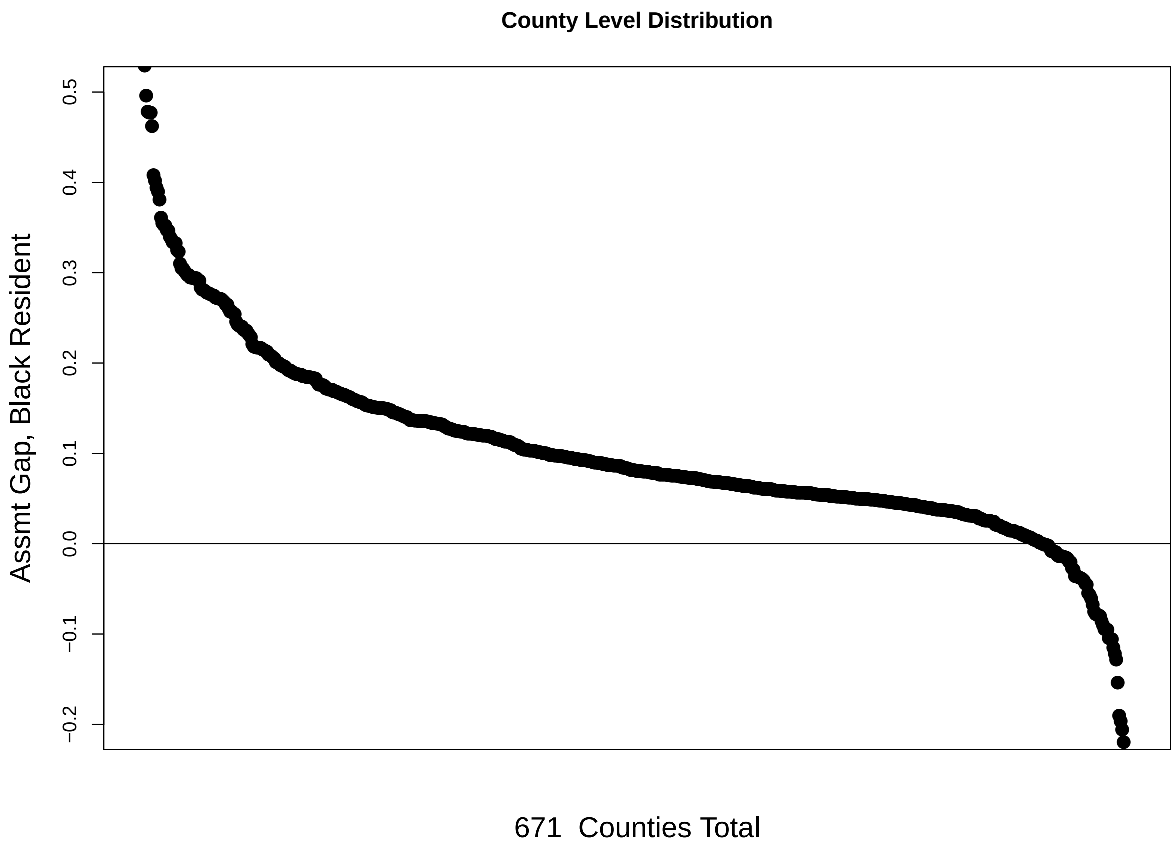


Panel B: Black or Hispanic Homeowners



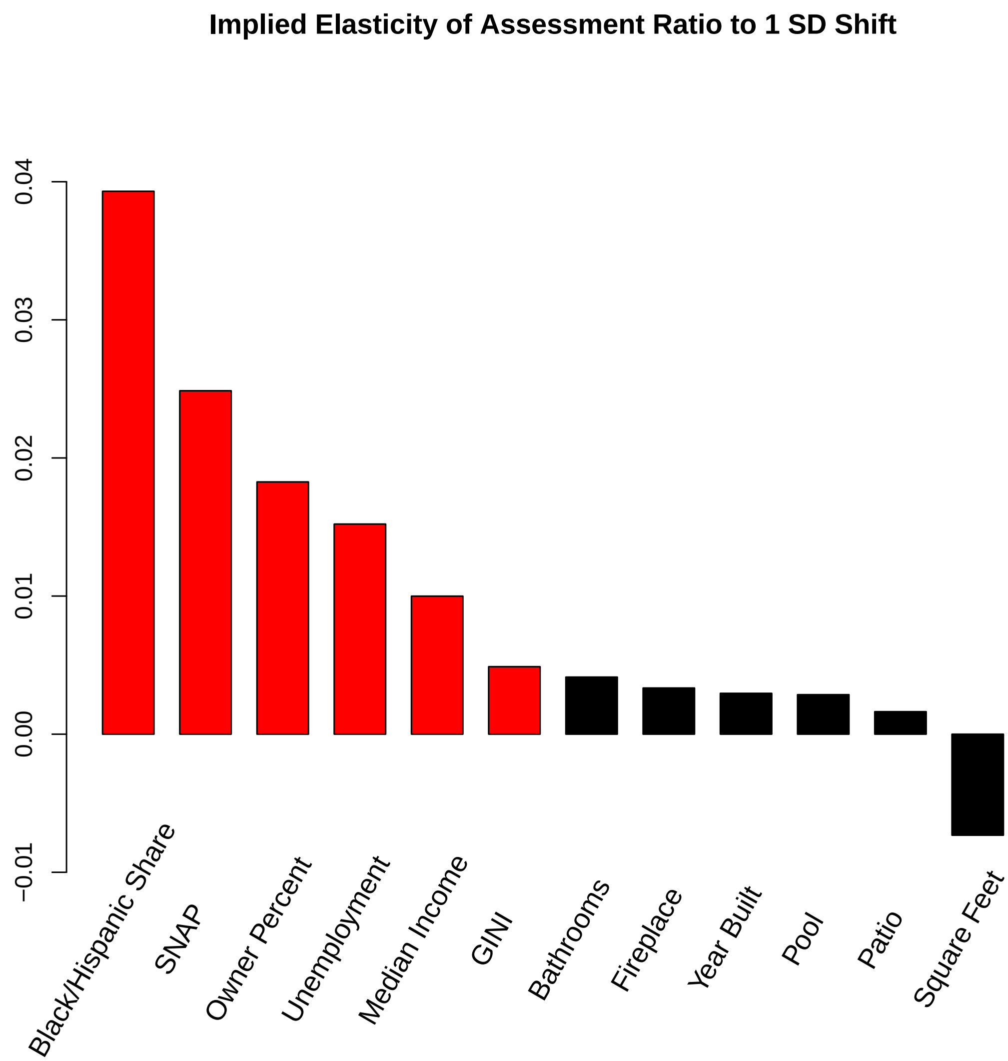
Note: These graphs show state-level estimates of the assessment gap. For every state with at least 500 observations, we regress log assessment ratio on a jurisdiction-year fixed effect and categorical variables for race and ethnicity. The top graph plots the estimated coefficient for Black mortgage holders, along with a 95% confidence interval. The reference group is non-Hispanic White residents. Standard errors in the underlying regressions are clustered at the jurisdiction level.

Figure 3: County Level Estimates of Assessment Gap



Note: These graphs show county-level estimates of the assessment gap for Black residents. For every county with at least 500 observations, we regress log assessment ratio on a jurisdiction-year fixed effect and categorical variables for race and ethnicity. We have sufficient data in 671 counties. We plot the estimated coefficient. For visual clarity, we do not include confidence intervals. Point estimates are positive and significant at 5% in 391 counties, positive and insignificant in 219 counties, negative and insignificant in 53 counties, and negative and significant at 5% in 8 counties. The reference group is non-Hispanic White residents. Standard errors in the underlying regressions are clustered at the jurisdiction level.

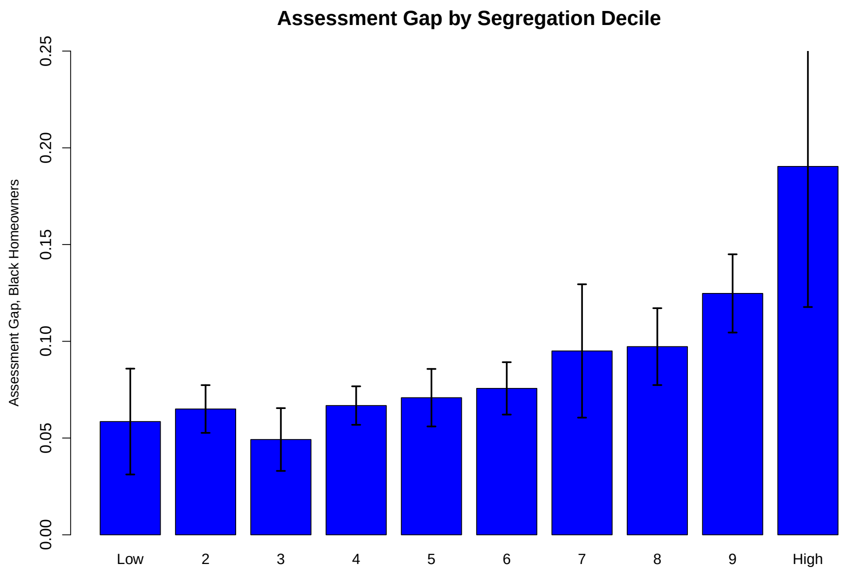
Figure 4: Hedonic Models: Mismatch



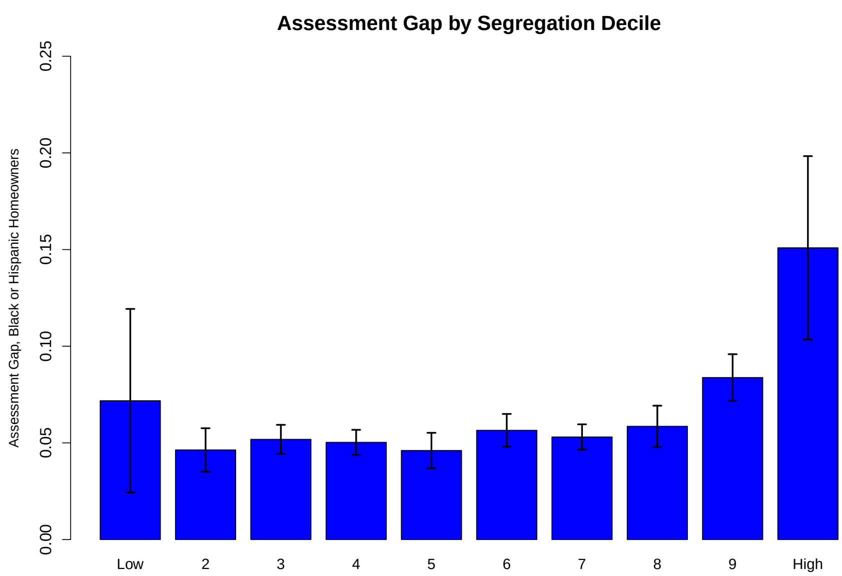
Note: Each bar in this figure plots the difference between two estimated hedonic prices: one estimated from a model with market values as the dependent variable, and one from a model with assessment values as the dependent variable. Otherwise, the two hedonic models are identical: all regressors are the same. Both market values and assessed values are logged in the underlying models, so the difference between the two estimated hedonic prices represents a proportional shift in the assessment ratio that arises from a one standard-deviation shift in the underlying variable. Bars in red are tract-level characteristics. Bars in black are property-level characteristics. A bar at zero would denote that the market-hedonic is the same as the assessment hedonic price. Larger bars signify a greater disconnect between market-hedonics and assessment-hedonics. Finally, bars above zero denote that estimated *market* hedonic prices are greater in (absolute) magnitude than assessed hedonic prices. Bars below zero denote that the assessment hedonic price is larger. Table **??** shows the estimated prices which underlie this figure.

Figure 5: Assessment Gap by Racial Segregation

Panel A



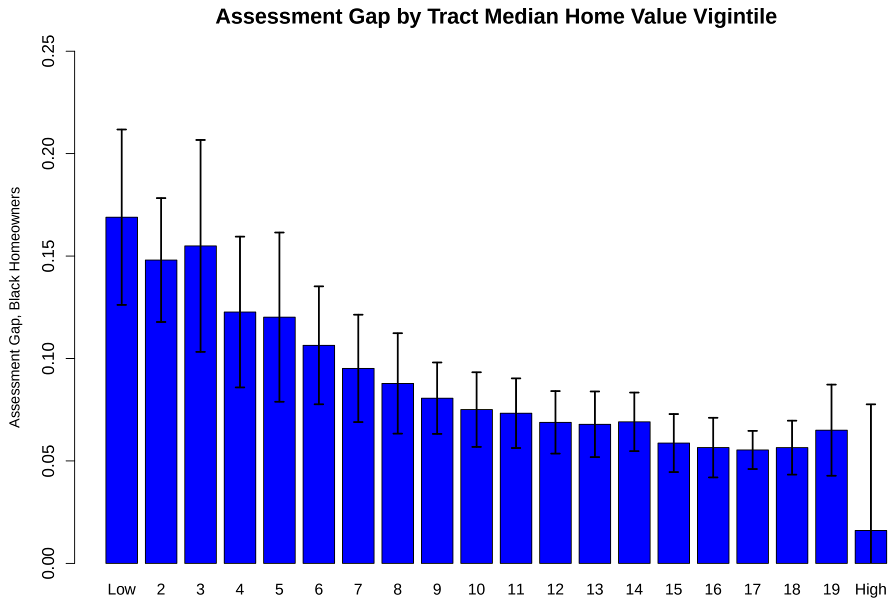
Panel B



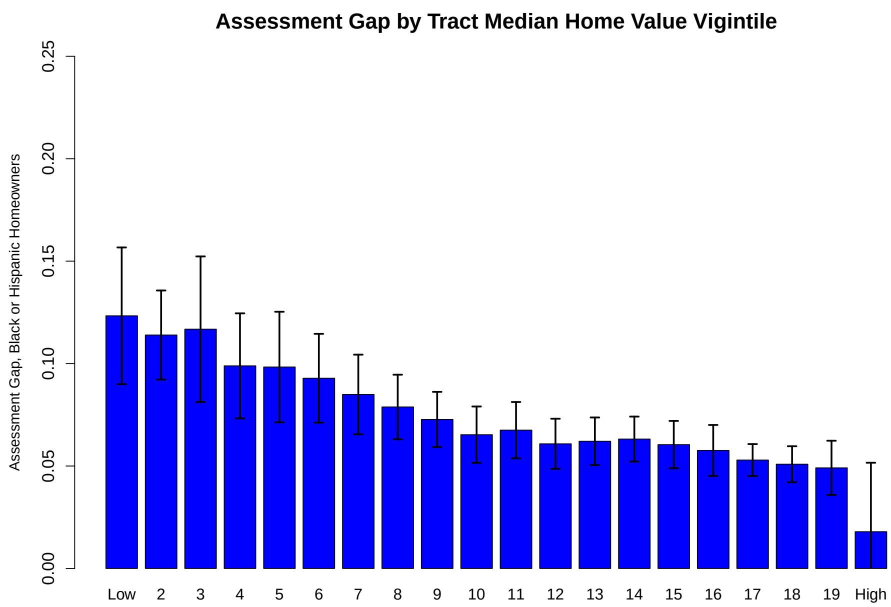
Note: In each panel, we assign counties to deciles by a county-level segregation measure, constructed from tract-level demographics from the 2000 Decennial Census. It is a stylized fact that larger counties have more segregation. As a result, the lowest deciles have substantially fewer observations than higher deciles. We estimate inequality separately in each decile following Equation 1. Full regression output is available in our Online Appendix.

Figure 6: Assessment Gap by Neighborhood Home Value

Panel A: Black Homeowners

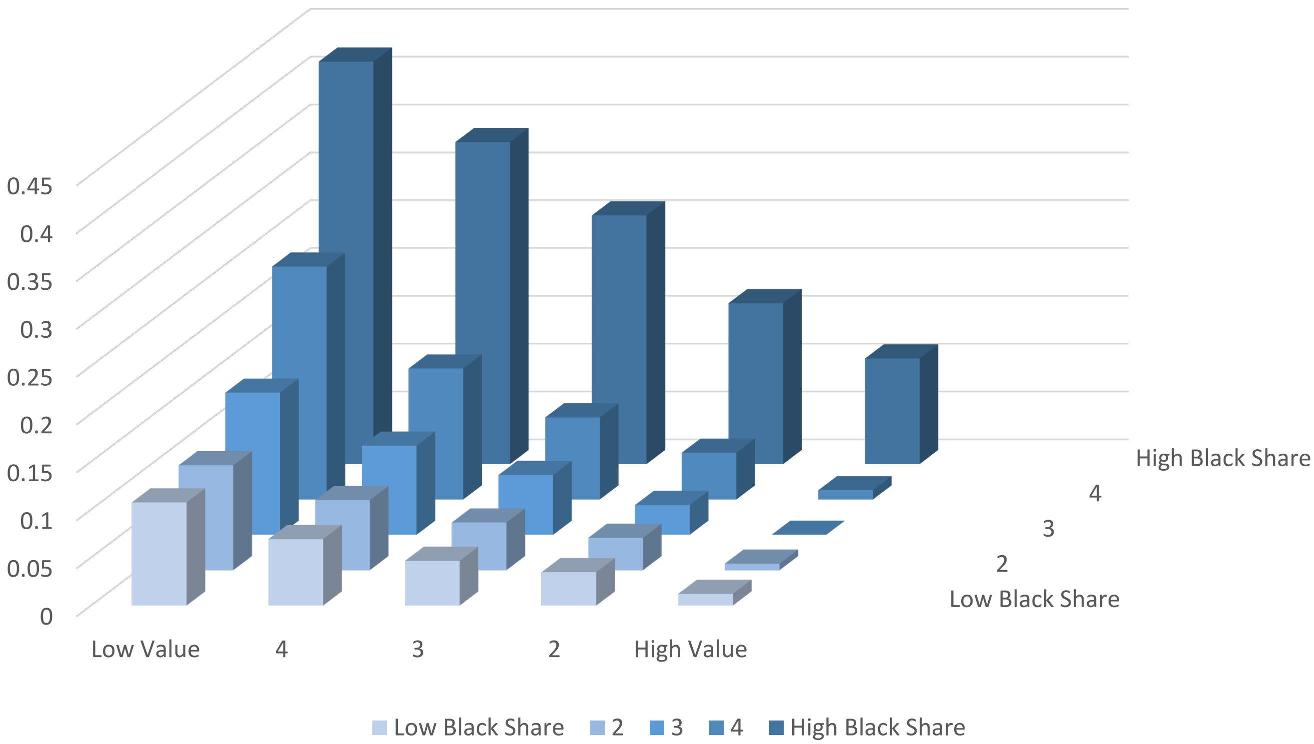


Panel B: Black or Hispanic Homeowners



Note: This figure presents tract-level average assessment gaps by neighborhood-level home values. In each panel, we assign tracts to each of 20 quantiles based on the tract-level distribution of median home value.

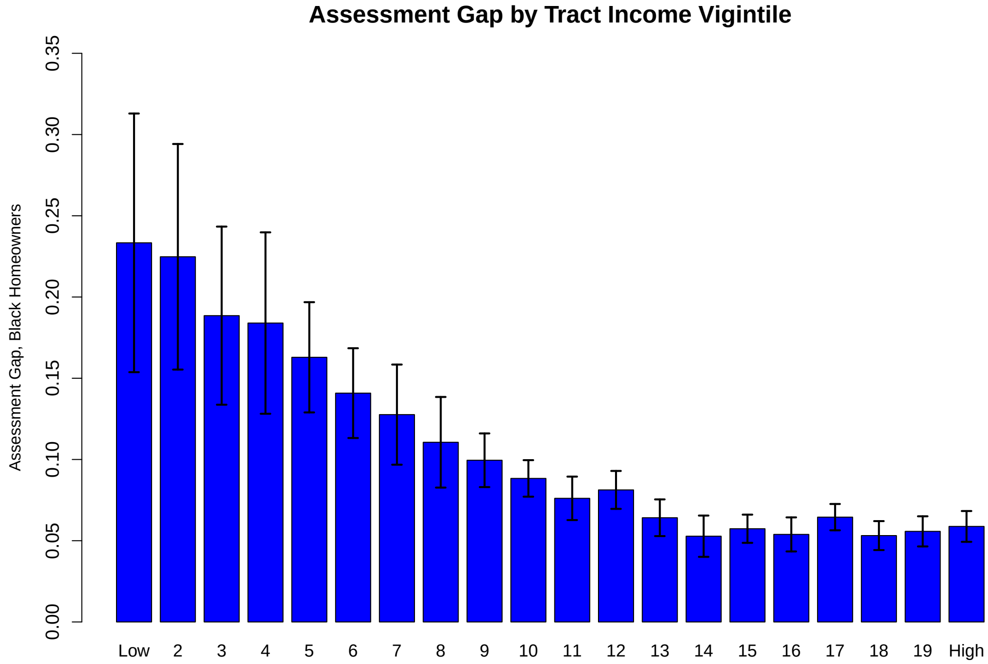
Figure 7: Average “Excess” Assessment by Demographics and Neighborhood Home Value



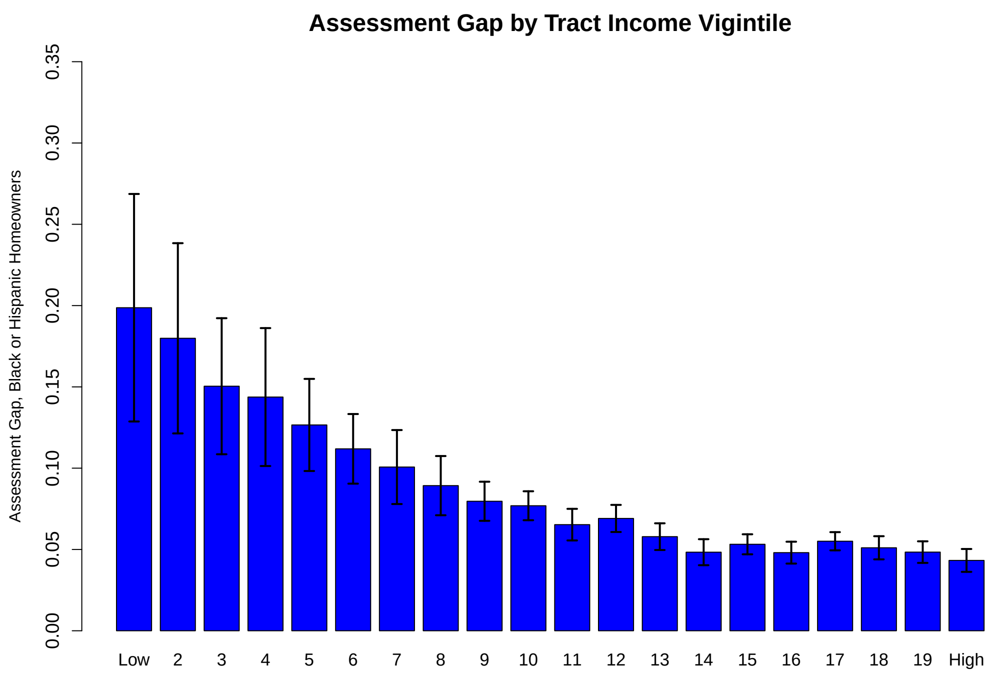
Note: This figure splits neighborhoods into quantiles based on median home value using tract-level measures from the ACS and, within each quantile, splits homes by neighborhood demographic share. Using a pooled regression, we estimate “excess” assessment – i.e., assessment ratio deviation from taxing jurisdiction-year average – for each bin.

Figure 8: Assessment Gap by Neighborhood Income Quantile

Panel A



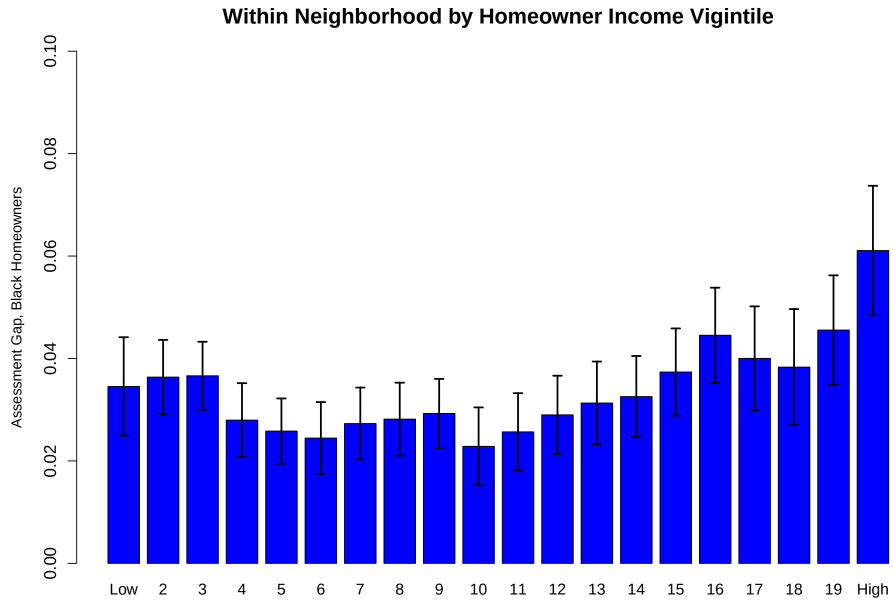
Panel B



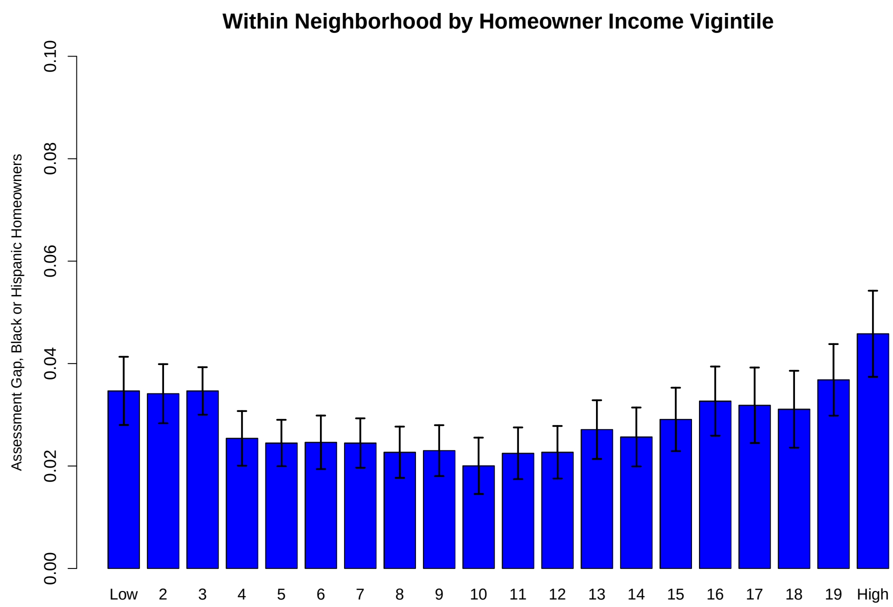
Note: This figure presents tract-level average assessment gaps by neighborhood-level income. In each panel, we assign tracts to each of 20 quantiles based on the tract-level distribution of median income.

Figure 9: Assessment Gap by Homeowner Income Quantile

Panel A: Black Homeowners



Panel B: Black or Hispanic Homeowners



Note: In each panel, we assign tracts to each of 20 quantiles based on homeowner reported income in HMDA records.

Table 1: Balance Table for Sample Construction

Tract or Property Attribute	Observed Transaction	Merge to HMDA
Panel A: Property Features		
Square Feet	-29.85883***	-10.37782***
	(1.79071)	(2.96618)
# Baths	0.01367***	0.0158***
	(0.00181)	(0.00341)
Year Built	0.96571***	1.7324***
	(0.23695)	(0.11026)
Patio or Porch (Binary)	-0.00516***	0.00906***
	(0.00060)	(0.00096)
Pool (Binary)	-0.00652***	0.00933***
	(0.00047)	(0.00071)
Fireplace (Binary)	-0.01475***	0.02363***
	(0.00082)	(0.00127)
Number of Stories	0.00318***	0.03054***
	(0.00149)	(0.00211)
Panel B: Neighborhood Attributes		
Population Share Black	-0.00379***	-0.00657***
	(0.00064)	(0.00113)
Population Share Non-White	-0.00318***	-0.00642***
	(0.00063)	(0.0012)
Population Share Black or Hispanic	-0.00503***	-0.00668***
	(0.00085)	(0.00136)
Population Share White	0.00421***	0.00616***
	(0.00078)	(0.00133)
Population (log)	0.00657***	0.01472***
	(0.00101)	(0.0014)
Owner Percentage	-0.00395***	0.00703***
	(0.00045)	(0.0006)
Median Age (Yrs)	-0.08956***	-0.15295***
	(0.01747)	(0.05312)
Median Year Purchased	0.28292***	0.08712***
	(0.01839)	(0.01941)
Median Home Value (log)	0.00696***	0.01448***
	(0.00156)	(0.00261)
Median HH Income (log)	0.00236***	0.02008***
	(0.00105)	(0.00207)
Unemployment Rate	-0.00044***	-0.00177***
	(0.00011)	(0.00024)
Not In Labor Force Share	-0.00107***	-0.00386***
	(0.00023)	(0.00044)
Gini Coefficient	0.00072***	-0.00247***
	(0.00014)	(0.0002)
Share SNAP	-0.00119***	-0.00471***
	(0.00022)	(0.00059)
Panel C: Valuation		
Transaction Price (log)	–	0.03896***
		(0.00469)
Assessment Ratio (log)	–	0.00932***
		(0.00185)
Note:		*p<0.1; **p<0.05; ***p<0.01

Note: This table reports OLS estimates relating to sample selection on two margins. Column (1) compares the set of observed transactions with a 20% sample of properties which do not transact. Column (2) compares cleaned assessment ratios that can be associated with race and ethnicity (via HMDA) with cleaned assessment ratios that are not matched. For each row in both columns, the dependent variable is a dummy variable equal to 1 if an observation enters the relevant sub-sample, and 0 otherwise. All estimates include jurisdiction-year fixed effects. Errors clustered at the jurisdiction level.

Table 2: Baseline Assessment Gap Estimate

	log(Assessment Ratio)		
	(1)	(2)	(3)
Panel A: Black Homeowners			
Black Mortgage Holder	0.1266***	0.0640***	0.0588***
	(0.0150)	(0.0020)	(0.0019)
Panel B: Black or Hispanic Homeowners			
Black or Hispanic Mortgage Holder	0.0984***	0.0530***	0.0485***
	(0.0106)	(0.0015)	(0.0014)
Fixed Effects	Jurisd-Year	Jurisd-Tract-Year	Jurisd-BG-Year
No. Clusters	37723	37723	37723
Observations	6,987,915	6,987,915	6,987,915
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: This table shows our baseline findings of a racial assessment gap. Panel A presents our results for Black homeowners, and Panel B presents our results for Black or Hispanic homeowners. We regress the log assessment ratio on a set of fixed effects at the year $\times$ geography level and on categorical groupings by racial and ethnic identity. Columns (1), (2), and (3) show results using fixed effects at the jurisdiction-year, jurisdiction-tract-year, and jurisdiction-block group-year level, respectively. In all columns, the reference group is non-Hispanic White residents, and for clarity coefficients for groups not being considered in a given column are not reported. The estimates in this table reflect an assessment ratio differential for the given grouping of minority residents relative to non-Hispanic White residents. Standard errors are clustered at the jurisdiction level.

Table 3: Effective Tax Rate, Sale Year

	Effective Tax Rate - In Sale Year (%)					
	Assmt. Gap	Before Exemptions	Tax Bill	Assmt. Gap	Before Exemptions	Tax Bill
	(1)	(2)	(3)	(4)	(5)	(6)
Black Mortgage Holder	12.9048***	14.6577***	15.0242***			
	(1.6993)	(1.6639)	(1.6245)			
Black or Hispanic Mortgage Holder				9.7134***	11.1112***	11.4488***
				(1.2502)	(1.2029)	(1.1553)
Jurisd-Year FE	Y	Y	Y	Y	Y	Y
No. Clusters	29242	29242	29242	29242		
Observations	5,574,777	5,574,777	5,574,777	5,574,777	5,574,777	5,574,777
R^2	0.8857	0.6755	0.6405	0.8856	0.6753	0.6403
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This table repeats our baseline estimation, but uses effective tax rate as the dependent variable instead of assessment ratio. Coefficients are percentages. For each racial and ethnic grouping, we present two sets of results. In odd columns, we show results using an effective rate computed using the gross (preexemption) tax bill and observed market value in the same year. In even columns, we compute a postexemption effective tax rate, by subtracting reported exemptions from the observed tax bill, and then dividing by market value. We trim any observation above a calculated effective tax rate of 25% both before and net of exemptions. We believe this to be a conservative choice as 25% is far higher than any property tax rate of which we are aware (the national median is approximately 1.4%), and is more likely than not to be a data error. All specifications use jurisdiction-year fixed effects to hold constant the level of intended taxation. Standard errors are clustered at the jurisdiction level.

Table 4: Racial Differential in Transacted Prices

	Unexpected Component of Transaction Price	
	(1)	(2)
Black Seller	0.022***	
	(0.002)	
Black or Hispanic Seller		0.033***
		(0.002)
Fixed Effects	Jurisd-BG-Yr	Jurisd-BG-Yr
No. Clusters	18854	18854
Observations	2,135,966	2,135,966
Note:		*p<0.1; **p<0.05; ***p<0.01

Note: This table shows results from regressing the log difference of realized market price and predicted market price on a block-group-year fixed effect and categorical groupings by racial and ethnic identity. In all columns, the reference group is non-Hispanic White residents, and for clarity coefficients for groups not being considered in a given column are not reported. The estimates in this table reflect a racial differential in transaction prices net of predicted price. The predicted price is generated using ZIP code level home price indexes. Standard errors are clustered at the jurisdiction level.

Table 5: Assessment Gap with Attribute-Price Controls

	log(Assessment Ratio)						
	Baseline	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Attributes And Jurisdiction (Not Interacted)						
Black Mortgage Holder	*0.1201****	0.1189***		0.1201***		0.1201***	
	(0.0082)	(0.0081)		(0.0082)		(0.0082)	
Black or Hispanic Mortgage Holder	*0.0920****		0.0915***		0.0920***		0.0920***
	(0.0056)		(0.0055)		(0.0056)		(0.0056)
	Panel B: Attributes × Jurisdiction						
Black Mortgage Holder	*0.1201****	0.1092***		0.1195***		0.1218***	
	(0.0082)	(0.0081)		(0.0087)		(0.0093)	
Black or Hispanic Mortgage Holder	*0.0920****		0.0852***		0.0910***		0.0921***
	(0.0056)		(0.0053)		(0.0060)		(0.0065)
	Panel C: Attributes × Tract						
Black Mortgage Holder	*0.0675****	0.0562***		0.0602***		0.0553***	
	(0.0022)	(0.0020)		(0.0023)		(0.0023)	
Black or Hispanic Mortgage Holder	*0.0559****		0.0463***		0.0494***		0.0454***
	(0.0016)		(0.0015)		(0.0017)		(0.0017)
	Panel D: Attributes × Block Group						
Black Mortgage Holder	*0.0614****	0.0484***		0.0530***		0.0475***	
	(0.0021)	(0.0018)		(0.0021)		(0.0020)	
Black or Hispanic Mortgage Holder	*0.0510****		0.0409***		0.0440***		0.0400***
	(0.0015)		(0.0013)		(0.0015)		(0.0016)
Price FE	Baseline	Att. Bin	Att. Bin	200Q	200Q	500Q	500Q
No. Clusters	25798	25798	25798	25798	25798	25798	25798
Observations	4,674,430	4,674,430	4,674,430	4,674,430	4,674,430	4,674,430	4,674,430

Note: *p<0.1; **p<0.05; ***p<0.01

Note: This table shows our baseline findings of a racial assessment gap controlling for attributes of the property and attribute-implied home value. Panel A presents results controlling for attributes of the property and attribute-implied home value without intersecting these with geographic fixed effects. Panel B controls for attributes of the property and attribute-implied home value intersected with jurisdiction-year fixed effects. Panel C controls for attributes of the property and attribute-implied home value intersected with tract-year fixed effects. Panel D controls for attributes of the property and attribute-implied home value intersected with block group-year fixed effects. In all specifications, we regress the log assessment ratio on geography-year fixed effects and on categorical groupings by racial and ethnic identity. Baseline estimates are presented on the left for ease of interpretation. Columns (1) and (2) control for attributes using attribute fixed effects. Columns (3) and (4) use 200 attribute-implied home value bins as fixed effects, as constructed in §§B.iv of the Data Appendix. Columns (5) and (6) use 500 attribute-implied home value bins as fixed effects. Columns (1), (3), and (5) present results for Black homeowners only. Columns (2), (4), and (6) present results for Black and Hispanic homeowners. In all columns, the reference group is non-Hispanic White residents, and for clarity coefficients for groups not being considered in a given column are not reported. The estimates in this table reflect an assessment ratio differential for the given grouping of minority residents relative to non-Hispanic White residents. Standard errors are clustered at the jurisdiction level.

Table 6: Race and Demographic Shares

	log(Assessment Ratio)	
	(1)	(2)
Black Mortgage Holder	0.079***	
	(0.004)	
Black Share	0.299***	
	(0.046)	
Black or Hispanic Mortgage Holder		0.067***
		(0.003)
Black or Hispanic Share		0.277***
		(0.042)
Fixed Effects	Jurisd-Year	Jurisd-Year
No. Clusters	37679	37679
Observations	6,944,439	6,944,439
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: This table augments our baseline assessment gap findings in Table 2 with one measure of spatial variation: tract-level demographic shares. We regress the log assessment ratio on a jurisdiction-year fixed effect, categorical groupings by racial and ethnic identity, and tract-level demographic shares from the American Community Survey. In all columns, the reference group for mortgage holder race and ethnicity is non-Hispanic White residents, and for clarity other mortgage holder coefficients are not reported. The mortgage holder coefficients in this table reflect an assessment ratio differential for the given grouping of minority residents relative to non-Hispanic White residents. The share coefficients represent additional variation in the assessment ratio that correlates with demographic composition of the surrounding tract, holding mortgage holder race fixed. Standard errors are clustered at the jurisdiction level.

Table 7: Assessment Gap by Reassessment Cycle

	log(Assessment Ratio)								
	1yr	2yrs	3yrs	4yrs	5yrs	6yrs	8yrs	9yrs	none
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Black Homeowners									
Black Mortgage Holder	0.1081***	0.1113***	0.1855**	0.1277***	0.1565***	0.1919***	0.1202***	0.1231***	0.2502***
	(0.0078)	(0.0337)	(0.0833)	(0.0186)	(0.0250)	(0.0323)	(0.0156)	(0.0224)	(0.0447)
Panel B: Black or Hispanic Homeowners									
Black or Hispanic Mortgage Holder	0.0898***	0.0892***	0.1420***	0.1017***	0.1055***	0.1504***	0.1026***	0.1096***	0.1970***
	(0.0056)	(0.0189)	(0.0530)	(0.0117)	(0.0206)	(0.0300)	(0.0142)	(0.0226)	(0.0449)
Fixed Effects	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year
No. Clusters	11686	3867	4424	7887	5639	5636	1783	66	2358
Observations	2,437,030	701,784	880,924	558,264	863,890	545,436	231,146	35,077	68,180

Note: *p<0.1; **p<0.05; ***p<0.01

Note: This table shows our findings of a racial assessment gap in areas with different reassessment cycles. Panel A presents our results for Black homeowners, and Panel B presents our results for Black or Hispanic homeowners. In all specifications, we regress the log assessment ratio on jurisdiction-year fixed effects and on categorical groupings by racial and ethnic identity. Columns (1)–(8) present results for areas with a reassessment cycle in place but with varying cycle lengths. Column (9) presents results for areas with no reassessment cycles in place. In all columns, the reference group is non-Hispanic White residents, and for clarity coefficients for groups not being considered in a given column are not reported. The estimates in this table reflect an assessment ratio differential for the given grouping of minority residents relative to non-Hispanic White residents. Standard errors are clustered at the jurisdiction level.

Table 8: Cook County Appeals

	Dependent Variable:				
	Assessment Ratio/BG (%)	Appeal	Win Appeal	Reduction	Total Effect
	(1)	(2)	(3)	(4)	(5)
	Panel A: Black Homeowners				
Black Mortgage Holder	5.231***	−1.075***	−2.243***	−0.478***	−0.202***
	(0.585)	(0.104)	(0.368)	(0.119)	(0.021)
	Panel B: Black or Hispanic Homeowners				
Black or Hispanic Mortgage Holder	5.118***	−1.158***	−2.054***	−0.259***	−0.161***
	(0.426)	(0.080)	(0.254)	(0.075)	(0.014)
Baseline Rate	NA	14.6	67.4	12.0	N/A
Fixed Effects	BG-Year	BG-Year	BG-Year	BG-Year	BG-Year
No. Clusters	426	3954	3924	3881	3954
Observations	141,535	3,072,521	617,157	441,424	3,071,538

Note: *p<0.1; **p<0.05; ***p<0.01

Note: This table uses administrative microdata on property tax appeals in Cook County. Column (1) shows the baseline within-block group assessment gap in Cook County. Column (2) shows unconditional propensity to appeal. Column (3) conditions on a homeowner having filed an assessment appeal. Column (4) conditions on a successful appeal. Column (5) estimates the total impact of appeals on inequality within tax year. In columns (2) and (3), the dependent variable is a binary indicator. In column (4), the dependent variable is the reduction amount divided by the proposed assessment. In column (5), the dependent variable is the log difference between pre-appeal and post-appeal assessments. Homeowners who don't appeal are assumed to have zero change. Fixed effects across all columns are at the block-group-year level. Standard errors are clustered at the block-group level. The baseline rates for (i) appeal propensity, (ii) winning appeal, and (iii) reduction conditional on a successful appeal are reported in the first line below the estimates. Coefficients and baseline rates are reported as percents.

Table 9: Sample Split by Racial Attitudes

	log(Assessment Ratio)				
	Baseline	By Media Market		By State	
	(1)	(2)	(3)	(4)	(5)
Black Mortgage Holder	0.128***				
	(0.015)				
Black, High Animus		0.150***	0.070***	0.145***	0.076***
		(0.022)	(0.003)	(0.011)	(0.003)
Black, Low Animus		0.084***	0.055***	0.106***	0.049***
		(0.008)	(0.002)	(0.033)	(0.002)
Wald Test F-Stat	N/A	8.13	14.55	1.24	55.61
Fixed Effects	Jurisd-Yr	Jursid-Yr	Jurisd-Tract-Yr	Jurisd-Yr	Jursid-Tract-Yr
No. Clusters	37106	37106	37106	37106	37106
Observations	6,856,585	6,856,585	6,856,585	6,856,585	6,856,585
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: This table shows results of using the measures of racial animus described in Stephens-Davidowitz (2014) to split our sample into regions of above- and below-median prejudice. Column 1 shows baseline results before splitting the sample. Columns 2 and 3 use a media-market measure of animus. We use a Nielsen crosswalk to associate media markets with individual counties. Columns 4 and 5 use a state-level measure of animus. For each measure, the first result (column 2 or 4) shows the overall assessment gap. The second result shows the homeowner effect estimated within jurisdiction-tract-year. For all specifications, standard errors are clustered at the jurisdiction level.

Table 10: Assessment Gap by Year

	log(Assessment Ratio)											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Black Homeowners												
Black Mortgage Holder	0.0309***	0.0354***	0.0844***	0.1765***	0.1914***	0.1701***	0.1628***	0.1822***	0.1497***	0.1691***	0.1254***	0.1077***
	(0.0082)	(0.0084)	(0.0111)	(0.0217)	(0.0334)	(0.0339)	(0.0244)	(0.0283)	(0.0116)	(0.0316)	(0.0089)	(0.0100)
Panel B: Black or Hispanic Homeowners												
Black or Hispanic Mortgage Holder	−0.0001	0.0190***	0.0586***	0.1526***	0.1637***	0.1334***	0.1293***	0.1375***	0.1093***	0.1208***	0.0842***	0.0724***
	(0.0075)	(0.0068)	(0.0086)	(0.0150)	(0.0194)	(0.0224)	(0.0182)	(0.0197)	(0.0080)	(0.0221)	(0.0056)	(0.0064)
Fixed Effects	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year
No. Clusters	14683	15799	16563	15456	16457	17749	18177	18963	18719	19756	24269	15898
Observations	666,184	609,361	579,293	489,501	524,133	473,830	502,070	522,700	584,978	561,824	820,940	648,098

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: This table shows our findings of a racial assessment gap by year. Panel A presents our results for Black homeowners, and Panel B presents our results for Black or Hispanic homeowners. In all specifications, we regress the log assessment ratio on jurisdiction-year fixed effects and on categorical groupings by racial and ethnic identity. In all columns, the reference group is non-Hispanic White residents, and for clarity coefficients for groups not being considered in a given column are not reported. The estimates in this table reflect an assessment ratio differential for the given grouping of minority residents relative to non-Hispanic White residents. Standard errors are clustered at the jurisdiction level.

Online Appendix
The Assessment Gap: Racial Inequalities in Property Taxation

Carlos F. Avenancio-León Troup Howard

December 2021

A. Equitable Tax Null

We formalize the intuition behind our null hypothesis of an equitable tax as follows. We consider first a property tax system that does not establish individual tax exemptions, and then show the theory easily incorporates an arbitrary exemption structure. Let i denote property, j taxing jurisdiction, and t year. Further, let V^* be the true value of the property being taxed. Given an intended rate of taxation r_{jt}, by definition an ad valorem tax must satisfy:

$$equitable\ tax_{ijt} = r_{jt} V^*_{ijt}. \tag{1}$$

Note that r is an effective tax rate. Let c be the local target assessment ratio, and let r^{pol} be the policy tax rate that rationalizes equation 1: $r_{jt} = r^{pol}_{jt} c_{jt}$. This last equation simply reflects that if assessments are deliberately scaled to be half of market value, the policy rate must double in order to achieve the level of tax burden implied by r.

Property tax bills are generated by applying the policy rate to an assessed valuation, A_{ijt}:

$$actual\ tax_{ijt} = r^{pol}_{jt} A_{ijt}. \tag{2}$$

Our equitable tax null is simply that $actual\ tax_{ijt} = equitable\ tax_{ijt}$. We observe A_{ijt}, the realized assessed valuation assigned to the house. We observe market prices for homes, M_{ijt}, and accordingly will let $M_{ijt} = V^*_{ijt}$.[1] Equating 1 and 2, and taking logs yields a necessary condition for equitable administration of an ad valorem tax:

$$ln(A_{ijt}) - ln(M_{ijt}) = ln(c_{jt}) := \gamma_{jt} \qquad \forall i. \tag{3}$$

Equation 3 is a theoretical statement that does not allow any errors at all in assessments.

Empirically, we define a deviation from our fair tax benchmark in context of arbitrary delineations. Partition the homes of any jurisdiction into M subsets, and denote by $m \in \{1, 2...M\}$. Let $\bar{c}_{mjt} := \frac{1}{N} \sum_{i \in m} c_{ijt}$. Our fair taxation null is:

$$\bar{c}_{mjt} = \bar{c}_{m'jt} \qquad \forall m, m'. \tag{4}$$

Equation 3 states that assessment ratios should not vary at all within jurisdiction. While strictly true, this represents unattainable precision. Equation 4 says that average assessment ratios should not vary within jurisdiction for any arbitrary group. Our central estimating equation is the empirical counterpart of the theoretical statement:

$$ln(A_{ijt}) - ln(M_{ijt}) = \gamma_{jt} + \beta^r race_{ijt} + \epsilon_{ijt}. \tag{5}$$

[1] It is worth reiterating that state laws regularly and explicitly state that property taxation should be levied upon the "fair cash value" that would be received in an arm's-length transaction. Therefore, our reliance on market prices is not a strong statement about market efficiency, but rather a reflection of the legal intent underlying the taxation.

Here *race* is a vector of indicator variables for racial and ethnic groups. The fixed effect γ_{jt} absorbs the realized average assessment ratio within jurisdiction. Then, since *race* is a categorical variable, β^r is a vector of estimated group-level deviations from average realized assessment ratio.

The derivation above abstracts away from tax exemptions. As noted in Section 2.1 of the paper, most jurisdictions establish individual-level criteria for tax exemptions. Incorporating these exemptions, the expressions for equitable tax and actual tax bills become:

$$actual\ tax_{ijt} = r^{pol}_{jt}(A_{ijt} - E_{jt}(i)) \tag{6}$$

$$equitable\ tax_{ijt} = r_{jt}(V^*_{ijt} - E^*_{jt}(i)). \tag{7}$$

$E_{jt}(i)$ is the homeowner-level exemption established by law, and is written as a function of i to highlight dependency on personal characteristics (e.g. age or residency status). $E^*_{jt}(i)$ is the corresponding portion of the market value shielded by tax. This differs from E_{jt} only due to the scaling factor c_{jt}. If assessments in a given jurisdiction are done at 50% of market value, an exemption that reduces assessed value by \$10,000 corresponds to a reduction in market value of \$20,000: $E^*_{jt} = c_{jt}E_{jt}$. Given this relationship, the equitable tax benchmark implied by equations 6 and 7 is equivalent to equation 3.

B. Data Construction

B.i Taxing Jurisdictions

Local governments are highly spatially complex. Across the U.S. more than 75,000 entities potentially impose a property tax. Homeowners typically face taxation from multiple local units simultaneously. Cities and counties are key examples of local government units. However, it is very common for regions to have a range of separate autonomous taxing entities. Chief examples here are: school districts, park districts, and municipal utility districts. Taxing authority may also be embedded in a special purpose district like an airport authority or regional economic development initiative. As a rule, the boundaries of these units are not naturally coincident. Counties are a complete partition of space in the US: every point in a given state lies in exactly one county. However, no such logical precision applies to other local entities. Cities often lie across county boundaries. In low-population-density areas, school districts often cover multiple towns (and potentially portions of different counties); in urban areas, there may be multiple school districts within a given metropolitan region. Units like park districts or utility districts typically have a delineation governed by a service area that reflects physical geography and may have little to do with nearby civic boundaries. Excluding state governments, the average home in the United States is touched by 4.5 local entities, all of which potentially levy a property tax.[2]

Panel A of Figure A1 illustrates our approach in a stylized example. There are three govern-

[2] Author's calculations using Atlas Muni Data shapefiles.

ments in this example: the county, which contains a city and an independent school district. The city and the school district have partial overlap. This spatial overlay of governments generates 4 taxing jurisdictions. Jurisdiction one contains those homes which receive services from, and are taxed by, the county alone. Homes in jurisdiction two are served and taxed by both the county and the city; homes in jurisdiction three are served and taxed by all governments; and homes in jurisdiction four are served and taxed by the school district and the county. Panel B of Figure A1 highlights our focus on within-jurisdiction inequality. In this stylized example, the county realizes assessment ratios of either 50% or 20%. This generates inequality in the taxing jurisdiction comprised of just the county: there is large (binary) variation in assessment ratio. This does not generate inequality in the jurisdiction served by both the city and the county: everyone paying taxes and receiving public services in this region has the same assessment ratio. For any cross-jurisdiction comparisons, we cannot rule out Tiebout sorting along preferences for public goods or intended levels of property tax. Our focus is solely on inequality between residents who are subject to the same set of taxes and who have access to the same bundle of public goods.

The example in Panel A of Figure A1 is, in fact, quite common across the county. However, jurisdictions can be complex, especially in more urban regions. Figure A2 shows the example of Harris County, Texas. Including the county, there are 12 local units of government which overlap in varying combinations. Each combination forms a distinct jurisdiction. One such jurisdiction is the region defined by the nexus of all 12 governments (this region is not visually identifiable in Figure A2). In our full sample, we observe a market transaction (paired with an assessment) for approximately 100 homes within this particular jurisdiction. This is a relatively small jurisdiction. Others are the size of cities and encompass tens of thousands of home transactions.[3]

While our jurisdictions have both a natural economic and political interpretation, it is certainly reasonable to wonder whether our results are driven in any way by the partitioning of geography. We can test this fairly directly. Practically speaking, assessments are most commonly done at the county level. Often this is a provision of state law, but even when not required, it seems that either custom or natural considerations of efficiency and resource management often result in counties "owning" assessments. While it does not make any sense to compare effective tax rates within county (because so many sub-county units impose other property taxes and provide services), if target assessment ratios are unlikely to vary within county, we can meaningfully compare assessment ratios within county instead of within jurisdiction. In Section C., we show that our baseline results establishing racial differences in assessment ratio are robust to conducting our analysis within county. Within county estimations, in fact, generate slightly higher estimates. Our preferred specifications all use the more rigorous partitioning into jurisdictions of unique overlapping governments.

[3] In some regions, all substate units of government are spatially aligned; Philadelphia is one such example: the county and city of Philadelphia, along with the school system, are all entirely coincident. This is relatively rare.

B.ii Constructing Assessment Ratios

We obtain property-level records for both market transactions and assessed valuations from ATTOM Data Solutions. We use two linked datasets from ATTOM: (i) the Recorder Deeds data, which contains the near universe of real estate transactions; and (ii) the Assessor/Tax data, which contains an annual panel of property attributes including property assessments for the near-universe of residential properties.

We construct property-level assessment ratios as follows. Transactions are identified by a date-of-sale and a unique (static) property identifier. Starting from every residential transaction listed in the Recorder data, we exclude: (i) any transaction other than a resale, (ii) any transaction flagged as a partial sale, and (iii) any transaction for less than full consideration. We also exclude any record with zero reported transaction value.[4] We further remove any property for which multiple transaction records exist for the same day, unless the price information is exactly duplicated.[5] The result is 124M resale observations spanning 59.8M distinct properties.

For each of these properties, we then pull the full time-series of assessed valuations, each associated with an assessment year in the underlying administrative records. We remove properties with missing assessment information, along with any records which duplicate over property and assessment year while diverging on assessment value. We then merge the assessment and transaction records by property ID and year. In the recorder data, year comes directly from transaction date; and in the assessment data, year comes from the stated assessment year. Assessment ratios are formed as assessed value divided by market (transaction) value. We restrict attention to assessment ratios from 2005 onward, to match availability of tract-level data from the American Community Survey 5-year estimates.[6] As described in the paper, we remove California properties from our core dataset.[7] At this stage, we have 28.8M assessment ratios associated with 21.7M unique properties.

We implement the following final cleaning steps: (i) remove any property which we are unable to match to a census tract, (ii) remove any property for which the sale value is less than $500, (iii) remove any property which we are unable to associate with government shapefiles, (iv) remove any property with a residential classification other than: single family home, condominium, duplex, or apartment, (v) trim any observation with an assessment ratio less than 3 or 0.01.[8] Collectively, these steps remove 4.3M observations spanning 3.0M properties from our final sample. We are left with 24.5M assessment ratios associated with 18.6M properties.

[4] Several states either do not mandate disclosure of sales price, or do not distribute the records publicly.

[5] This occurs in 0.8% of the properties that transact.

[6] This restriction removes 5.8 million assessment ratios from 2003-2004. The ATTOM assessor records extend back to 2003. The recorder data extends back substantially further into the 1900s; counts become substantially lower prior to the late 1980s.

[7] This removes 4.19M transactions spanning 3.10M properties. Standalone results for CA are presented in this Online Appendix in Section C..

[8] There are regions which target assessment ratios of 10% or less. We are unaware of any region targeting a ratio exceeding 100%. This step removes 1.2M observations across 1.0M properties.

B.iii Associating Assessment Ratios with Homeowner Race and Ethnicity

To establish homeowner race and ethnicity, we merge the ATTOM dataset with Home Mortgage Disclosure Act (HMDA) records. These records include HMDA applies to financial institutions meeting certain criteria – the major one being an asset threshold which is currently $46M for depository institutions and $10M for for-profit mortgage lenders. During the 2005–2016 period we consider, between 6,900 and 8,900 institutions reported loans ranging in number from 14.3 to 33.6M annually.[9]

HMDA loan records are identified by: year, census tract, lender name, and dollar amount (rounded to thousands). The ATTOM data contains: transaction date, latitude and longitude of the property, lender name, and dollar amount. We restrict our sample to the highest quality matches, requiring an exact match on year (permitting a one-month overlap between December and January), an exact match on tract, an exact match on (rounded) transaction amount, and a fuzzy string match on lender name. The diversity of retail-outlet names within a single financial institution can make exact string-matching a challenge in some regions. We rely on a natural language algorithm developed by the Real Estate and Financial Markets Laboratory at the Fisher Center for Real Estate and Urban Economics to match names. The algorithm trains itself within region on perfect singleton matches across all variables other than name, and then uses that mapping to assign a confidence index to each HMDA-ATTOM string-pairing.

Our central challenge is that HMDA records pin down the race and ethnicity of the individual establishing a mortgage. We wish to associate assessment ratios with the race and ethnicity of the home *seller*, since this is the owner at the time when the relevant assessment was generated. We proceed as follows. For every property in the final sample of assessment ratios (described in prior section), we extract *every* transaction associated with that property. We match each transaction to a HMDA record, if possible. Out of the 18.6M properties in the final set of cleaned assessment ratios, we are able to match 14.7M properties to at least one HMDA record.

For every transaction denoted in ATTOM as "resale" or "refinance," we associate the property with primary applicant's race and ethnicity listed in HMDA, for the transaction year. We code race and ethnicity as unknown for any resale or refinancing transaction which does not match the HMDA data, for any instance where the HMDA record itself reflects unknown race or ethnicity, or for any instance where multiple HMDA records match a single transaction and conflicting race and ethnicity information is given.[10] For multiple transactions within a year, we associate race and ethnicity with each transaction (including the unknown designation, as necessary) and then sort by date so that we have race/ethnicity at both year beginning and year end.

This leaves us with an incomplete panel of property-year-race/ethnicity observations. We transform this into a complete panel by filling race/ethnicity, including the unknown designation: (i)

[9] Summary statistics from www.ffiec.gov.

[10] This latter case does not necessarily denote an error. It could arise, for instance, from applicant and co-applicant switching on a given loan record. In the case of two records, one of which has missing race/ethnicity information, we do use the data from the populated record.

forward from resale transactions until the next observed transaction, and (ii) filling backwards from refinance transactions until a previously observed transaction. When multiple transactions occur within a year, we fill forward from the last transaction, and backward from the first transaction (only if that first transaction is a refinance).

Finally, using the sample described in Section B.ii, we associate each assessment ratio arising from a transaction in year t with the race and ethnicity of the homeowner in year $t-1$. For public officials, producing assessments is a process of designing and validating a model, disseminating new values to homeowners, and often allowing for a set period for homeowners to appeal assessments before they are final. All of this takes time, which means that assessments applying to tax year t are, in general, produced towards the end of year $t-1$: therefore the relevant race/ethnicity for a home selling in year t is the race/ethnicity of the individual who owns the home in $t-1$. We exclude from our sample homes that sell in year t and also in year $t-1$, because multiple homeowners in year $t-1$ means that we cannot be sure which individual owned the home when the assessment was generated (we observe only the year of the assessment, not a precise date of estimation). We do not use observations with unknown race/ethnicity in our regressions.

The result is 6.99M observations spanning 6.11M homes. The major factor driving the reduction from 14.7 million properties which we match to HMDA is the need to observe two transactions in order to pin down race/ethnicity of home seller: either two sales, or a refinance transaction preceding a sale. Our sample is roughly evenly split between these two cases.

B.iv Attribute-Bundle Fixed Effects and Attribute-Implied Prices

We extract the following property-level characteristics from the assessor portion of the ATTOM dataset: square footage of livable space on the property, number of bathrooms, number of stories, year built, and three separate indicators for the presence of a pool, patio, and fireplace. We trim the sample to remove outliers, restricting attention to properties with fewer than 20 bedrooms, fewer than 20 bathrooms, less than 50,000 square feet, and less than 10 stories. This removes less than half a percent of available observations. We exclude any observations listing zero square feet, both zero bedrooms and zero bathrooms, or a number of stories greater than the total number of rooms, as well as any observation missing information in the six attribute fields.

We create categorical variables from the continuous measures by binning properties. For size: between 0 and 6,000 square feet, cutpoints are every 500 square feet; between 6,000 and 10,000 square feet, cutpoints are every 1,000 square feet; and from 10,000 to 50,000 cutpoints are every 5,000 square feet. For year built: cutpoints are every 10 years; we also group together all homes built before 1900. For bathrooms, cutpoints are: 0, 1, 2, 3, 4, 5, 7, 10, 15, 20.

We then create an overall attribute bundle variable by interacting: square footage bin, bathrooms bin, year built bin, and each of the three amenity indicators. This yields 5,450 distinct attribute-bundle fixed effects, in a sample with 4.67M assessment-ratio observations across 4.11M properties. The reduced sample relative to our baseline dataset is due to missing housing stock attributes in the ATTOM dataset.

We also construct a continuous measure of price based on housing stock attributes. At a high level, this variable is the inner product of a given home's attributes and the implied prices of those attributes:

$$\hat{p}_{ijt} = X'_{ijt}\hat{\beta}^{X}_{t,-s(j)} \tag{8}$$

where X is a vector of property attributes for house i in jurisdiction j during year t. $beta^X$ is a vector of estimated hedonic prices for each attribute. Crucially, these hedonic prices are estimated from transactions in <u>other states</u>, as denoted by $-s$ in the subscript. We write $s(j)$ to make explicit that a taxing jurisdiction defines a state by construction. The resulting price estimate, $\hat{p}$ therefore contains no local market information. Hedonic prices are estimated according to:

$$p_{ijt,-s(j)} = \alpha_{jt} + Z'_{ijt,-s(j)}\beta^{Z}_{t,-s(j)} \tag{9}$$

where $Z = [X\ W]$, is a vector that includes the property attributes X as well as W, the same set of tract-level covariates we use in the hedonic analysis of Section 5.3.1, and $\beta^Z = [\beta^X\ \beta^W]$. That is: for every house, we estimate attribute implied prices from transactions in all other states with a jurisdiction fixed effect, property-level characteristics, and neighborhood-level characteristics as independent variables. We estimate this specification separately for each year. Then, to construct $\hat{p}$, we take only the implied prices for the property attributes and multiply those by actual property characteristics. Without loss of generality, we can omit any jurisdictional scaling, because every subsequent regression using $\hat{p}$ includes a jurisdiction-year fixed effect.

C. Results - Extensions

C.i Additional Baseline Results

Table A1 shows estimates of inequality for all non-Hispanic homeowners identified as a racial minority in HMDA other than Black or Hispanic. The included racial designations in HMDA records are: (i) American Indian or Alaskan Native, (ii) Asian, and (iii) Native Hawaiian or Other Pacific Islander. Column (1) presents inequality within taxing jurisdiction, and columns (2) and (3) estimate inequality within census tract and census block group respectively. Inequality is substantially smaller for this grouping: just below 3% on average within a taxing jurisdiction, and approximately 2% within neighborhoods.

Table A2 shows estimates of inequality for California. Assessment ratios are 4.13% higher for Black homeowners, 10.6% higher considering Black or Hispanic homeowners together, and 6.5% higher for other non-black, non-Hispanic racial minorities. Results are presented separately because of how stringently assessment growth in governed by the provisions of Proposition 13. In this setting, the most relevant restriction is that assessments can grow only at the lessor of inflation or 2% during a given homeowner's tenure. During our sample period, home prices exceeded these caps in the majority of regions.[11] As a result, misalignment between assessed values and market values is largely a mechanical function of homeowner tenure, making a subsequent exploration of how inequality arises less relevant in California. Proposition 13 is a canonical example of an administrative policy creating inequality that correlates with race. Other states impose policies with the potential to cap assessment growth, but California is unique both for its size (if included in the national sample, the 1.8M observations reflected in Table A2 would be 20% of the total) and for the frequency with which the administrative cap binds.[12]

In Table A3, we re-estimate the assessment gap using county-year fixed effects rather than jurisdiction-year. The point of this exercise is to show that our careful partitioning of space into taxing jurisdictions is not somehow mechanically driving our results. Differing levels of intended taxation by cities, towns, schools and others makes a within-county analysis of effective tax rate meaningless. However, counties are most often the entity which produces assessments. We can therefore reasonably consider assessment ratio variation within county-year. The results are very consistent with our baseline finding. Inequality in assessment ratios is approximately 4% higher within-county than it is within-jurisdiction. Our preferred specifications all employ the more rigorous within-jurisdiction analysis, not only because it is more likely to hold local assessment practices fixed, but more importantly because jurisdictions are able to hold fixed intended level of taxation and the set of entities providing public services.

We also split the national sample into quintiles based on minority population share at the county-level. The first quintile contains counties with the smallest minority share and the 5th quintile is comprised of counties with the largest. We estimate the assessment gap in each of these sub-samples. Figure A3 shows results from these regressions graphically, and Table A4 shows the regression estimates. The assessment gap is clearly increasing in minority population share. Since we have shown that a large portion of the assessment gap is linked to spatial sorting, this finding is unsurprising: it has been documented that spatial sorting increases as minority population increases (Card, et. al 2008).

For completeness, Table A5 shows the estimated hedonic prices associated with the results in Figure 4, and Table A6 shows the results of adding the neighborhood-level covariates used in our hedonic pricing analysis to the baseline estimation of the assessment gap. As implied by our findings in Section 5.3.1, spatial variation across the range neighborhood attributes induces misalignment between assessments and market values. The effect of racial demographics is still statistically and economically significant with the inclusion of these other controls; but more importantly, as a consequence of racial segregation in the U.S., exposure to neighborhood traits that generate assessment inequality (as a consequence of assessors failing to mirror the market's pricing of these

[11] Author's calculation using Zillow's zip-code ZHVI index for single family residences, computed January to January.

[12] For example, Oregon's Measure 50 establishes a Maximum Assessed Value that grows at 3% annually. This cap may not bind even with growth above 3%, if home prices have recently declined. Florida's Save Our Homes amendment to the state constitution caps assessment growth at the minimum of 3% or the CPI inflation rate. This policy applies only to properties designated as a homeowner's primary residence.

traits) is highly correlated with race.

Also for completeness, Table A7 shows the regression output underlying Figure 4 in the paper: the assessment gap estimated within deciles of county-level racial segregation.

Our test for racial differences in transaction prices (Table 4) necessarily relies on observing multiple sales, because we take an initial observed sale price, grow that sale price according to a local Home Price Index, and then measure whether race correlates with the difference between expected sale price and realized sale price in a subsequent transaction. Repeat sales are a distinct subset of the market, and may be a selected sample. Table A8 explores robustness on this margin. Our test of transaction prices is based on 2.1 million observations that also enter our core dataset. We can compare both balance and racial inequality between this subset ("test-sample"), and the other 4.9 million observations which are not used for the transaction price test because we don't observe a sufficient number of sales ("non-test sample"). Columns (1)–(4) estimate the assessment gap in each subsample. In the set of homes used for our transaction test, we find no evidence that minority sellers receive lower prices, thereby pushing inequality up (Table 4). If this pattern were reversed in the other sample, and all else remains the same, inequality would be higher as a matter of algebra. However, we find that inequality is actually lower in the non-test sample. This is not dispositive evidence. It is possible that Black sellers receive lower prices in the non-test sample – which would algebraically suggest inequality above 14.4% – but then some other unobserved difference between the two samples brings inequality back down to 11.7%. Our paper shows that one major factor driving inequality is racial demographics. Columns (5)–(6) show that the test-sample and non-test sample are evenly balanced on both Black and Hispanic share: homes in the test-sample are in regions with 1 percentage point lower Black or Hispanic share. We cannot directly test for racial differences in transaction prices within the non-test sample, but the results of Table A8 shows that the evidence we can examine does not strongly point to different racial transaction price dynamics between the test-sample and non-test sample.

Tables A9 and A10 explore the relationship between homeowner tenure and the assessment gap. The evidence on assessment appeals in Section 5.3.3, suggests that the assessment gap will increase in homeowner tenure. However, inequality arising through the neighborhood composition channel would not vary with homeowner tenure. Therefore, we would expect a large portion of the assessment gap to remain even while controlling for tenure. The data does not permit us to know the homeowner tenure for our entire sample: for about 40% of the sample, we pin down race and ethnicity using HMDA records from a refinancing transaction, and therefore do not observe original purchase (the transaction data in ATTOM becomes scarce prior to the late 1990s). For the remaining 60%, which represents just over 4 million transactions, we observe both the initial purchase and the subsequent sale which generates the assessment ratio. This permits us to observe tenure directly. Table A9 shows the results of augmenting our baseline specification with a control for homeowner tenure. The baseline assessment gap remains large and highly statistically significant. In this subsample of our full data, in fact, the assessment gap is approximately 3 percentage points greater than in the full sample. The estimate on tenure implies that the assessment gap increases by approximately 50bps per year. Table A10 relaxes the linearity assumption and estimates inequality across three tenure-bins: 1-5 years, 6-10 years, and >10 years. Estimates suggest inequality has an inverse U-shaped pattern with respect to tenure — rising by a total of approximately 2% from the short-tenure bin to the medium-tenure bin, but then decreasing in the longest-tenure bin. The decision to appeal is likely a function both of current (perceived) inequality and anticipated future time in the home. The non-linear dynamics suggested by Table A10 may reflect this complexity.

Finally, Table A11 builds on our analysis of within-neighborhood inequality in Section 5.3.3. The evidence from analyzing appeals within a single, large county shows a racial differential in appeals outcomes that will, over time, generate different assessment growth rates. White homeowners appeal with greater frequency and success, which will generate lower assessment growth relative to black or Hispanic homeowners. Absent other data on appeals, we cannot directly test the assessment appeals channel in other jurisdictions. We can, however, test whether the national data shows evidence of the patterns which this channel would generate. We exploit the time-series structure of assessments in the ATTOM dataset to ascertain whether assessment growth varies by homeowner race or ethnicity.

We will exploit the fact that for a large number of homes in our sample, the racial ownership changes pursuant to a transaction. We test for a racial differential in the trajectory of assessments over time, using a generalized difference in differences model:

$$a_{icjt} = \alpha_i + \gamma_{cjt} + \beta^r race_{icjt} + \epsilon_{icjt}. \tag{10}$$

In equation 10, a is the log assessment ratio, α_i is a property-level fixed effect, and γ_{cjt} is a jurisdiction-tract-year fixed effect, and *race* is the usual categorical variable. Each property in this sample is sold at some point. β^r is identified from properties which undergo a change in racial ownership as a consequence of the transaction. Property fixed effects absorb the between-home variation, and the geographic fixed effects absorb local housing market variation.

Table A11 shows the results. As homeowners typically can appeal their assessments each year, the channel we posit is most relevant to growth. Accordingly, columns (1) and (2) use the assessment growth (log differences) as the dependent variable. The coefficient in column (1) says that assessment growth is 7bps higher when a black person owns a property, relative to when a white person owns the same property. This is significant only at the 10% level. For black or Hispanic residents the difference in growth is 41bps, and is strongly statistically significant. Given that the assessment dataset spans only 13 years, and that an initial transaction is necessary to pin down the race and ethnicity of the homeowner (which further reduces the T-dimension of the usable sample), our estimating sample is large in the cross-section, but is on average fairly short in the T-dimension. This reduces the power of our estimation. Estimating growth rates exacerbates this challenge. In columns (3) and (4), we use (log) levels as the dependent variable instead. The level difference is 29bps and 79bps, respectively. This is consistent with the growth evidence. Within property, assessment levels are higher for minority residents. Given the length of our sample, the estimates in columns (3) and (4) should be thought of as reflecting two to three assessment cycles, which suggests reasonable consistency between the growth estimates and level estimates.

C.ii Pass-Through of Assessment Ratios to Tax Burden

As a matter of theory, any wedge between assessments and market prices must create a distortion in an ad valorem tax. We are able to observe taxes paid, and therefore can provide the empirical evidence showing that this theoretical relationship does, in fact, hold. Our central focus on assessment ratios is deliberate. Assessed values and market prices are observable by the econometrician with little ambiguity. Taxes are more complicated, chiefly due to exemptions.

Every state provides for a variety of tax exemptions in state legislative codes. Most localities have further autonomy to create exemptions. A common example would be a principal residence exemption: Michigan, for example, exempts primary homes from school taxation up to the amount of 18 mills (180bps).[13] Another very common exemption holds for residents of retirement age: New York State permits an exemption of up to 50% for residents over 65 whose income is between $3,000 and $29,000.[14] Within these parameters, local units have autonomy to select the precise cutpoints. While these are relatively straightforward, many exemptions are much more complicated. Even at a state level, the list of exemptions tends to be very long and complex. With tens of thousands of local authorities also potentially creating additional exemptions, even observing these exemptions becomes a significant challenge. While the ATTOM data includes a field for exemptions, it is unclear how consistently or accurately this data is reported. We show results: (i) using the reported gross tax bill directly, and (ii) removing the reported exemptions to create a post-exemption tax bill.

Exemptions matter in general because spatial distribution of the exemptions may very well be correlated with racial demographics. If some parts of Florida have more elderly white residents than young Black residents, a senior citizen exemption policy would create something that looks like a distortion in the tax burden, but which would be entirely consistent with the legislative intent and public administration of the tax system. We are unable to observe, and thus control for, age of the homeowner – let alone any other individual-level drivers of more complicated exemption policies. The strength of considering the assessment ratio is that none of these confounding factors matter. Using tax dollars paid, we are less able to rigorously strip out potential confounding factors.

Another complicating factor is partial-year tax bills. In some jurisdictions the homeowner of record on a certain date is liable for a full year's worth of property taxes. In others, a partial year of ownership would result in a tax bill spanning only that portion of the year. We do not observe this policy choice at a local level. To provide robustness around this issue, we will compute effective tax burden during the sale year, as well as one year before and one year after sale.

We first estimate the pass-through of the assessment ratio to the effective tax rate. We regress the log effective tax rate on the log assessment ratio. The mechanics of property tax administration

[13] Michigan Compiled Laws, Section 211.7cc and 380.1211.
[14] https://www.tax.ny.gov/pit/property/exemption/seniorexempt.htm.

would suggest a coefficient of 100%, unless homeowners have not fully exhausted available exemptions. If a region permits homeowners to deduct $5,000 from the assessed value of their primary residence before computing the tax bill and many homes are assessed at less than $5,000 then the pass-through would be less than 100%. Table A12 shows these estimated pass-through rates. Column (1) presents estimates for all homeowners in aggregate, and columns (2) and (3) show results by racial and ethnic grouping. Results for Black residents alone are very similar, and we do not include them here. Columns (1) and (2) use the gross (pre-exemption) tax bill. Column (3) uses the computed post-exemption tax bill. In all columns, estimates are very close to 1, as predicted. Across columns (2) and (3), differences by racial or ethnic identity are not evident.

Tables A13 – A15 extend the analysis of effective tax rates shown in Table 3. This is a robustness exercise to rule out bias arising from partial-year tax bills. We construct effective tax rates using tax bills from the year prior to sale and the year post-sale. The denominator remains the sale price of the home. Columns (1) and (4) show the estimated assessment gap in this reduced sub-sample (restricted to homes where tax bills and exemptions are observed in all three years): 13.7% for Black homeowners, and 10.1% for Black and Hispanic homeowners. For Black residents, we estimate an effective tax rate that is 15.9% higher in the actual tax bill and 15.4% higher before exemptions. Considering Black or Hispanic residents together, we find a 11.6% higher effective tax rate from tax bills and 11.3% increase before exemptions. Appendix Tables A14 and A15 show very similar patterns using tax bills one year on either side of the sale.

C.iii Formula-Driven Assessments Can Reduce Inequality

Having carefully documented the extent and magnitude of the distortion, it is natural to ask how easily the problem could be fixed. Perhaps it is the case that market prices are so sensitive to geographic variation and property prices so temporally unpredictable, that even the most skilled and attentive assessors office would not be able to equalize tax burdens by racial status. In this section, we show that a relatively simple approach can address a large portion of this inequality.

As more than half of the assessment gap relates to mispricing of local characteristics, we explore whether small-geography home price indexes (HPIs) can be used to reduce inequality. We use zip-code level HPIs to produce imputed assessments, and then compare the racial variation in assessment ratios obtained using our synthetic assessments to the variation obtained using true assessments. We find this simple procedure reduces inequality by 55–70%. The average zip code is about twice as large as a census tract. We conjecture that more geographically precise HPIs would be additionally effective in removing assessment ratio variation.

We use publicly available zip-code level HPIs from Zillow to construct assessments. Zillow constructs these HPIs monthly for 15,500 zip codes. This covers 84% of the U.S. population.[15] As some transaction density is needed for a sample size sufficient to produce a reasonable HPI index, these zip codes are highly skewed towards more populous urban areas. The monthly time-series

[15] Author's calculations using 2010 decennial census data.

from 1996 can be directly downloaded from Zillow's website at no cost. Zillow began providing these indexes in 2006 and has backwards constructed them to 1996. Zillow has also been increasing its coverage over time.

We construct synthetic assessments using the zip-code HPIs. The algorithm for a synthetic assessment is simple: in any zip code, we take the first observed transaction price and allow this to be the assessment in the month-year of sale. Then we grow that assessment according to the relevant monthly HPI. That is:

$$\hat{A}_{ijzt} = M_{ijz0} \frac{HPI_{ijzt}}{HPI_{ijz0}} \tag{11}$$

where 0 denotes the base month-year of the 1st transaction, z denotes zip code, and M_{ijz0} is the observed transaction price in the base year.

We next test the inequality which would be generated by using these synthetic assessments as the basis for property taxation. To do this, we apply the algorithm to carry the synthetic assessment forward in time until we arrive at the month-year of a subsequent transaction. We then form a synthetic assessment ratio at that time t by taking the log difference between our synthetic assessment and the observed transacted price: $\hat{ar}_{ijzt} = log(\hat{A}_{ijzt}) - log(M_{ijzt})$. We evaluate the success of this algorithm for generating assessments by comparing inequality in synthetic assessment ratios to inequality in the realized assessment ratios. Because this simple approach requires two transactions, and is by construction limited to the zip codes that Zillow covers, we end up with a significantly smaller subsample of 2.1M homes. We first document that the assessment gap still exists – and looks similar – in this subsample. Then we document that using synthetic assessments reduces inequality by 55–70%.

The first three columns of Table A16 show the assessment gap in the subsample covered by Zillow HPIs. Magnitudes are similar to our baseline findings. The figures in columns (1) and (2) are respectively 1.7% and 1.4% larger than the findings in our baseline sample. Columns (4) & (5) repeat the same regressions using our synthetic assessments. A perfect procedure would produce zeros on the racial and ethnic variables. The synthetic assessments completely reverse the assessment gap, and in fact overshoot. The estimates in columns (4) & (5) of Table A16 reflect a *lower* tax burden on minority residents. Of course, this is also an inequality in the tax burden. However, the overall distortion is much smaller in magnitude: 4.1% for Black homeowners and 5.1% for Black or Hispanic homeowners.

Two things are worth emphasizing here. One is that such a straightforward approach is only feasible if some valid HPI exists for small geographic regions. We use Zillow's zip-code HPIs to demonstrate that inequality can be reduced by using publicly available, easy to obtain data. Zip codes are, however, well known to be formed with little consideration for the institutions and characteristics of the underlying geography. Also, the average zip code contains 9,000 people. This is relatively large: our results suggest that there is meaningful spatial variation between tracts, which are less than half this size on average. We think this is likely to be one important reason that this simple implementation still generates a 4–5% racial difference in assessment ratios. The discussion in Section 5.2.1 also suggests that a racial or ethnic difference in transaction prices could explain 2–3 percentage points of the remaining inequality.

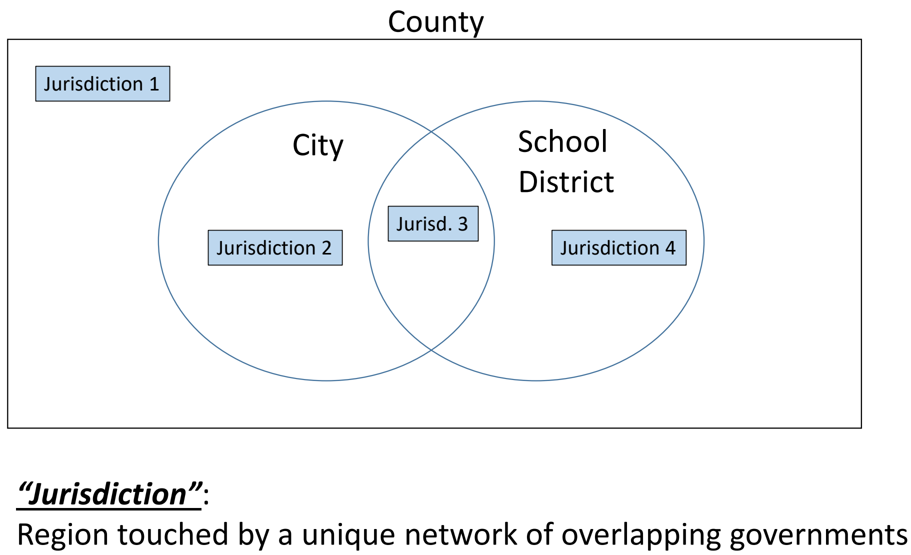
In addition, as a practical matter, assessment values need to be set at the beginning of the tax year, and sales may occur at any time during the next 12 months. Accordingly, racial sorting into areas of higher or lower growth would cause some amount of measured inequality in the realized assessment ratio to arise within the year. To see how important this channel would be, we reproduce a set of synthetic assessments where the assessment is set annually in January of each year. Every transaction then includes up to 12 months of home price growth which is not reflected in the assessment. Appendix Table A17 shows results from this exercise. The estimates are almost unchanged.

The second point of emphasis is that our procedure uses an observed transaction price for the base year value. In order to apply to all properties within a jurisdiction, assessors would need some method for imputing a base-year price for properties which have not sold at any point during the period spanned by the HPI index. Our neighborhood composition findings suggest that this will require assessors to permit prices to vary between small geographic regions. However, racial equity in the initial values is empirically observable and testable. So assessors should be able to iterate a model for initial pricing to land on an equitable distribution of base-year assessments, and then grow those by using some HPI index.[16] The point remains that assessors can make significant strides towards equity by linking assessment growth to small geographic regions within their jurisdiction.

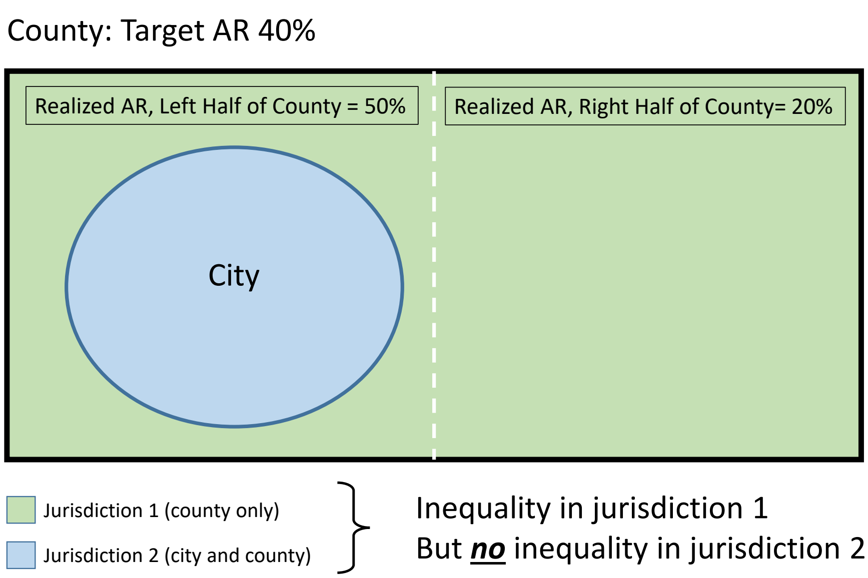
[16] This is, in fact, not particularly dissimilar from the process advocated by IAAO (2018) and other professional guides. However the bulk of this paper serves to show that regardless of process, the outcomes articulated in standards like these are not being widely achieved.

Figure A1: Taxing Jurisdiction Stylized Examples

Panel A

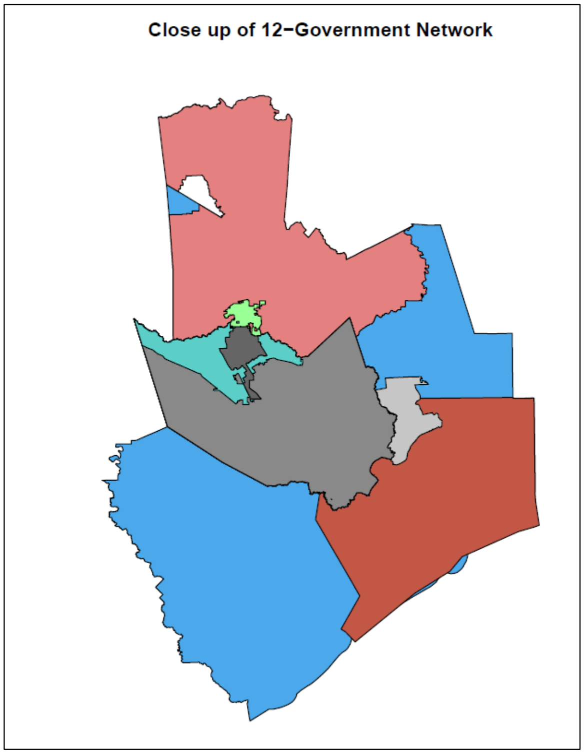


Panel B



Note: This figure shows two examples to illustrate how we form taxing jurisdictions. Panel A shows a stylized example with 3 governments: a county (the large rectangle) which fully contains a city and a school district. The latter two units of government are not spatially coincident. This spatial overlay generates 4 distinct jurisdictions. Panel B presents an example with two governments: the county is again the large rectangle, and a city is entirely contained within the left (blue) portion of the county. In this example, we assume that the county is targeting a 40% assessment ratio, but realizes 50% for every home in the blue region, and realizes 20% for every home in the green region.

Figure A2: 12-Government Network in Texas



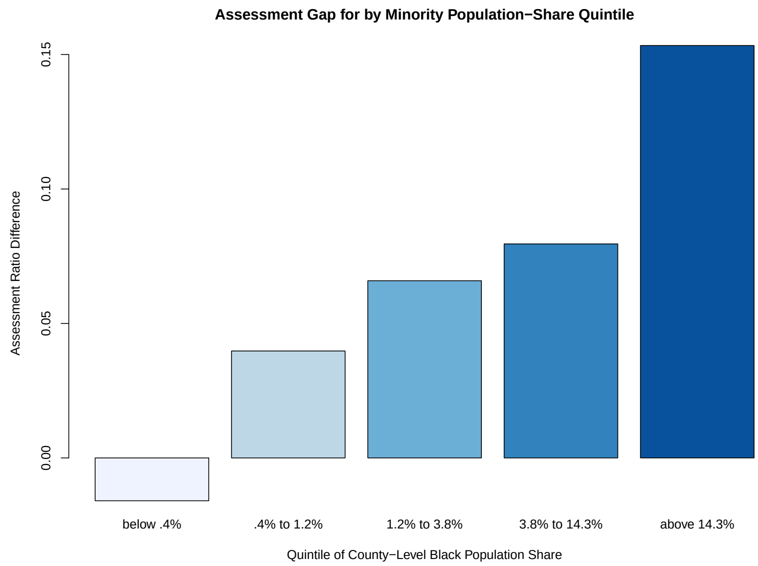
Harris County
City of Houston
Katy Independent School District
Houston Community Colleges
Harris County Flood Control
Port of Houston
Gulf Coast Waste Disposal
Coastal Water Authority
Willow Fork Drainage District
Cinco MUD
North Fort Bend Water Authority
Multi-County Economic Dev. Entity

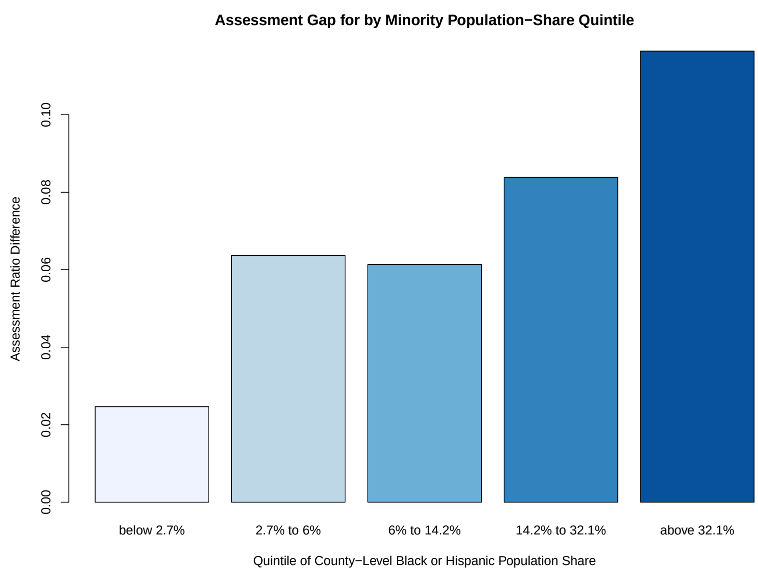
Twelve potential taxing units:

- Every unique combination of these overlapping entities is a jurisdiction
- *One example*: the intersection of all 12 entities

Note: This figure shows the spatial overlay of 12 different local government units in Texas. Some units are proper subsets, and thus fewer than 12 colors are evident in the figure at right. All 12 are listed at upper right. They include "standard" local governments: a county (Harris) and a city (Houston) plus two independent school districts. In addition, there are a range of entities which are related to municipal utilities or economic development initiatives. Each entity listed may, or may not, levy a property tax. Our empirical strategy generates no bias by including an entity as a taxing unit even if it does not, in fact, levy a tax in any particular year. Each unique overlapping combination of these units defines a taxing jurisdiction.

Figure A3: Sample Split by County-Level Minority Population Share





Note: These graphs show results from estimating the assessment gap in sub-samples by minority population share at the county level. We split the sample into quintiles by on average county black or black and Hispanic population share between 2005 to 2016. The quintile range is reflected below each bar. The regression output underlying this table is shown in Table A4.

Table A1: Inequality for all other minority homeowners

	log(Assessment Ratio)		
	(1)	(2)	(3)
Other Nonwhite Mortgage Holder	0.0278***	0.0198***	0.0190***
	(0.0016)	(0.0006)	(0.0007)
Fixed Effects	Jurisd-Yr	Tract-Yr	BG-Yr
No. Clusters	37723	37723	37723
Observations	6,987,915	6,987,915	6,987,915
R^2	0.8798	0.9005	0.9166
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: This table complements Table 2 and shows our baseline findings of a racial assessment gap for all other minority homeowners. We regress the log assessment ratio on a set of fixed effects at the year × geography level and on categorical groupings by racial and ethnic identity. Columns (1), (2), and (3) show results using fixed effects at the jurisdiction-year, jurisdiction-tract-year, and jurisdiction-block group-year level, respectively. In all columns, the reference group is non-Hispanic white residents. Standard errors are clustered at the jurisdiction level.

Table A2: Assessment Ratio Differentials in California

	log(Assessment) - log(Market)		
	(1)	(2)	(3)
Black Mortgage Holder	0.0413***		
	(0.0101)		
Black or Hispanic Mortgage Holder		0.1060***	
		(0.0044)	
Other Nonwhite Mortgage Holder			0.0653***
			(0.0030)
Fixed Effects	Jurisd-Year	Jurisd-Year	Jurisd-Year
No. Clusters	5603	5603	5603
Observations	1,186,388	1,186,388	1,186,388
R^2	0.3816	0.3820	0.3820
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of our baseline assessment gap analysis for California alone. We regress the log assessment ratio on a jurisdiction-year fixed effect and on categorical groupings by racial and ethnic identity. In all columns, the reference group is non-Hispanic white residents, and for clarity coefficients for groups not being considered in a given column are not reported. The estimates in this table reflect an assessment ratio differential for the given grouping of minority residents relative to non-Hispanic white residents. Standard errors are clustered at the jurisdiction level.

Table A3: Assessment Gap, Using Counties instead of Taxing Jurisdictions

	log(Assessment Ratio)		
	(1)	(2)	(3)
Black Mortgage Holder	0.1687***		
	(0.0187)		
Black or Hispanic Mortgage Holder		0.1356***	
		(0.0138)	
Other Nonwhite Mortgage Holder			0.0321***
			(0.0024)
Fixed Effects	County-Year	County-Year	County-Year
No. Clusters	1982	1982	1982
Observations	6,987,915	6,987,915	6,987,915
R^2	0.8507	0.8508	0.8508
Note:		*p<0.1; **p<0.05; ***p<0.01	

Note: This table repeats our baseline assessment gap analysis, but uses county-year fixed effects rather than jurisdiction-year. We regress the log assessment ratio on a county-year fixed effect and on categorical groupings by racial and ethnic identity. In all columns, the reference group is non-Hispanic white residents, and for clarity coefficients for groups not being considered in a given column are not reported. The estimates in this table reflect an assessment ratio differential for the given grouping of minority residents, relative to non-Hispanic white residents. Standard errors are clustered at the county level. This specification shows that our results are not driven by the way we form jurisdictions. Our preferred specifications all use the more rigorous within-jurisdiction analysis.

Table A4: Sample Split by County-Level Minority Population Share

Panel A

	Assessment Value / Market Value				
	Quintile of County-Level Minority Population Share				
	(1)	(2)	(3)	(4)	(5)
Black Mortgage Holder	−0.016	0.040***	0.066***	0.080***	0.153***
	(0.054)	(0.007)	(0.004)	(0.006)	(0.021)
Fixed Effects	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr
No. Clusters	2087	6718	9619	12876	6445
Observations	54,188	412,164	919,591	3,129,016	2,472,956
R^2	0.857	0.938	0.905	0.888	0.847
Note:					*p<0.1; **p<0.05; ***p<0.01

Panel B

	Assessment Value / Market Value				
	Quintile of County-Level Minority Population Share				
	(1)	(2)	(3)	(4)	(5)
Black or Hispanic Mortgage Holder	0.025*	0.064***	0.061***	0.084***	0.116***
	(0.013)	(0.006)	(0.003)	(0.006)	(0.018)
Fixed Effects	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr
No. Clusters	3452	6097	11116	12122	4969
Observations	78,526	303,353	1,443,303	2,803,100	2,359,633
R^2	0.816	0.784	0.860	0.879	0.881
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: Each panel shows the results from estimating the assessment gap on sub-samples based on county-level demographics. For Panel A, we split our baseline sample into quintiles by average county black population share. In Panel B the sample is split by black or Hispanic population share. In each panel, column 1 shows the estimated assessment gap within the lowest minority-population quintile, and column 5 shows results for the highest quintile. Regressions are run separately rather than pooled. We include jurisdiction-year fixed effects in all specifications. Standard errors are clustered at the jurisdiction level.

Table A5: Hedonic Prices

	Market	Assessment	Market	Assessment
	(1)	(2)	(3)	(4)
Black Share	−0.092***	−0.056***		
	(0.004)	(0.004)		
Black or Hispanic Share			−0.117***	−0.078***
			(0.006)	(0.005)
Median HH Income	0.157***	0.144***	0.145***	0.135***
	(0.008)	(0.008)	(0.008)	(0.008)
Unemployment	−0.027***	−0.013***	−0.030***	−0.015***
	(0.003)	(0.002)	(0.004)	(0.002)
SNAP Share	−0.089***	−0.061***	−0.075***	−0.050***
	(0.006)	(0.004)	(0.006)	(0.004)
Owner Share	−0.049***	−0.032***	−0.053***	−0.035***
	(0.005)	(0.003)	(0.005)	(0.004)
GINI	0.066***	0.059***	0.058***	0.053***
	(0.004)	(0.004)	(0.004)	(0.004)
Square Feet	0.256***	0.264***	0.256***	0.264***
	(0.029)	(0.030)	(0.029)	(0.030)
Bathrooms	0.107***	0.103***	0.107***	0.103***
	(0.017)	(0.017)	(0.017)	(0.017)
Year Built	0.031***	0.028***	0.030***	0.028***
	(0.003)	(0.003)	(0.003)	(0.003)
Other Attributes	Y	Y	Y	Y
Fixed Effects	Jurisd-Year	Jurisd-Year	Jurisd-Year	Jurisd-Year
No. Clusters	26152	26152	26152	26152
Observations	4,877,658	4,877,658	4,877,658	4,877,658
R^2	0.773	0.942	0.773	0.942
Note:			*p<0.1; **p<0.05; ***p<0.01	

Note: This table reports estimated hedonic prices from two separate hedonic models. The first model uses (log) market as the dependent variable. These estimates are reported in columns 1 and 3. The second model uses (log) assessed values as the dependent variable. These estimates are reported in columns 2 and 4. Otherwise, the two hedonic models are identical: all regressors are the same. The table omits estimated coefficients for indicator variables stating whether a property has a patio, pool, or fireplace. Standard errors are clustered at the jurisdiction level. Figure **??** shows the difference between attribute-coefficients graphically.

Table A6: All Neighborhood Correlates

	log(Assessment Ratio)	
	(1)	(2)
Black Mortgage Holder	0.077***	
	(0.003)	
Black Share	0.027***	
	(0.005)	
Black or Hispanic Mortgage Holder		0.065***
		(0.003)
Black or Hispanic Share		0.035***
		(0.006)
Median HH Income	−0.021***	−0.015***
	(0.005)	(0.004)
Unemployment	0.015***	0.017***
	(0.004)	(0.004)
SNAP Assistance	0.033***	0.030***
	(0.004)	(0.003)
Owner Percentage	0.021***	0.020***
	(0.004)	(0.004)
GINI Coef	−0.011***	−0.009***
	(0.002)	(0.002)
Median Age	0.003*	0.008***
	(0.002)	(0.003)
Fixed Effects	Jurisd-Year	Jurisd-Year
No. Clusters	37679	37679
Observations	6,944,439	6,944,439
R^2	0.881	0.881
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: This table augments our baseline assessment gap findings in Table 2 with several measures of spatial characteristics. All regressors are tract-level variables from the American Community Survey 5-year estimates. Standard errors are clustered at the jurisdiction level. We continue to hold homeowner race fixed in this regression: those coefficients are reported in the first line of notes immediately under the estimated coefficients. Standard errors are clustered at the jurisdiction level.

Table A7: Assessment Gap by Segregation Decile

Panel A: Black Homeowners

	log(Assessment Ratio)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Black Mortgage Holder	0.0585***	0.0650***	0.0492***	0.0668***	0.0709***	0.0757***	0.0950***	0.0973***	0.1248***	0.1904***
	(0.0140)	(0.0063)	(0.0083)	(0.0051)	(0.0076)	(0.0069)	(0.0176)	(0.0101)	(0.0103)	(0.0371)
Fixed Effects	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr
No. Clusters	418	1265	2036	3517	3454	4348	4341	6096	5875	6348
Observations	28,109	124,642	254,298	466,978	632,892	911,707	698,160	946,883	1,252,737	1,670,456
R^2	0.9246	0.8592	0.9008	0.9093	0.8849	0.9443	0.8785	0.8268	0.8603	0.8233

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B: Black or Hispanic Homeowners

	log(Assessment Ratio)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Black or Hispanic Mortgage Holder	0.0718***	0.0464***	0.0518***	0.0503***	0.0461***	0.0565***	0.0531***	0.0586***	0.0838***	0.1509***
	(0.0242)	(0.0057)	(0.0038)	(0.0033)	(0.0047)	(0.0043)	(0.0033)	(0.0054)	(0.0062)	(0.0242)
Fixed Effects	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr	Jur-Yr
No. Clusters	359	1393	2489	2513	3556	3125	3805	5329	6318	8811
Observations	11,241	66,821	210,686	239,072	376,861	329,217	595,845	1,166,829	1,672,469	2,317,821
R^2	0.9146	0.8489	0.9311	0.8870	0.8859	0.8956	0.9226	0.8598	0.9054	0.8332

Note: *p<0.1; **p<0.05; ***p<0.01

Note: This table provides point estimates for Figure 4 on the paper.

Table A8: Robustness for Test of Transaction Prices

	Assessment Gap				Black Share	B/H Share
	(1)	(2)	(3)	(4)	(5)	(6)
Black Seller	0.144***	0.117***				
	(0.015)	(0.015)				
Black or Hispanic Seller			0.110***	0.089***		
			(0.011)	(0.011)		
Test Sample					−0.011***	−0.011***
					(0.002)	(0.002)
Sample	Test	Not Test	Test	Not Test	Full	Full
Fixed Effects	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr	Jurisd-Yr
No. Clusters	18854	37193	18854	37193	37723	37723
Observations	2,135,966	4,851,949	2,135,966	4,851,949	6,987,915	6,987,915
R^2	0.910	0.870	0.910	0.870	0.618	0.686
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This figure splits our core dataset to compare the assessment gap within the sample of homes used for our test of racial differences in transaction prices (columns 1 and 3), and within the set which does not enter this test (columns 2 and 4). Columns 5 and 6 regress Black share and Black or Hispanic share respectively on an indicator for whether the observation is used in the test of transaction prices. All specifications include jurisdiction-year fixed effects and standard errors are clustered at the jurisdiction level.

Table A9: Assessment Gap by Homeowner Tenure (Continuous)

	log(Assessment) - log(Market)	
	(1)	(2)
Black Mortgage Holder	0.1533***	
	(0.0180)	
Black or Hispanic Mortgage Holder		0.1173***
		(0.0120)
Years Since Sale	0.0049***	0.0052***
	(0.0003)	(0.0003)
Fixed Effects	Jurisd-Year	Jurisd-Year
No. Clusters	32705	32705
Observations	4,216,379	4,216,379
R^2	0.8939	0.8939
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: This table estimates the assessment gap with a continuous control for homeowner tenure (years since purchase). Standard errors are clustered at the jurisdiction level.

Table A10: Assessment Gap Homeowner Tenure Bin

Panel A: Black Homeowners

	log(Assessment) - log(Market)		
	1-5 Years	6-10 Years	10+ Years
Black Mortgage Holder	0.1435***	0.1630***	0.1368***
	(0.0189)	(0.0188)	(0.0162)
Fixed Effects	Jurisd-Year	Jurisd-Year	Jurisd-Year
No. Clusters	28682	27330	14874
Observations	2,313,454	1,546,116	356,809
R^2	0.9038	0.8866	0.9012
Note:			*p<0.1; **p<0.05; ***p<0.01

Panel B: Black or Hispanic Homeowners

	log(Assessment) - log(Market)		
	1-5 Years	6-10 Years	10+ Years
Black or Hispanic Mortgage Holder	0.1087***	0.1237***	0.0933***
	(0.0122)	(0.0133)	(0.0106)
Fixed Effects	Jurisd-Year	Jurisd-Year	Jurisd-Year
No. Clusters	28682	27330	14874
Observations	2,313,454	1,546,116	356,809
R^2	0.9037	0.8866	0.9011
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: This figure estimates the assessment gap by three homeowner tenure bins: 1-5 years, 6-10 years and greater than 10 years. Regressions are run separately, rather than pooled. Standard errors are clustered at the jurisdiction level.

Table A11: Effect of Black or Hispanic Ownership on Assessments

	Assessments			
	Growth		Levels	
	(1)	(2)	(3)	(4)
Black Mortgage Holder	0.0711*		0.2917***	
	(0.0386)		(0.0415)	
Black or Hispanic Mortgage Holder		0.4103***		0.7923***
		(0.0255)		(0.0274)
Fixed Effects	Two-Way	Two-Way	Two-Way	Two-Way
No. Clusters	12268641	12268641	12268641	12268641
Observations	54,970,191	54,970,191	54,970,191	54,970,191
R^2	0.6925	0.6925	0.9910	0.9910
Note:		*p<0.1; **p<0.05; ***p<0.01		

Note: This table shows the results of a generalized difference-in-differences estimation. The dependent variable is logged assessment value. Every home in this sample is transacted at least once. Fixed effects are two-way: property and tract-year. In columns 1 and 2, the dependent variable is growth rates (log difference in assessed value). In columns 3 and 4, the dependent variable is the logged assessment. Standard errors are clustered at the property level.

Table A12: Assessment Ratio Pass Through to Tax Bill

	Effective Tax Rate - Year of Sale (%)		
	Before Exemptions	Before Exemptions	Tax Bill
	(1)	(2)	(3)
All Mortgage Holders	0.9842***		
	(0.0042)		
White Mortgage Holder		0.9858***	0.9941***
		(0.0038)	(0.0041)
Black or Hispanic Mortgage Holder		0.9773***	0.9836***
		(0.0067)	(0.0069)
Other Nonwhite Mortgage Holder		0.9823***	0.9892***
		(0.0042)	(0.0043)
Fixed Effects	Jurisd-Year	Jurisd-Year	Jurisd-Year
No. Clusters	34776	34776	34776
Observations	5,574,777	5,574,777	5,574,777
R^2	0.9096	0.9097	0.8658
Note:		*p<0.1; **p<0.05; ***p<0.01	

Note: This table shows the results of regressing log effective tax rate on log assessment ratio. Column 1 presents estimates for all homeowners. Columns 2 and 3 show a breakdown by racial and ethnic grouping. Results for black homeowners alone are very similar to those reported here. In columns 1 and 2, the dependent variable is an effective rate formed using the gross (pre-exemption) tax bill reported in the ATTOM dataset. Column 3 computes a post-exemption effective rate by subtracting reported exemptions from the reported tax bill. The effective rate is computed by using the tax bill reported in the same year as the sale. All specifications use jurisdiction-year fixed effects. Standard errors are clustered at the jurisdiction level.

Table A13: Effective Tax Rate, Sale Year

	Effective Tax Rate - In Sale Year (%)					
	Assmt. Gap	Before Exemptions	Tax Bill	Assmt. Gap	Before Exemptions	Tax Bill
	(1)	(2)	(3)	(4)	(5)	(6)
Black Mortgage Holder	13.6796***	15.3594***	15.8591***			
	(2.0953)	(2.1055)	(2.1254)			
Black or Hispanic Mortgage Holder				10.1349***	11.2948***	11.6403***
				(1.5904)	(1.5689)	(1.5320)
Jurisd-Year FE	Y	Y	Y	Y	Y	Y
No. Clusters	25267	25267	25267	25267	25267	25267
Observations	3,027,748	3,027,748	3,027,748	3,027,748	3,027,748	3,027,748
R^2	0.8956	0.6961	0.6488	0.8955	0.6958	0.6484

Note: *p<0.1; **p<0.05; ***p<0.01

Note: This table repeats our baseline estimation, but uses effective tax rate as the dependent variable instead of assessment ratio. Coefficients are percentages. For each racial and ethnic grouping, we present two sets of results. In odd columns, we show results using an effective rate computed using the gross (pre-exemption) tax bill and observed market value in the same year. In even columns, we compute a post-exemption effective tax rate, by subtracting reported exemptions from the gross tax bill, and then dividing by market value. We trim any observation above a calculated effective tax rate of 25% both before and net of exemptions. We believe this to be a conservative choice as 25% is far higher than any property tax rate of which we are aware (the national median is approximately 1.4%), and is more likely than not to be a data error. All specifications use jurisdiction-year fixed effects to hold constant the level of intended taxation. Standard errors are clustered at the jurisdiction level.

Table A14: Effective Tax Rate, One Year Before Sale

	Effective Tax Rate - One Year Before Sale (%)			
	Before Exemptions	Tax Bill	Before Exemptions	Tax Bill
	(1)	(2)	(3)	(4)
Black Mortgage Holder	15.8285***	16.5085***		
	(2.2103)	(2.2371)		
Black or Hispanic Mortgage Holder			11.6723***	12.2055***
			(1.6216)	(1.6311)
Jurisd-Year FE	Y	Y	Y	Y
No. Clusters	25267	25267	25267	25267
Observations	3,027,748	3,027,748	3,027,748	3,027,748
R^2	0.6798	0.6324	0.6795	0.6321
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: This table repeats our analysis in Table A13, but uses the tax bill from the year before sale. The denominator for computing the effective tax rate remains the observed market value. Coefficients are percentages. For each racial and ethnic grouping we present two sets of results.In odd columns, we show results using an effective rate computed using the gross (pre-exemption) tax bill and observed market value in the same year. In even columns, we compute a post-exemption effective tax rate, by subtracting reported exemptions from the gross tax bill, and then dividing by market value. We trim any observation above a calculated effective tax rate of 25% both before and net of exemptions. We believe this to be a conservative choice as 25% is far higher than any property tax rate of which we are aware (the national median is approximately 1.4%), and is more likely than not to be a data error. All specifications use jurisdiction-year fixed effects to hold constant the level of intended taxation. Standard errors are clustered at the jurisdiction level.

Table A15: Effective Tax Rate, One Year After Sale

	Effective Tax Rate - One Year After Sale (%)			
	Before Exemptions	Tax Bill	Before Exemptions	Tax Bill
	(1)	(2)	(3)	(4)
Black Mortgage Holder	13.6175***	13.9837***		
	(1.9898)	(1.9776)		
Black or Hispanic Mortgage Holder			9.9325***	10.1185***
			(1.4818)	(1.4179)
Jurisd-Year FE	Y	Y	Y	Y
No. Clusters	25267	25267	25267	25267
Observations	3,027,748	3,027,748	3,027,748	3,027,748
R^2	0.7155	0.6599	0.7152	0.6595
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: This table repeats our analysis in Table A13, but uses the tax bill from the year after the sale. The denominator for computing the effective tax rate remains the observed market value. Coefficients are percentages. For each racial and ethnic grouping we present two sets of results. In odd columns, we show results using an effective rate computed using the gross (pre-exemption) tax bill and observed market value in the same year. In even columns, we compute a post-exemption effective tax rate, by subtracting reported exemptions from the gross tax bill, and then dividing by market value. We trim any observation above a calculated effective tax rate of 25% both before and net of exemptions. We believe this to be a conservative choice as 25% is far higher than any property tax rate of which we are aware (the national median is approximately 1.4%), and is more likely than not to be a data error. All specifications use jurisdiction-year fixed effects to hold constant the level of intended taxation. Standard errors are clustered at the jurisdiction level.

Table A16: Synthetic Assessments Using Zip Code HPIs

	log(Assessment) - log(Market)			
	Real Assessments		Synthetic Assessments	
	(1)	(2)	(3)	(4)
Black Mortgage Holder	0.144***		−0.041***	
	(0.015)		(0.003)	
Black or Hispanic Mortgage Holder		0.110***		−0.051***
		(0.011)		(0.003)
Jurisd-Year FE	Y	Y	Y	Y
No. Clusters	18853	18853	18853	18853
Observations	2,135,943	2,135,943	2,135,943	2,135,943
R^2	0.910	0.910	0.712	0.713
Note:			*p<0.1; **p<0.05; ***p<0.01	

Note: This table shows the results from our proposed approach for correcting the assessment gap. Using the algorithm described in Section **??**, we construct synthetic assessments using zip-code-level HPIs. We use Zillow's publicly available ZHVI series by zip-code. Our approach uses an initial transaction to pin down the base assessment value. At every subsequent transaction, we observe a realized assessment ratio along with our synthetically constructed assessment ratio. Columns 1 & 2 show that the overall assessment gap looks similar in the subset of homes to which can we apply this approach (smaller chiefly because the first transaction is not included in the analysis). Columns 3 & 4 show the assessment gap using our synthetic assessment ratios. All specifications include jurisdiction-year fixed effects. Standard errors are clustered at the jurisdiction level.

Table A17: Synthetic Assessments, Stopping Growth in January Each Year

	log(Assessment) - log(Market)			
	Real Assessments		Synthetic Assessments	
	(1)	(2)	(3)	(4)
Black Mortgage Holder	0.144***		−0.040***	
	(0.015)		(0.003)	
Black or Hispanic Mortgage Holder		0.110***		−0.049***
		(0.011)		(0.003)
Jurisd-Year FE	Y	Y	Y	Y
No. Clusters	18853	18853	18853	18853
Observations	2,135,943	2,135,943	2,135,943	2,135,943
R^2	0.910	0.910	0.692	0.693
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: This table shows an alternative implementation of our proposed approach for correcting the assessment gap. The analysis in Table A16 uses constructed assessments which increase with the zip-code HPI until the month of sale. In this table, we use constructed assessments which change only in January of each year. This more closely parallels the actual assessment practice of generating a single value each year. In this approach, when a sale occurs, the assessment is out of date by up to 12 months. Columns 1 & 2 are identical to Table A16 and show that the overall assessment gap looks similar in the subset of homes to which we can apply this approach. Columns 3 & 4 show the assessment gap using January-revised synthetic assessments. All specifications include jurisdiction-year fixed effects. Standard errors are clustered at the jurisdiction level.

Table A18: Effect of Assessment Caps on Inequality

	log(Assessment Ratio)		
	No Cap	Cap Exists	Cap Exists and Binds
	(1)	(2)	(3)
Panel A: Black Homeowners			
Black Mortgage Holder	0.1384***	0.1366***	0.0860***
	(0.0115)	(0.0373)	(0.0089)
Panel B: Black or Hispanic Homeowners			
Black or Hispanic Mortgage Holder	0.1065***	0.1080***	0.0607***
	(0.0084)	(0.0230)	(0.0052)
Fixed Effects	Jurisd-Year	Jurisd-Year	Jurisd-Year
No. Clusters	28589	9374	4492
Observations	4,025,841	2,295,890	509,245
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: This table shows our findings of a racial assessment gap in areas with different policies regarding a cap rate of growth. Panel A presents our results for Black homeowners, and Panel B presents our results for Black or Hispanic homeowners. In all specifications, we regress the log assessment ratio on jurisdiction-year fixed effects and on categorical groupings by racial and ethnic identity. Column (1), (2), and (3) respectively present results for areas with no known cap policy, areas with a cap, and areas with a cap that is binding. In all columns, the reference group is non-Hispanic white residents, and for clarity coefficients for groups not being considered in a given column are not reported. The estimates in this table reflect an assessment ratio differential for the given grouping of minority residents relative to non-Hispanic white residents. Standard errors are clustered at the jurisdiction level.