Racial Bias in Property Taxation in Atlanta: The Difficulty of Reversing a Legacy of Discrimination

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[Version: June 16, 2024]

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Abstract

Early 20th Century Jim Crow laws targeted black neighborhoods for higher property taxes across the south. In Atlanta, the struggle to reverse discriminatory property taxation lasted throughout the 1970s and 1980s until a divisive suit compelled county-wide reappraisal. Multiple works examined the success of the Court order. Customary in this literature, using Fair Market Value (FMV)/Sales Price as a dependent variable, Makovi (2022) found that discriminatory taxation has abated over the three decades since the reform order. One obstacle this work addresses is the data on which assessments are based. A legacy of Jim Crow era rules in public data is the absence of home features, prominently the square footage of each property in the public property descriptions. Lack of full information on home size complicates the task of appraisals by assessors as it creates obstacles for local homeowners to challenge an assessment. Further, information on the actual real estate tax charged is very difficult to collect. Unlike FMV, this public data cannot be downloaded and must be extracted one by one. These obstacles make the use of FMV in most analyses. Using census block group level demographic data, actual taxes paid, and updated housing characteristics, we compare actual property taxes-to-sales price to specific property sales in 2015 and 2016 across Atlanta. This work finds that the actual tax/sales price systematically disadvantages black residents. This may be a good example of structural racism. Many city leaders and officials have included some of the leading lights in the civil rights movement. Nonetheless the legacy of the data reporting structure from the Jim Crow era persists in disadvantaging black neighborhoods. This result appears robust to several estimation strategies, from simple descriptive data through linear regression onto recent methods of submarket division – all showing that the property tax following a sale and after an updated assessment after the sale, shows on-going taxation bias.

1. Introduction

Historically, the homes of black residents in many US cities were subject to over-valuation. This, of course, led to higher property taxes paid by black residents. Recent literature is divided on whether there may be sustained racial bias in property taxation across the US, especially cities in the urban south (see Harris, 2004; Atuahene, 2017; Capps 2015, Kahrl, 2018; Perry et al., 2018; Atuahene and Hodge, 2018; Kahrl, 2016; Kahrl, 2018). In Atlanta, concern for property tax discrimination has a long and tortured history, which is punctuated by the notorious 1991 tax revolt that received national attention. The 1991 tax revolt itself was the tail end of a highly contested legal challenge to rectify property tax discrimination in Atlanta that had lasted for more than two decades. In 1991 a "reappraisal of property in Atlanta and Fulton County, Georgia, corrected systemic inequalities in property taxation…" (Connor, 2015). This correction is what led to the 1991 tax revolt as reassessed property values for residents in predominantly wealthy, white neighborhoods led to a very steep upward adjustment in city property taxes.

The recent Atlanta tax protest echoes this earlier controversy. The recent tax protest includes a failed petition for separation of a predominantly wealthy white Atlanta neighborhood from the city of Atlanta. A group of neighborhood residents sought separation, or relief, from very high city taxes for what they saw as degraded city services. Makovi (2022) analyzed this recent tax protest by comparing actual home sale prices to the most recent tax assessment. Makovi concluded that Atlanta taxation is now fair. What is noteworthy, Makovi was remarkably careful. In the conduct of this study, only recent, actual homes sales were used to evaluate the fairness of property assessments. Using public data on assessed value of properties, Makovi compared the assessed property value - fair market value (FMV) - to sales data between predominantly white and black neighborhoods (census block groups). Makovi (2022) also was careful to use only those assessed property values that followed a sale, only when assessment 'reset' appeared, and only for those assessments established *after* the citizen protest period had passed. In this way, assessed values could be used to control for protest advantages that might benefit wealthier, more educated white homeowners.

This work addresses the institutional legacy of Jim Crow laws that established discriminatory property taxation in Atlanta from roughly 1890 to 1930. Even as segregation was permitted, deliberate discriminatory taxation was illegal. Yet, we contend, discriminatory tax differences could be masked by strategic gaps in publicly reported data. Though overtly false information about a home to inflate or deflate taxation could be detected, we identify two reporting irregularities in the public data that remain today which might lead to discriminatory taxation, even unintentionally.

To determine tax fairness, this work uses the ratio of the actual tax paid to its recent sales price, or *Tax/Sales Price* rather than *FMV/Sales Price.* To do this requires data for the tax paid *after* a sale when property values are reassessed to reflect the new home sale price. Our question asks if the actual tax paid following a FMV (assessment) update *is* fair, even if the FMV reasonably may reflect the best true market value given available data.

Second, of greater importance, is the absence of home square footage data for properties in the Fulton County Board of Assessors record. To assess tax fairness in a multivariate setting, we need to explain sales price using home features such as property location, local amenities and housing characteristics. Square footage in particular is an important touchstone covariate for any prediction of home price at a given moment in time. The absence of square footage information in the Atlanta housing public record clearly removes one of the most robust indicators of home price variation within a neighborhood or census block group, and one easily reviewed. Differences in price per square foot between neighborhoods or census block groups is often the first and most plausible trigger to adjust taxes up or down if differences exceed reasonable expectations.

As we review the literature treating tax fairness, such as the works listed above, we find no work that assesses the fairness of the property tax as a proportion of market home price by using both the observed market sales price and the actual tax paid the next year after taxes adjust to that sale.

This work fills these two gaps. With over 5,000 single family home sales collected from 2015-2016, square footage and tax paid had to be extracted one by one. Fortunately, bankers and real estate appraisers require, and generate, square footage information in closing documents. Zillow collects this information from the sales and disclosure documents. These data had to be collected one by one, by address, from Zillow for each individual home record report. Similarly, property tax *paid* is held in a separate data collection record than the home description and identification - shifting between Fulton County Tax Commissioner's Office and Fulton County Board of Assessors records. This requires collecting the house parcel ID number from one record (Fulton County Board of Assessor) and then extracting the tax paid from another (Fulton County Tax Commissioner's Office), one by one. Given the centrality of these data to assess any finding of discriminatory or nondiscriminatory real estate taxes, we simply note that this difficult data extraction from irregularities in reporting of public data might have been intended for this purpose when the reporting system evolved from 1890 to the 1930s.

2. Outline of Work

Two novel features of this work compare it to other works on this topic. First our analysis is based on recent home sales prices; and these are compared directly to the actual tax charged to the resident. Other works, including Makovi's (2022), do use other variables such as 'sales price to the assessed fair market value'. This is the only work of which we know that directly compares the specific variable(s) of concern in the context of taxation fairness: how does the actual *property tax paid* compare to the recent market sale of a recently sold residential property and to the assessed fair market value of the same property. Unfortunately, tax data cannot be downloaded in bulk. Yet when collected, this laborious data collection effort alters the result in a meaningful way.

Once data is collected, it is relatively easy to show that taxation in census block groups in majority black neighborhoods is higher than census block groups in minority black neighborhoods. Atlanta residential location choices have lead to highly segregated neighborhoods. When sorting the percentage of the reported black residents into deciles, the largest black population in census block groups that are minority non-black is only 32% (the sixth decile when sorted by the percentage of black residents). Conversely, the largest non-black population in otherwise majority black neighborhoods is only 31% (the seventh decile). There were no 35% / 65% deciles in this record. Yet the distinctions in tax rates by race invites a more nuanced picture of the incidence and severity of racial bias in property taxation in Atlanta.

Second, we perform a simple aggregate OLS model to predict the tax to sales ratio. The variables to explain this ratio are a mix of house characteristics including square footage, demographics such as income and race in the surrounding census block groups, neighborhood characteristics, and location effects.

To add even sharper examination, we recognize that resident preferences among the vast mix of housing traits are not captured under a single peaked distribution, but instead residents sort into submarkets characterized by different composite bundles of housing features and location traits (Belasco et al. (2012); Shiroya (2012); and Goodman and Thibodeau (2003; 2007)). We examine differences in preference orderings of the housing stock, based on demographics and housing choices, from most to least preferred to examine neighborhood sorting. Income, household size and level of education are also important demographics that help to match housing preference types (submarkets) to a given home, in a given place, with given features, at a given price. This sorting suggests that the robustness of modest, yet persistent racial bias in single family residential real estate taxation cannot be explained by income and education. This opens the possibility that the Jim Crow laws which directly masked information needed to fingerprint discriminatory taxation may have been intentional; and, as a result, a racial institutional legacy persists that may be unintentional.

We find evidence that poverty leads to modest proportional tax increases for Atlanta homeowners. Yet homeowner submarkets are stratified by joint correlation of income, local middle school quality and by race. Each has a predictive influence. Higher incomes and stronger school quality do lead to lower proportional property taxes between submarkets which are large majority black. Yet race has a more prominent and regular influence. It appears that as public data on residential property formed between the1890s and 1930s, it was made difficult to navigate, arguably for this purpose. The advent of progressive racial policy in Atlanta that aggressively pressed this inequality in taxation directly has moderated this tax effect. Yet the difficulty of extracting critical information that would evidence ongoing tax inequality continues; and the modern ability for rapid downloading of bulk data in the thousands does not help us here.

3. Data and Methods

Sales and assessment data are obtained from the Fulton County Board of Assessors for the years 2015 and 2016. The dataset includes all the expected variables such as sales price, sale date, assessed value, and physical attributes of the house. The parcel ID in this data is used to match with spatial data (X, Y) coordinates and school attendance zones. This data is supplemented by neighborhood and demographic characteristics data at the block group level from the American Community Survey 2012-2016 5-year estimates, also matched using the (X, Y) coordinates and census block group spatial files. Crime data is obtained from Atlanta Police Department Open Data for the year before sale and matched with census block group spatial files. In the final dataset, each observation of a household is associated with its physical attributes and block group demographic characteristics and neighborhood amenities. Square footage data is also extracted one by one from Zillow using property address. Finally, tax, which distinguishes this study from past studies on tax discrimination, is collected on each property separately from the Fulton County Tax Commissioner's Office. Appendix Table 1 reports the summary statistics for the data in this paper.

We use multiple regression methods adapted from hedonic OLS methods with the *Tax/Sales Price*, *Tax/FMV*, and the *FMV/Sales Price* as the dependent variable. Physical structural features of the house included in the regression include the age of the house, square footage, lot size, total number of rooms and the number of years since last remodeling. Special attention is paid to spatial dependence and autocorrelation since a house's price is not merely a function of its physical characteristics but also its location. Failure to include such neighborhood effects will induce omitted variables bias (Basu and Thibodeau, 1998). Since a house's price is influenced by its neighborhood context, not just its own features, we also include average structural characteristics of the homes in each neighborhood. Specifically, we include median sales price, median age of house, and percentage of houses occupied by renters.

Locational fixed effects, especially school district fixed effects, and distance to the CBD (central business district) are often used to define housing submarkets and thereby correct for both omitted variables bias as well as spatial autocorrelation (Goodman and Thibodeau, 2003; Bourassa et al., 2007). Following these examples, our regressions will include demographic observables at the block group level including educational attainment levels, and average household size. Also included in the scaled average 8th grade mathematics score in the school district.

To capture spatial trends, we follow Farmer et al. (2024) by including terms for longitude (X), latitude (Y), and their squares (X^2, Y^2) relative to an arbitrary point (0, 0) located southwest outside the study area. This approach allows the mean value of the dependent variable to vary separately with latitudinal and longitudinal distances, and the squared terms account for potential non-linear relationships between distance and property values.

We test a series of regressions on the entire market in Atlanta, and also on submarkets in Atlanta. We use the fully endogenized finite mixture modelling from Belasco et al. (2012). This method is relatively robust in delineating housing submarkets based on the characteristics of the residents who occupy houses. To simultaneously characterize (i) the number of submarkets; and (ii) how residents in each submarket value each amenity, the method uses latent class analysis in the form of a finite mixture model. This can be thought of as a mechanism to combine latent class membership through traditional discrete choice modeling and utilizing maximum likelihood estimation that is based on latent class membership and independent variables. This method gives discrete submarket classifiers, which allow us to segment the market and run the hedonic models to examine property tax discrimination in each submarket.

4. Results

4.1 Stratified Means

Three data arrays are used to evaluate tax fairness. These are: Fair Market Value (*FMV*), which is the assessed value set by the tax authority; Tax, which is the actual property tax charged to the owner; and Sales Price (*Sales*), the observed market sales price of a home.

These data create our variables of interest. Three ratios examine discriminatory taxation.

- *FMV/Sales* is the most common ratio used in this literature (e.g. Makovi (2022); Atuahene (2018); Faulk and Hicks (2015)).
- *Tax/FMV* with tax data extracted, we evaluate fairness in the tax process.
- *Tax/Sales Price* directly to evaluate tax fairness.

These variables invite different interpretations of tax fairness and administrative processes. We distinguish between administrative process outcomes and policy outcomes. Clearly, *Tax/Sales Price* is the explicit policy outcome we evaluate. Yet administrators are charged to establish *FMV* and, then, manage taxation, *Tax*. Because public assessors establish FMV and the public, with administrative input, determines how tax is charged, variation in *Tax/FMV* broadly reflects fairness in the administrative processes that manage property taxes. Finally, *FMV/Sales* tracks public administration processes.

Each home sale (n=5,417) is matched to a corresponding census block group. Table 1 sorts census block groups into deciles of the percentage of black residents in those census block groups. The first six deciles reflect majority non-black neighborhoods, which range from 68.07%-99.75% non-black residents. The last four deciles (7th-10th) reflect majority black neighborhoods, which range from 69.35%-98.60% of black residents. Clearly, Atlanta neighborhoods are highly segregated (decile 5 has

31.93% black residents while the next decile, 6, has 69.35% black residents). *Tax/Sales Price* data shows that majority black neighborhoods realize a gross average property tax of 1.49% to sales price while minority black neighborhoods realize a gross average tax of 1.25% to sales price. As a policy outcome, this tax difference represents a property tax increase of just over $240 per $100,000 sale price for houses in majority black neighborhoods.

Table 1: Mean ratios by decile

Decile	N	Pct black (%)	Median Income ($)	Tax/sales price (%)	Tax/FMV (%)	FMV/Sales price
1	542	0.25	160,669 (57,100)	1.33 (0.34)	1.76 (1.53)	0.807 (0.201)
2	542	2.73	140,287 (49,443)	1.33 (0.37)	1.69 (0.34)	0.808 (0.404)
3	542	7.84	110,372 (43,582)	1.28 (0.42)	1.62 (0.27)	0.799 (0.242)
4	542	15.14	81,490 (15,275)	1.29 (0.36)	1.90 (1.94)	0.757 (0.208)
5	542	22.13	81,046 (17,613)	1.19 (0.43)	1.81 (1.20)	0.695 (0.225)
6	542	31.93	75,490 (12,888)	1.11 (0.38)	1.72 (0.78)	0.676 (0.201)
7	542	69.35	34,816 (17,481)	1.16 (0.74)	2.60 (2.14)	0.538 (0.357)
8	541	90.85	31,630 (11,399)	1.45 (0.86)	2.87 (1.93)	0.588 (0.308)
9	541	95.04	30,816 (13,024)	1.73 (0.98)	3.07 (1.51)	0.608 (0.300)
10	541	98.60	33,479 (11,209)	1.62 (0.96)	2.85 (1.57)	0.603 (0.306)

To measure the accuracy of property assessments, *FMV/Sales*, we note that *FMV* is expected to lag Sales prices. *FMV* adjusts most strongly after a sale presents a direct, updated record of market value. Table 1 also records *FMV/Sales Price*, which tends to decline with the percentage of black residents in a neighborhood. This suggests an administrative process that may advantage black residents. This is what Makovi (2022) found. Yet when we compare the actual tax to the fair market assessment, *Tax/FMV*, over the deciles, there is a deep disparity in tax incidence based on *FMV*. It is significant that both *Tax* and

FMV are under administrative charge. Non-black majority neighborhoods had a gross average tax of 1.75% to *FMV* as black majority neighborhoods faced a tax of 2.84%. On its face, this represents an average increase in property tax for majority black neighborhood of $1,090 per $100,000 *FMV*. While the true policy outcome is $240 (*Tax/Sales Price*), far less severe than $1,090, *FMV/Sales* is a wholly administrative outcome, raising concerns for fairness in the process of property assessment and taxation.

We supplement the analyses above with two sets of graphs. The first set, in Appendix Figure 1, shows scatterplots stratified by deciles. Consistent with the empirical evidence, these graphs reveal a positive association between the percentage of black residents and *Tax/Sales Price* and the distribution of points within the scatterplots indicates that the mean statistic is not disproportionately weighted by outliers, as a large number of data points lie above the mean. Appendix Figure 2 presents a choropleth map constructed at the census tract level for the Atlanta metropolitan area. Each individual tile corresponds to a specific census tract, with darker shades denoting a higher concentration of black households. Superimposed on the maps are the locations of the residential samples, with the shade of each point corresponding to the three ratios. The maps corroborate the previously established findings.

4.2 OLS Results

Table 2 presents the results of the regression model, with the natural logarithm of the *Tax/Sales Price* as the dependent variable. The independent variables cover both neighborhood-level amenities and individual property characteristics. Neighborhood factors include the percentage of renters, median household income, educational attainment (8th grade math score by school district, high school and college graduation rates), and median house value within each census block group. Property-specific variables comprise square footage, age, number of floors and rooms, lot size, time since last remodeling, and binary and categorical indicators covering features such as central heating, attic presence, condition-desirability-utility (CDU) rating, topography, external wall material, street type, sale month, location, and lot classification. All continuous independent variables are log-transformed. (We also provide results from the linear model specification in Appendix Table 2.)

To evaluate the potential regressivity of the property tax system with respect to sales price, we focus on the coefficient estimates for the "percentage black" variable. A statistically significant positive coefficient would indicate higher *Tax/Sales Price* in neighborhoods with larger black populations. As shown in Table 2, the coefficient estimate for the percentage of black residents is 0.644, statistically significant at the 5% level suggesting that a one percent increase in the black population corresponds to a 0.644% increase in the *Tax/Sales Price*.

To illustrate the economic significance of these findings, consider a property in a census block group with a black population of 43%. Assuming a sales price of $420,119 and a current *Tax/Sales Price* of 1.355%, the annual property tax would be $5,693. Based on the estimated coefficient (0.644) and holding all other factors constant, a one percent increase in the black population would be associated with an increase in the *Tax/Sales Price* to 1.364%. This would result in a new property tax bill of $5,729, or an increase of approximately $36.

Examining other control variables in our regression models yields several noteworthy findings. The coefficient for median income is negative (-0.116, statistically significant) indicates affluent neighborhoods face lower relative tax burdens. Educational attainment also plays a role: the coefficient for high school diploma attainment (0.500, statistically significant) is positive, while that for college degree attainment (-0.193, statistically significant) is negative, implying neighborhoods with higher education levels tend to have lower effective tax rates. The coefficient for 8th grade mathematics assessment scores reinforces this trend. We also find a negative association with median house value (-0.070, statistically significant), indicating lower tax rates for more expensive properties. This pattern may be explained by the spatial distribution of housing values, with pricier homes more likely to be located in predominantly white neighborhoods that may have lower effective tax rates.

Table 2: OLS regression results (log-log model)

	Estimate (Std. Error)
Percent black	0.6438** (0.3245)
Percent renter occupied	-0.0018 (0.0044)
Median income (‘000s)	-0.1163*** (0.0296)
Percent with high school diploma	0.5001*** (0.1330)
Percent with college degree	-0.1931*** (0.0358)
Percent with graduate degree	-0.0118 (0.0074)
Math score	1.0665*** (0.2623)
Household size	-0.2820*** (0.0482)
Median house value (‘000s)	-0.0708*** (0.0246)
Square footage	-0.1748*** (0.0264)
Age	-0.0555*** (0.0155)
Lot size	0.0631*** (0.0192)
Years since remodeled	0.0204*** (0.0074)
Number of floors	0.1426*** (0.0425)
Central heating (0/1)	-0.1318*** (0.0328)
Total bathrooms	0.0043 (0.0229)
Total rooms	-0.0030 (0.0068)
Total fixtures	-0.0015 (0.0052)
X-distance	0.0000 (0.0000)
X-distance squared	-0.0000

	Estimate (Std. Error)
	(0.0000)
Y-distance	0.0000 (0.0000)
Y-distance squared	-0.0000 (0.0000)
Adjusted R-squared	**0.1301**

Note: Other control variables in the regression include the following categorical variables: style (style of individual home); external wall (material construction of external wall); fuel (type of fuel system); fronting (type of street fronting); topography; utility (type of utility connection); sale month, CDU (condition, desirability, utility – denoting physical depreciation of property); revision code (code for method appraisal); deed (type of deed); location (type of location, e.g., residential, central business district, etc.); lot type; LUC (land-use code); zoning designation.
*0.001 '***' 0.01'**' 0.1 '*' (Standard errors clustered at the block group level)*

Analysis of house characteristics reveals several significant relationships with the *Tax/Sales Price*. The coefficients for square footage (-0.175) and age (-0.055) are both negative and statistically significant. This suggests an inverse relationship between property taxes and both the size and age of residences. Conversely, lot size and time since last remodel show positive associations with the *Tax/Sales Price*. Their coefficients (0.063 and 0.020, respectively) are statistically significant, implying that properties with larger acreage and those that have not been recently remodeled tend to have higher *Tax/Sales Price*.

4.3 OLS Regression with Tax/FMV and FMV/Sales Price

Appendix Table 3 records OLS results that reiterate the conclusions above using the same three dependent variables: *FMV/Sales; Tax/FMV;* and *Tax/Sales Price*. These examine an increasing series of OLS results using different independent variables intended provide possible insight into the administrative processes which could explain these results.

The first two OLS results use data that an assessor can be expected to rely on. Assessors consult very local and very recent sales data in a census block group or a small defined neighborhood. Assessors of course consider local sales prices (median sales price) and income (median household income). Beyond that assessors may perform a local, quasi-appraisal based on the most comparable nearby sales, which includes home characteristics. Assessors as a rule are usually restricted from consulting more information. With such restrictions and without home size information, fair market value assessments can be inconsistent across neighborhoods. For example, absent home size information, it seems likely that an assessment may overtax smaller homes.

To assess overall fairness, the last two regressions conduct a full residential housing economic study across the city to examine factors that explain shifts in value between neighborhoods. The last two OLS examinations, in sequence, consider zoning issues that may affect the prices of single-family residences in different neighborhoods, such as an allowance for muti-family housing, commercial shops or industrial operations. In progressing through the OLS results, the use of any set of home characteristics shows taxation tends to increase taxation as a share of FMV as the share of black residents in a census block group increases. As the last model tracks more information regarding home location effects, such as the overall position of a home within the city or, discriminatory taxation become quite sharp.

In the baseline scenario (model (i)) with the *Tax/Sales Price* as the dependent variable, the coefficient for the percentage of black households is 0.992 and statistically insignificant. As we move to model (ii) with house characteristics, the coefficient shows a marginal increase (1.037 in column (ii)) and subsequently diminished with the introduction of locational and zoning controls (0.770 in column (iii)), and then distance correction variables (0.644 in column (iv)). Notably, the coefficients remain statistically significant across models (i) to (iv).

A parallel pattern emerges when examining the coefficient for the percentage of black residents in the *Tax/FMV* model. The coefficient exhibits a slight increase from the baseline model (i) at 0.627 to 0.647 in model (ii) with house characteristics, followed by a decrease to 0.472 in model (iii) and a slight uptick to 0.496 in model (iv). Notably, the estimates remain statistically significant across all models.

Finally, our analysis of the *FMV/Sales Price* model yields a coefficient that consistently displays a negative sign across all models, ranging from -0.43 in model (i) to -0.21 in the complete model (iv).

Although not statistically significant at the 5% level, they suggest a potential assessment bias: properties in neighborhoods with higher percentages of black residents may be systematically assessed at lower values relative to their sales prices.

Overall multiple regression examinations of greater resolution confirm the basic analyses represented in the simple docile analyses. Results continue to show a significant departure in the effect of *Tax/FMV* and *FMV/Sales Price* **-** as locational information helps to explain difference in sales price from neighborhood to neighborhood, introducing location information shows that tax/sales price increases as the proportion of black residents increases. The next questions to explain ask how this discriminatory taxation has been sustained and what are the contours of the housing market and settlement patterns across Atlanta that contribute to sustained discriminatory taxation?

It is easy to conclude that a separation of actual tax information, to be collected one by one from a separate filing makes tax and sales difficult to unite into a single record. That is a product of historical decisions. If, in addition, property traits such as prices/square-foot are not available in the public record, discriminatory taxation can escape notice, perhaps even unintentionally, for decades.

4.4 Submarket Examination

Evidence of discriminatory taxation is difficult to ignore; yet it also is difficult to adjudicate an assessor's intent. The identification of racial averages in the deciles shows that Atlanta is still quite segregated. Remarkably, very few census block groups reflect a slightly below 50% black representation in Atlanta at the time of our study data. Black representation in a census block group is typically greater than or equal to 60% or less than or equal to 40%. So, discriminatory taxation may show an incidence that suggests, for example, both wealth and race as critical to explain differences in favorable (or unfavorable) taxation from one census block group to another. For this, we look to submarkets in Atlanta to better isolate a few broad prototypes of residents living in Atlanta at the time of a sale.

To identify different submarkets, we do not presort persons into discrete, exogenous categories, which are often applied through fixed effects, such as the choice of a city in which a person locates (Seig, *et al*., 1998) in large regional analyses of ‘locational equilibria;’ or, more locally through school district fixed effects, exemplified by the classic works of Goodman and Thibodeau (1998; 2007). Instead, we sort submarkets *endogenously* based on the demographics of a consumer who chooses a particular home, with particular home characteristics, at a particular sales price and a particular time (Belasco *et al*., 2012. This strategy works especially well when evaluating willingness to pay for real property as each individual ‘product unit’ sold is unique, not homogenous. That means a home sale is a specific package of characteristics bought by a consumer drawn from a particular type of consumer willing to pay the highest price for that specific package at that time. Recalling the arguments of an indirect utility function, demand would include home characteristics along with the income of the representative consumer. We interpret the representative consumer as drawn from that submarket likely to offer the highest price, above other submarkets, which hold distinctly different preference orderings.

The estimation method applied is a fully endogenous finite mixture (Belasco, et al., 2012). Summarized in the appendix, what makes this fully endogenized is two cointegrated unknowns: the likelihood that a given home buyer is a member of a submarket (fits a coherent typology of relatively similar residents) and the parameter estimates for home characteristics that best fit the sales price observed. An EM algorithm, which manages iterated joint uncertainties, estimates membership of a buyer in a submarket type that purchases a given house as the most likely to offer the highest willingness to pay for those home characteristics as it jointly estimates the marginal contribution of those characteristics to overall value (i.e. OLS parameter estimates). The analyst must choose the number of submarkets; and each submarket generates a distinct vector of parameter estimates for characteristics.

In this work we analyze and compare submarkets of two, three, and then four submarkets to illuminate the incidence of differential taxation among different groups. We run the same OLS models, regressing the same three dependent variables *Tax/FMV*, *FMV/Sales Price* and *Tax/Sales Price*.

Appendix Table 4 shows the results for two submarkets. This simple partition is perhaps the most telling for our story. As the estimator isolates the most distinct subset from other purchasers, the result finds a strongly separate group of wealthy, mostly white (71%) residents who sell (and buy) homes almost twice the size of the remaining average. They also enjoy much better schools, much lower crime rates, fewer renters in the neighborhood, and homes on much larger lots. Expectedly, residents in these neighborhoods have much higher incomes and own houses that sell for much higher prices - on average 80% and 123% higher, respectively. The difference in tax incidence based on the percentage of black residents in the neighborhood echoes the previous correlation-based study above.

The separate effect estimates for the tax incidence to the percentage of black residents in the census block group shows no significant effect on *Tax/Sales Price* nor *Tax/FMV.* There is a slightly lower tax for *Tax/Sales Price* in the affluent submarket and lower in the other submarket; and slightly lower tax for black residents when regressed against *Tax/FMV.* With approximately 125 black residents expected over slightly more than a dozen census block groups from which submarket 1 is drawn, racial variation itself is very low. The smaller submarket 2 includes more middle to lower income persons; and estimates show a more severe and statistically significant discriminatory tax on *Tax/Sales Price.* This suggests both race and income play a role in discriminatory taxation.

The expansion of analyses to three or four submarkets reiterates this key finding. In each case the submarket with the lowest income has the highest percentage of black residents. In the four submarkets scenario, the two submarkets with the highest percentage of black residents are also the two submarkets with the lowest incomes. In all three cases, the ratio of property tax to sales price increases with the percentage of black residents in the associated census block groups.

This pattern presents a slight contrast to our city-level findings. While the city-level analysis showed a positive, significant coefficient on the percent black variable, this relationship dissipates when we segment the city into distinct submarkets. This loss of statistical significance within individual submarkets can be attributed to their homogeneity. For instance, in predominantly black submarkets, the uniformity in racial composition may lead to more consistent property valuation practices (and vice-versa), so the variations in *Tax/Sales Price* and *Tax/FMV* (within the submarkets) are either low or are less likely to be driven by racial demographics. The property tax system seems to operate consistently within these homogeneous areas, treating properties similarly regardless of minor variations in racial makeup.

Differences by race and income for the variable *Tax/FMV* tend to follow the pattern for *Tax / Sales Price* though imperfectly. Yet FMV itself suggests reasons to be concerned about fair taxation. Critically, for these data the tax charged and FMV were recorded very soon after each sale - within the first year and in some cases during the second calendar year following a sale. Assessments, or fair market value estimates, that follow so closely to an actual home sale should display very little variation. That there is some systematic process guiding *Tax/FMV* suggests the possibility of the results we find.

5. Conclusion

Results for discriminatory property taxation in the city of Atlanta replays concern for a now familiar question: Are disproportional negative social outcomes a product of race or of income? Akin to much of this literature, we submit it is both.

We find evidence that lower incomes lead to modest proportional tax increases for Atlanta homeowners. Yet homeowner submarkets stratify by joint correlations of income, local middle school quality and race; and each has predictive influence. So, higher incomes and stronger school quality also correlate to lower proportional property taxes, even when comparing two large majority black neighborhoods. Yet race arguably may have a more prominent and regular influence on taxation. We also looked at the year following the same. It may be that there is correction over time as tax assessments keep up with new real estate values, perhaps appreciating at a faster rate in wealthier areas.

Evidenced in our singular analyses such as decile comparisons, or standard multivariate analyses, and onto analysis of different submarkets (persons with different preference orderings), the observed differences in this study among persons by place, race, income and distinct preferences between neighborhoods exposes systematic differential taxation; yet it is difficult to uncover by professional economists even with rigorous and thorough city-wide economic analyses using FMV/Sales Price. This may be difficult to solve independently by the City of Atlanta of Fulton County.

Finally, some partial remedies to Atlanta's rapidly increasing property taxes fall outside the domain of the City of Atlanta or Fulton County. Atlanta's property tax rates are higher than her neighbors; somewhat higher than nearby Brookhaven and Kennesaw, and much higher than, for example, Marietta a few miles north; or even nearby Roswell which lies within Fulton Couty. These areas are less diverse with lower crime rates and sometimes even lower priced homes than many homes in the key Atlanta neighborhoods in question. This means Atlantans with above average incomes face higher taxes than those only a few miles away. To make up for this rising affordability problem in areas with property taxes critical to provision of public services, there is a high city sales tax, that adds a 3% Fulton County tax and a 1.5% City of Atlanta tax on top of Georgia's 4% sales tax. Property tax revolts among wealthier Atlantans have a lot to do with the perception of somewhat lower city services at higher property taxes than their demographically similar neighbors just beyond Atlanta, with comparable in income and ethnic composition.

Aggravating this mounting public fiancé challenge, it is noteworthy that far fewer higher income Atlantans commute outside of the city for work. Yet more residents outside the city commute into Atlanta for work or regular business. As Georgia does not permit a city income tax, commonly between 0.5%-3% where they exist nationwide, local services needed to support those jobs of those living outside Atlanta from local sales taxes, which still fall disproportionately on Atlanta citizens. Of course, property taxes are paid entirely by Atlantans. Absent a small city income tax, property taxes make up this difference.

So, there is a strong political economy, game theoretic pressure for Atlanta public authorities to engage in 'tax shaving,' or a modestly softer tax and assessment regime to offset political conflict. Yet also to avert a real threat of movement of some long-term residents or, more likely, a softening of inmigration to certain high valued Atlanta neighborhoods comparable to homes outside Atlanta become more attractive with slight property tax repression at the high end. These wealthier, historical legacy neighborhoods declare openly that they represent 22% of the citizenry while paying 44% of the taxes. If we add the difficulty of making easy value comparisons that arise when data such as price per square foot are unavailable, detecting these differences in the effective tax *rate* becomes more difficult; and these obstacles to fair taxation has a deep institutional history.

Finally, in evaluating Atlanta's public finance ecosystem, it appears public data irregularities have played a part. The public reporting rules and traditions that formed between the1890s and 1930s failed to report information such as home size. We suggest that these data lapses likely were deliberately structured for this very purpose. The advent of progressive racial policy and political leaders in Atlanta, especially black political leadership, has moderated only slightly what had been long standing historical discriminatory taxes. Nonetheless, the overwhelming evidence from many different evaluation perspectives show, some discriminatory taxation continues; and shows that the critical information that might expose this tax discrimination and open a larger public debate continues to suppress this dialogue..

Appendices

Table 1: Summary statistics

	Mean	Standard deviation
Tax/Sales Price (%)	1.30	0.70
Tax/FMV (%)	2.20	1.60
FMV/Sales Price	0.69	0.30
Sales price	417,196.68	391,152.46
Percent black	43.36	38.86
Percent renter occupied	43.96	24.18
Median income	78,034.96	53,898.12
Mean math score	502.03	28.20
Household size	2.47	0.58
Percent high school diploma	91.08	9.50
Percent college degree	59.28	26.90
Median house value	316,860.81	259,074.37
Lot size	0.30	0.27
Age	57.95	30.21
Square footage	2,232.47	1,302.79
Total bath	2.14	1.00
Total rooms	6.84	1.68
Central heating	0.93	0.26
Stories	1.29	0.44
Total fixtures	9.79	4.53
Years since remodeling	51.38	31.28

Note: Other variables in the regression include the following categorical variables: style (style of individual home); external wall (material construction of external wall); fuel (type of fuel system); fronting (type of street fronting); topography; utility (type of utility connection); sale month, CDU (condition, desirability, utility – denoting physical depreciation of property); revision code (code for method appraisal); deed (type of deed); location (type of location, e.g., residential, central business district, etc.); lot type; LUC (land-use code); zoning designation.

Table 2: OLS regression results (linear model)

	Estimate (Std. Error)
Percent black	0.00370*** (0.00094)
Percent renter occupied	-0.00257*** (0.00065)
Median income (‘000s)	0.06906 (0.04094)
Percent with high school diploma	0.00521*** (0.00183)
Percent with college degree	-0.00492*** (0.00130)
Percent with graduate degree	-0.00085 (0.00174)
Math score	0.00257*** (0.00058)
Household size	-0.13879*** (0.02158)
Median house value (‘000s)	-0.09525*** (0.03011)
Square footage	-0.00001 (0.00001)
Age	0.00504*** (0.00180)
Age squared	-0.00006*** (0.00002)
Lot size	0.06508 (0.04563)
Years since remodeled	0.00020 (0.00046)
Number of floors	0.05649 (0.03214)
Central heating (0/1)	-0.16708*** (0.03646)
Total bathrooms	-0.04396 (0.02524)
Total rooms	-0.00966 (0.00746)
Total fixtures	0.00644 (0.00581)

	Estimate (Std. Error)
X-distance	0.00001 (0.00001)
X-distance squared	-0.00000 (0.00000)
Y-distance	0.00003*** (0.00001)
Y-distance squared	-0.00000*** (0.00000)
Adjusted R-squared	**0.1823**

Note: Other control variables in the regression include the following categorical variables: style (style of individual home); external wall (material construction of external wall); fuel (type of fuel system); fronting (type of street fronting); topography; utility (type of utility connection); sale month, CDU (condition, desirability, utility – denoting physical depreciation of property); revision code (code for method appraisal); deed (type of deed); location (type of location, e.g., residential, central business district, etc.); lot type; LUC (land-use code); zoning designation.
*0.001 '***' 0.01'**' 0.1 '*' (Standard errors clustered at the block group level)*

Table 3: Stepwise OLS regression results with Tax/FMV and FMV/Sales Price

	Baseline (i)	House features (ii)	Location (iii)	Lat-Lon (iv)
	Dependent variable: Tax/Sales Price			
Pct Black	-0.992*** (0.326)	-1.037*** (0.323)	-0.770** (0.323)	-0.644** (0.324)
R-sq	0.044	0.096	0.124	0.130
	Dependent variable: Tax/FMV			
Pct black	-0.627** 0.283	-0.647** 0.279	-0.472* 0.280	-0.496* 0.281
R-sq	0.145	0.193	0.211	0.211
	Dependent variable: FMV/Sales Price			
Pct black	-0.430 (0.265)	-0.449 (0.255)	-0.358 (0.254)	-0.211 (0.253)
R-sq	0.160	0.243	0.273	0.283
	Independent variables			
Pct renter occupied	X	X	X	X
Pct HS diploma	X	X	X	X
Pct college degree	X	X	X	X
Household size	X	X	X	X
Math score	X	X	X	X
Median income (000s)	X	X	X	X
Median property value	X	X	X	X
Sale month and year	X	X	X	X
House characteristics	-	X	X	X
Zoning & location	-	-	X	X
XY dist and dist sq	-	-	-	X

*Note: 0.001 '***' 0.01'**' 0.1 '*' (Standard errors clustered at the block group level)*

Table 4: Summary statistics by submarkets (2 submarkets)

	Submarket 1 (N = 3,651)		Submarket 2 (N = 1,705)	
	Mean	SD	Mean	SD
Tax/Sales Price (%)	1.20	0.10	1.70	0.90
Tax/FMV (%)	1.90	1.10	2.80	2.00
FMV/Sales Price	0.695	0.254	0.673	0.378
Sales price	505,612	339,008	226,461	428,076
Pct black	29.91	32.80	71.56	35.43
Pct renter occupied	39.72	23.72	52.75	22.90
Median income	91,124.28	51,487.5	50,628.03	48,790.45
Pct high school diploma	94.02	7.73	84.92	9.93
Pct college degree	69.06	21.71	38.62	25.25
Median house value	376,139	245,784	192,747	244,814
Household size	2.38	0.55	2.64	0.59
Lot size	0.30	0.27	0.28	0.27
Age	57.78	31.12	59.62	27.17
Square footage	2,376.70	1,349.91	1,889.01	1,111.63
Total bath	2.26	0.99	1.86	0.95
Total rooms	6.97	1.69	6.52	1.60
Central heating	0.94	0.22	0.88	0.32
Mean math score	510.15	26.39	484.87	23.75
Stories	1.31	0.45	1.20	0.40
Total fixtures	10.25	4.43	8.62	4.44
Years since remodeling	50.19	32.11	55.18	28.50

Table 5: OLS regression in submarkets (2 submarkets)

	Submarket 1	Submarket 2
Dependent variable: Tax/Sales Price		
Pct black	0.0308 (0.2775)	-0.9450 (1.0750)
R-sq	0.2839	0.2121
Dependent variable: Tax/FMV		
Pct black	-0.0140 (0.2451)	-0.9188 (1.0301)
R-sq	0.1183	0.2717
Dependent variable: FMV/Sales Price		
Pct black	0.0448 (0.2370)	-0.0262 (0.7871)
R-sq	0.4589	0.2314
Summary statistics		
N	3,651	1,705
Tax/Sales Price (%)	1.20	1.70
Pct black	29.91	71.56
Sales price	505,612	226,461
Square footage	2,376.70	1,889.01
Median income	91,124.28	50,628.03

*Note: 0.001 '***' 0.01'**' 0.1 '*' (Standard errors clustered at the block group level)*

Table 6: Summary statistics by submarkets (3 submarkets)

	Submarket 1 (N = 1,643)		Submarket 2 (N = 2,260)		Submarket 3 (N = 1,453)	
	Mean	SD	Mean	SD	Mean	SD
Tax/Sales Price (%)	1.20	0.40	1.20	0.50	1.80	0.90
Tax/FMV (%)	2.00	1.50	1.80	0.90	2.90	1.90
FMV/Sales Price	0.676	0.246	0.697	0.264	0.687	0.39
Sales price	508,802	368,651	480,180	327,854	213,996	434,076
Pct black	32.19	35.51	31.46	32.77	73.81	34.36
Pct renter occupied	40.06	24.83	40.38	22.86	53.58	22.93
Median income	90,113	55,832	88,048	47,947	49,531	50,342
Pct high school diploma	93.44	8.66	93.60	7.68	84.63	9.88
Pct college degree	66.82	24.54	68.10	21.41	37.35	24.77
Median house value	386,433	274,287	353,893	226,335	183,901	242,977
Household size	2.41	0.58	2.41	0.59	2.61	0.55
Lot size	0.30	0.26	0.30	0.28	0.28	0.28
Age	58.17	30.39	58.02	31.33	59.12	27.04
Square footage	2,340.66	1,164.49	2,347.43	1,441.87	1,890.69	1,141.54
Total bath	2.25	0.92	2.23	1.04	1.85	0.95
Total rooms	7.01	1.68	6.89	1.68	6.52	1.63
Central heating	0.95	0.21	0.93	0.24	0.88	0.32
Mean math score	511.48	27.37	507.29	25.94	483.44	23.24
Stories	1.31	0.44	1.30	0.45	1.20	0.41
Total fixtures	10.14	4.12	10.18	4.65	8.55	4.45
Years since remodeling	50.80	31.32	50.63	32.46	54.68	28.40

Table 7: OLS regression in submarkets (3 submarkets)

	Submarket 1	Submarket 2	Submarket 3
Dependent variable: Tax/Sales Price			
Pct black	0.0150 (0.3896)	0.1339 (0.4132)	-1.3590 (1.1850)
R-sq	0.2807	0.3174	0.2202
Dependent variable: Tax/FMV			
Pct black	-0.1086 (0.3740)	0.2972 (0.3668)	-0.7559 (1.1350)
R-sq	0.1989	0.1052	0.2795
Dependent variable: FMV/Sales Price			
Pct black	0.1236 (0.3508)	-0.1633 (0.3288)	-0.6028 (0.8519)
R-sq	0.4478	0.5189	0.2157
Summary statistics			
N	1,643	2,260	1,453
Tax/Sales Price (%)	1.20	1.20	1.80
Pct black	32.19	31.46	73.81
Sales price	508,802	480,180	213,996
Square footage	2,340.66	2,347.43	1,890.69
Income	90,113	88,048	49,531

*Note: 0.001 '***' 0.01'**' 0.1 '*' (Standard errors clustered at the block group level)*

Table 8: Summary Statistics of Submarkets (4 Submarkets)

	Submarket 1 (N = 1,154)		Submarket 2 (N = 2,064)		Submarket 3 (N = 835)		Submarket 4 (N = 1,303)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Tax/Sales Price (%)	1.20	0.40	1.20	0.50	1.20	0.60	1.80	0.90
Tax/FMV (%)	1.80	0.90	1.80	0.80	2.40	2.10	3.00	1.90
FMV/Sales Price (%)	0.72	0.21	0.71	0.27	0.59	0.27	0.69	0.40
Sales price	549,311	315,667	493,665	331,067	372,962	388,989	205,567	449,356
Pct black	19.38	19.41	31.88	34.73	53.00	40.21	75.83	33.10
Pct renter occupied	37.63	21.39	39.93	24.80	45.67	24.19	54.48	22.07
Median income	98,152	43,298	91,642	54,959	66,953	50,227	46,578	47,200
Pct high school diploma	94.60	7.47	94.49	7.14	89.29	9.85	83.89	9.77
Pct college degree	73.45	16.43	69.40	22.01	52.45	26.99	35.44	23.90
Median house value	404,816	234,749	375,571	246,380	277,308	254,634	175,002	240,492
Household size	2.33	0.53	2.39	0.56	2.54	0.61	2.66	0.60
Lot size	0.26	0.28	0.33	0.27	0.29	0.25	0.28	0.29
Age	56.26	33.48	57.28	30.21	61.85	28.01	59.74	26.97
Square footage	2,431	1,487	2,409	1314	2,020	1,044	1,868	1,138
Total bath	2.30	1.06	2.29	1.00	2.04	0.89	1.81	0.92
Total rooms	6.98	1.70	6.98	1.67	6.76	1.74	6.49	1.58
Central heating	0.96	0.20	0.94	0.24	0.91	0.29	0.89	0.32
Mean math score	519.66	29.25	507.67	22.99	495.42	25.61	482.04	22.19
Stories	1.36	0.48	1.31	0.45	1.21	0.40	1.21	0.41
Total fixtures	10.57	4.71	10.26	4.42	9.33	4.16	8.39	4.30
Years since remodeling	48.39	33.94	50.55	31.23	53.61	29.80	55.57	28.52

Table 9: OLS with Submarkets (4 Submarkets)

	Submarket 1	Submarket 2	Submarket 3	Submarket 4
Dependent variable: Tax/Sales Price				
Pct black	0.2760 (0.5447)	-0.2444 (0.3581)	-0.1869 (0.9044)	-1.2250 (1.1340)
R-sq	0.3731	0.2841	0.3058	0.2825
Dependent variable: Tax/FMV (%)				
Pct black	0.5396 (0.4701)	-0.1978 (0.2941)	-0.4465 (0.9737)	-1.7560 (1.0991)
R-sq	0.1496	0.1244	0.2325	0.3248
Dependent variable: FMV/Sales Price				
Pct black	-0.2636 (0.4901)	-0.0466 (0.3088)	0.2596 (0.6787)	0.5306 (0.8474)
R-sq	0.4918	0.4574	0.4708	0.2386
Summary stats				
N	1,154	2,064	835	1,303
Tax/Sales Price (%)	1.20	1.20	1.20	1.80
Pct black	19.38	31.88	53.00	75.83
Sales price	549,311	493,665	372,962	205,567
Square footage	2,431	2,409	2,020	1,868
Income	98,152	91,642	66,953	46,578

*Note: 0.001 ‘***’ 0.01‘**’ 0.1 ‘*’ (Standard errors clustered at the block group level)*

Figure 1: Scatterplot of stratified means by pct black deciles

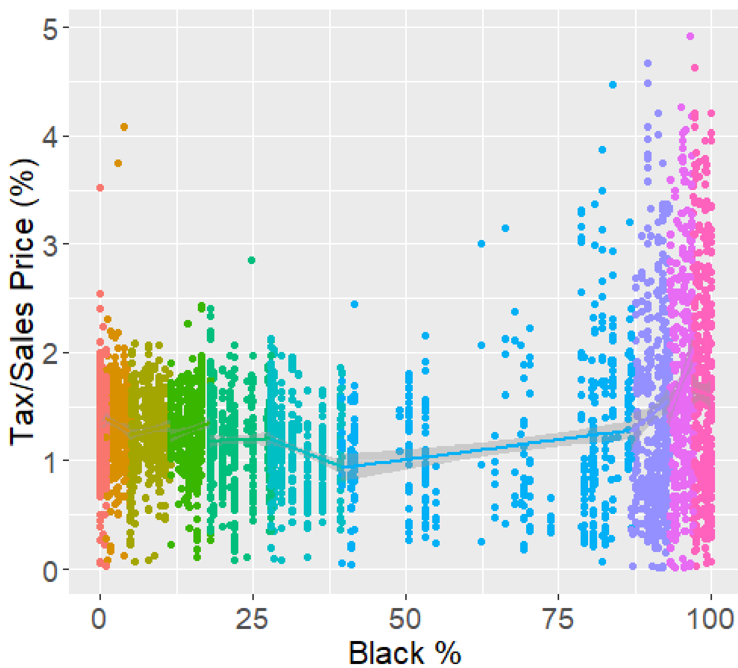

Figure 2: Map of Atlanta by mean ratios