Racial Bias in Property Taxation in Atlanta: The Difficulty in Reversing Structural Discrimination

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History of real estate taxation: over-assessed & over-taxed

- 2018: Philadelphia homes selling \$25K - \$50K over-assessed by 70% (or \$360/yr for a \$37,500 home); homes sold for \$1 -\$2 million in same period underassessed by 11% (or \$2,000/yr discount)
- Similar bias in Philadelphia; assessment bias was reported in Detroit and New Orleans
- 2017: Chicago southside residences note inconsistencies in tax rate hikes persisting the year after sales
- Assessors often must sort ‘bare land value’ from ‘improvement value’ and bare land value increases have limits
    - Higher end properties are more heterogenous in attributes and occur in area that have been fully developed for a longer period

History of real estate taxation: over-assessed & over-taxed

- Reflects the history of federal civil rights and subversive local attempts
- Over-assessment (1870s-1930s) to generate unpaid debt for prison labor
  - ➢Debt or unemployment supported industrialization in South
- Later Jim Crow
  - ➢Assessment to dispossess property directly (1920s though WW2)
  - ➢Below 4% of black-owned farmland enrolled in USDA lending, insurance & marketing
- Finally, Supreme Court Civil Rights (1950s – early 1980s)
  - ➢Designed to encourage movement north to protect Senate representation

History of real estate taxation: over-assessed & over-taxed

- 1972. First, the legislation removed municipalities from the conducting assessment. Municipalities could enact exemptions; yet municipalities had to use the County assessed value
- 1974. NAACP sued Fulton County on its Assessment Practices
- 1981. Compelled Reassessment to improve, clarify, and reform County Assessments

None of these worked!

- 1991. Tax Revolt: Widely considered a 'true implementation' of assessments as wealthy and white neighborhoods had to catch up all at once

Works (too numerous to mention) address the effects of redlining and how that suppresses home values

Kenneth K. Baar. ***Overassessment of properties; then taxed at same rate***

Property Tax Assessment Discrimination Against Low-Income Neighborhoods

Urban Lawyer. **(1981)**

P Bayer *et al. Blacks pay higher prices for identical houses in same neighborhood*

Racial and Ethnic Price Differentials in the Housing Market

Journal of Urban Economics. **(2017)**

Michael Makovi. *Overassessment not found in actual assessments to sales*

Is There Discrimination in Property Taxation? Evidence from Atlanta, Georgia, 2010-2016

Journal of Housing Economics. **(2022)**

Recent works on this issue

- Over-appraising of fair market value (FMV)
  - Assumes tax uniformly charged; so, a high FMV over-taxes (tax charge is inferred)
- Makovi (2022) shows FMV to subsequent Sales Value as others had; but finds no bias
  - Hence, FMV is fairly assessed in Fulton Country Georgia - City of Atlanta Residences
- We, however, *directly* test tax charged to subsequent sales price.
  - Also examines Fulton Country Georgia - City of Atlanta Residences (like Makovi 2022)
  - The *actual tax charged* to subsequent *sales price* is higher for African Americans

Recent works on this issue

- Prior research use assessed-to-sales price data.
- Assessments are also subject to appeals and challenges and there may be significant perceived or actual bias in assessment
  - ➢So these ‘biases’ are likely to be rectified in response to appeals and challenges
- Actual taxation may not be consistent to assessment for a number of reasons such as a house that hasn’t been sold in many years versus a house that has been sold more recently.

Atlanta politics and race – some notes

- Atlanta has had a Black Merchant class since reconstruction
  - ➢More black millionaires in absolute and percentage until late 1990s
- Georgia established rules in the 1880s preventing local income taxes and later local sales taxes, creating reliance on property
- Many new cities and townships established on the perimeter of Atlanta to avoid property taxes yet commute to city for work
- Atlanta now:
  - ➢Higher rate of home ownership than the national average
  - ➢Home to some of the leading black educational institutions such Clark Atlanta, Morehouse College, Spelman College.
- So, has taxation disparity been eliminated over time with increasing equity and strong Black leadership in the city?

Information deficiencies in Atlanta

- *Home Square Footage:*
  - Not easily available in public record (has to be downloaded item by item)
  - Easy to alter value assessment
  - Without square footage data, it becomes difficult to argue their case in front of the assessment authority
- *Actual Tax Charged:*
  - Not downloadable or scrapable in bulk (has to be downloaded item by item!)
  - Not available in public tax assessment record (has to be collected from Tax Commissioner's Office [not from the County Assessor's Office that has assessment records])
  - Over 5,000 last tax prior to sale, collecting the Parcel ID and tracking in tax roles filed by area, not numerical order
- Multiple sources of information; how do you harmonize?
  - No common identifier
  - Parcel ID/address in inconsistent formats

Data

- Sales and assessment data are obtained from the Fulton County Board of Assessors.
- A “Property Profile” file obtained from the Fulton County GIS Portal contains data matching every parcel ID to spatial data such as (X, Y) coordinates and school attendance zones.
- Demographic data – at the Census block group level obtained from the Census Bureau’s 5-year avg. ACS.
- Square footage and tax data from Tax Commissioners Office.
- In the final dataset, each observation is a sold house, each associated with Census block group demographics.

Data

- First, found data not available in bulk (square footage, actual tax paid by each residential unit)
  - ➢These clearly make assessment and assessment challenges difficult
  - ➢Actual taxes paid has not been common in this literature
- Collected all home sales data from Atlanta public records for 2015 and 2016
  - ➢Trimmed sales clearly less than arms length, plus all sales below $20K
- Performed reconciliation checks on sales prices (Zillow and tax record and square footage)
- Used highest resolution demographic data from ACS 5-year average
  - ➢Block group level, 200-600 homes typically

Summary statistics by %-black decile

Raw data
choice of
comparison
matters

Quartile	N	Pct black	Tax/salesprice (%)	Tax/FMV (%)	FMV/Salesprice
1	493	0.22	1.34 (0.35)	1.77 (1.60)	0.805 (0.200)
2	493	2.69	1.33 (0.37)	1.69 (0.32)	0.811 (0.419)
3	493	7.57	1.27 (0.43)	1.63 (0.28)	0.785 (0.244)
4	493	14.90	1.27 (0.35)	1.92 (2.03)	0.748 (0.210)
5	493	22.00	1.19 (0.42)	1.79 (1.13)	0.696 (0.217)
6	493	31.70	1.12 (0.38)	1.73 (0.67)	0.676 (0.201)
7	493	69.30	1.20 (0.77)	2.61 (2.03)	0.528 (0.310)
8	493	90.50	1.45 (0.89)	3.08 (2.12)	0.552 (0.311)
9	492	95.00	1.68 (0.97)	3.15 (1.73)	0.585 (0.300)
10	492	98.80	1.71 (0.98)	3.08 (1.80)	0.605 (0.316)

Summary statistics

	N	Mean	SD
Sales price	4928	420,118.945	395,210.599
Sqft	4928	2,229.630	1,312.458
Math score	4928	501.912	28.424
Lot size	4928	0.299	0.278
Median income	4928	78,427.453	54,539.744
Age of house	4928	58.054	30.250
Pct white	4928	51.288	37.068
Pct black	4928	43.244	38.886
Pct over-65	4928	8.200	6.800
Pct college degree	4928	59.036	27.274
Tract cover	4928	21.832	7.420
Crime	4928	0.152	0.101
Pct renter	4928	44.542	24.885

ANOVA

Dep. Var.	Sum of squares	df	F	P
Tax/Sales	180.3	9	47.98	0.000
Tax/FMV	1898	9	89.96	0.000
FMV/Sales	50.8	9	71.37	0.000

OLS on entire market

	Dep. Var.: Tax/Sales price
Pct Black	0.0033***
Pct Renter Occupied	-0.0119*
Median Income (000s)	0.0004
Pct with High School Diploma	0.0042**
Median property value (000s)	-0.0009***
Pct above 65 Years	0.3153
Sale above Median Sales Price	-0.2687***
Lot Size	0.0282
No. of Floors	0.0736**
Age of House	0.0023
Age-squared	-0.00003*
Square Footage	0.00004***
Central Heating	-0.0257
Total Baths	0.0184
Total Rooms	0.0115*
Years since Remodeling	-0.00007
xdist	0.0000
xdist_sq	0.0000
ydist	0.0000
ydist_sq	0.0000

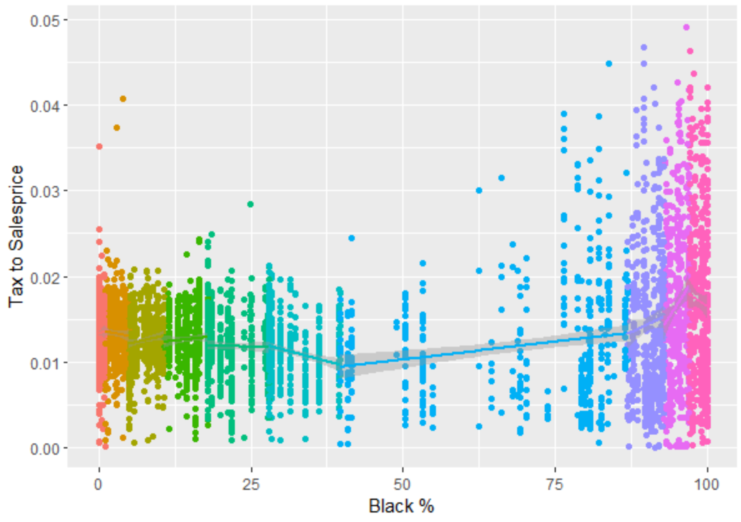
0.001 '***' 0.01'**' 0.1 '*'

OLS summary of full market

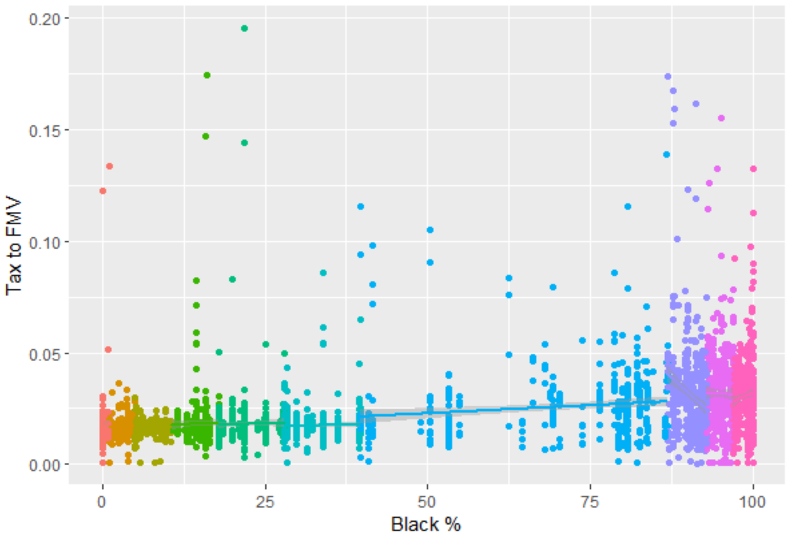
	Baseline	House characteristics	Location	Lat-Lon	Parcel and school
Dependent variable: Tax-to-Sales price					
Pct Black	0.0947	0.0827	0.0576	0.0022**	0.0033**
R-sq	0.1573	0.2136	0.2260	0.2475	0.2995
Dependent variable: Tax-to-FMV					
Pct black	0.0019	0.0029***	0.0029***	0.0046***	0.0026**
R-sq	0.1893	0.2229	0.2236	0.2302	0.2438
Dependent variable: FMV-to-Sales price					
Pct black	-0.0050*	-0.0066***	-0.0071***	-0.0059***	-0.0038**
R-sq	0.2205	0.3349	0.3499	0.3602	0.4254
CONTROLS AND FIXED EFFECTS					
Pct renter occupied	X	X	X	X	X
Pct over-65	X	X	X	X	X
Pct HS diploma	X	X	X	X	X
Pct veteran	X	X	X	X	X
Median income (000s)	X	X	X	X	X
Median property value	X	X	X	X	X
Sale above median	X	X	X	X	X
Sale month and year	X	X	X	X	X
House characteristics	-	X	X	X	X
Zoning	-	-	X	X	X
XY dist and dist sq	-	-	-	X	X
Parcel district FE	-	-	-	-	X
School FE	-	-	-	-	X

Tax by %-black decile

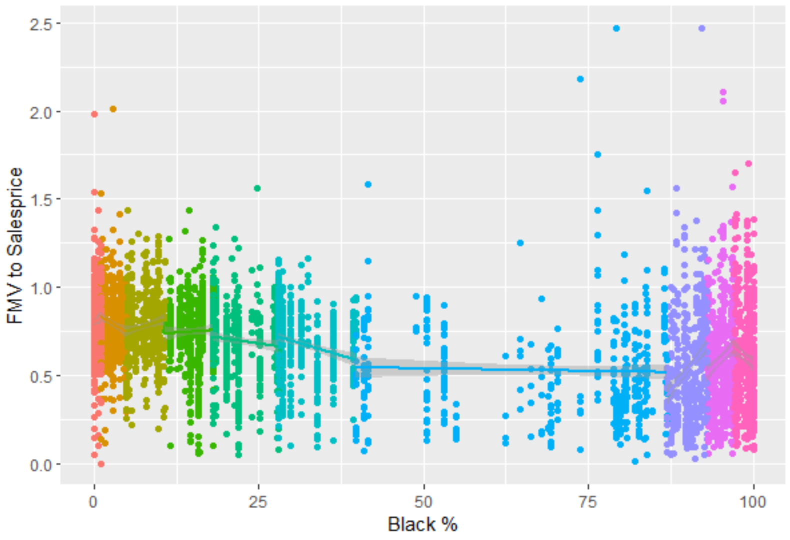
Tax-to-sales price



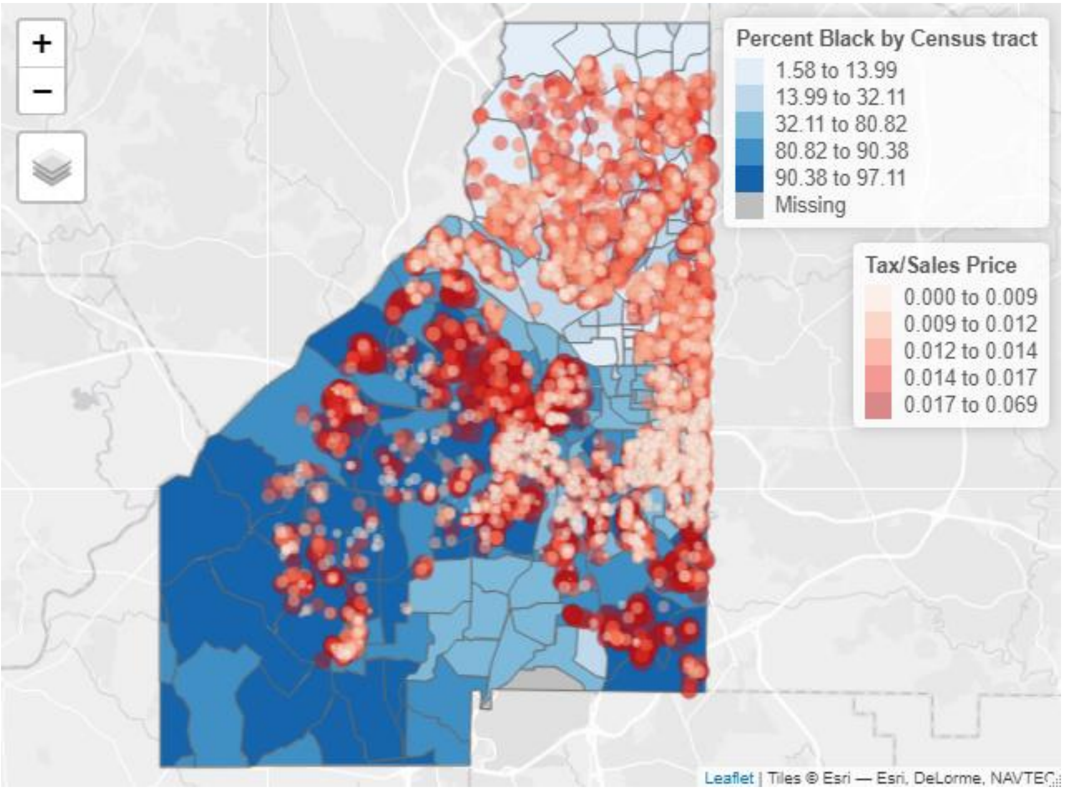
Tax-to-fair market value



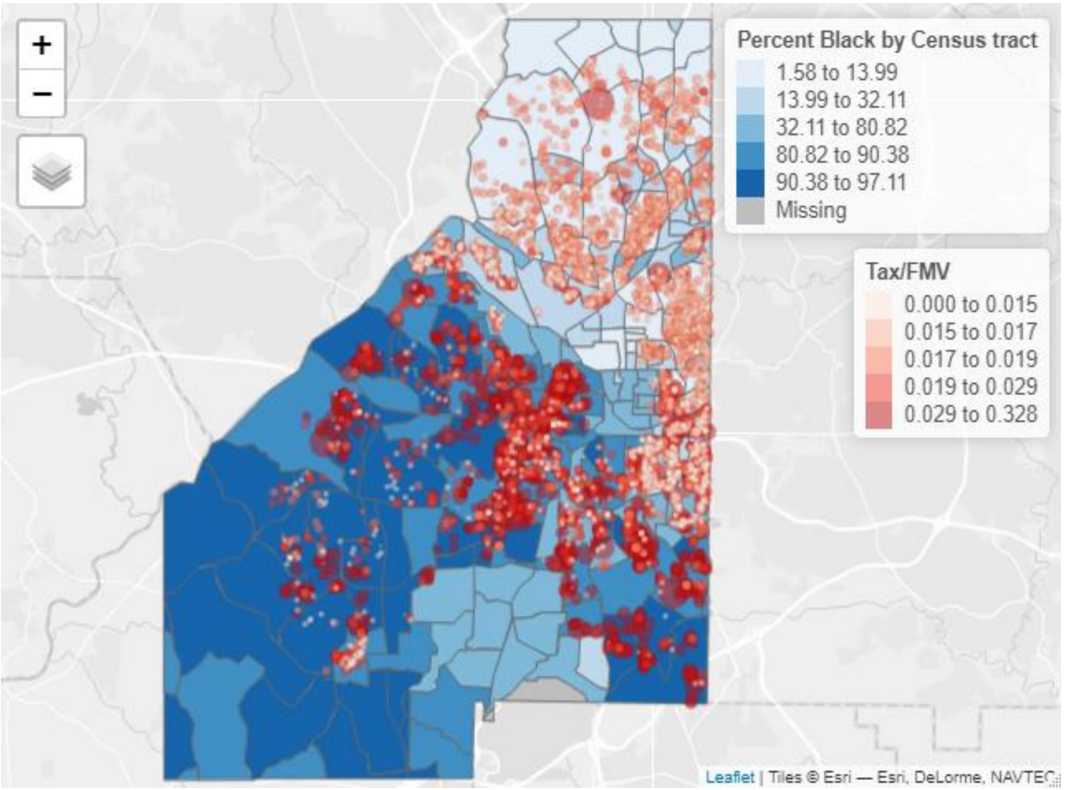
Fair market value-to-sales price



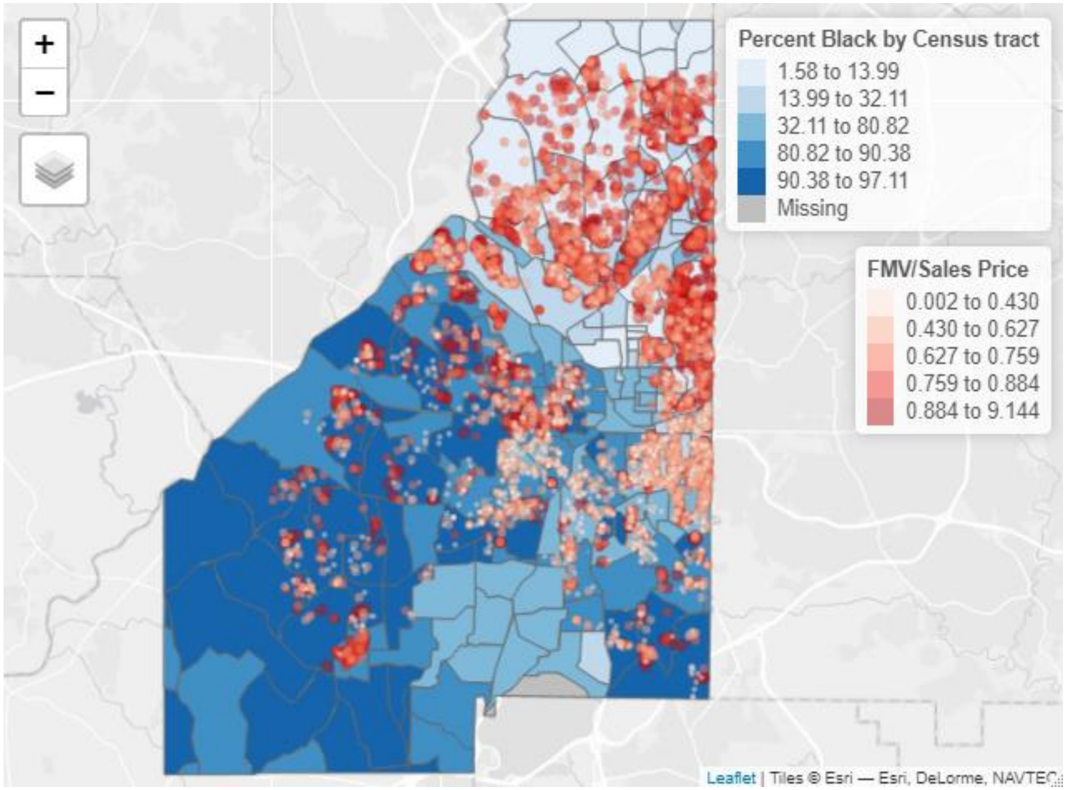
Tax/Sales by %-black by census tracts



Tax/FMV by %-black by census tracts



FMV/Sales by %-black by census tracts



Sorting into submarkets Account for heterogeneous preferences

- We want to test some demographics that seem to be treated differently
  - ➢We want to sort houses into like persons by their housing preferences, not demographics a priori
- We endogenize the sorting process of finite mixture into submarkets
  - ➢We test two, three, or four submarkets
- Each submarket displays a separate parameter array – identifies a perfect 'prototype'
  - ➢Yet each household has some unique probability, π, of membership in each submarket
- This eliminates potential endogeneity: if racial bias, then decoupled from poverty of lower income or education per se
- Individualize parameter array parallel to random coefficients

Fully endogenized finite mixture model: EM algorithm (1/5)

- This model employs a finite mixture model to sort households into endogenously determined latent submarkets. The finite mixture model to predict home prices is:

$$h(P_i|x_i, \beta_j, p_j) = \sum_{j=1}^{m} \pi(z_i) f(P_i|x_i, \beta_j)$$

- The mixing model $\pi(z_i)$, is used to assign each observation a percentage chance of belonging to each latent submarket and $f(.)$ is a submarket specific conditional hedonic regression. The home price is therefore a weighted average of predicted values across submarkets weighted by the probability of being located in the submarket.

Fully endogenized finite mixture model: EM algorithm (2/5)

- We also define $(d_i = d_{i1}, d_{i2}, \dots, d_{im})$ to be binary variables that indicate the inclusion of household i into each latent group. These are incorporated into the likelihood function based on a logistic function which are conditional on factors that do not directly influence the price of the house.
- Since the submarket identification (d) is not directly observable, an expectation maximization (EM) algorithm is used to estimate the likelihood of class identification:

$$d_{ij} = \frac{\pi_j f_j(P_i | x_i, \beta_j)}{\sum_{j=1}^{J} \pi_j f_j(P_i | x_i, \beta_j)}$$

Fully endogenized finite mixture model: EM algorithm (3/5)

- The Expectation step – the E step – involves imputation of the expected value of d_i given the mixing covariates, interim estimates of γ, β, π. The Maximization step – the M step – involves using estimates of d_i from the E step to update the component fractions of π_j and β. The EM algorithm can be summarized as:

1. Generate starting values for γ, β, π
2. Initiate iteration counter for the E-step, t(initial t at 0)
3. Use β^t and π^t from Step 2 to calculate provisional d^t from $d_{ij} = \frac{e^{\gamma_j z_i}}{1+\sum_{C=1}^{C} e^{\gamma_j z_i}}$

Fully endogenized finite mixture model: EM algorithm (4/5)

4. Initiate second iteration counter, v, for the M-step

5. Interim estimators of d^{t+1} are then used to impute new estimates of β^{v+1} and π^{v+1} with $d_{ij} = \frac{\pi_j f_j(P_i|x_i,\beta_j)}{\sum_{j=1}^{J} \pi_j f_j(P_i|x_i,\beta_j)}$

6. For each prescribed latent class, estimators of β^{v+1} are imputed, via M-step, as well as π^{v+1}

7. Increase v counter by 1, and repeat M-step until: $f(\beta^{v+1}y, x, \pi, d) - f(\beta^{v}y, x, \pi, d) < a$ prescribed constant; if so, then $\beta^{t+1} = \beta^{v+1}$

8. Increase t counter and continue from step 3 until: $f(\beta^{t+1}, \pi^{t+1}, d|y) - f(\beta^{t}, \pi^{t}, d|y) < a$ prescribed constant

Fully endogenized finite mixture model: EM algorithm (5/5)

- d_{ij} is estimated simultaneously with the estimation of the hedonic regression parameters, which are conditional on class identification.
- This process is repeated until there is no change in the likelihood function: $LogL = \sum_{i=1} \sum_{j=1} d_{ij} \log\left[f_j\left(P_i \middle| x_i, \beta_j\right)\right] + d_{ij} \log\left[\pi_j\right]$
- The steps above, particularly from Step 3-8 do not necessarily occur sequentially as outlined above but occur simultaneously as the continual updating of estimators. Each v iteration conditionally maximizes the likelihood function using interim estimates of observation latent class membership probabilities in one of the latent classes; while each t iteration updates latent class memberships.
- The modified hedonic regression is: $y_{ij} = d_{ij}\left(\beta_j X_i\right) + \epsilon_{ij}$

FMM betas (2 submarkets)

Not much distinction in submarkets by race: Just separates ***white north*** from ***black south***

	Submarket 1	Submarket 2
Pct black	-0.021*	-0.020*
Sqft	1.011*	1.021*
Age	0.001	0.008
Age_sq	0.114*	-0.015*
Total bath	1.098	0.329
Lot size	1.114*	0.192
Math score	0.020	0.022
Crime	0.469	-0.072
Tract cover	0.048	0.046
Above median	1.039*	0.426*
xdist	6,592.569	6,592.566
xdist_Sq	-564.278	-564.275
ydist	-39,091.317	-39,091.528
ydist_sq	8,432.446	8,433.154
RMSE	345,044.8	70,143.27
Weighted RMSE	163,129.2	
AIC	23,366.83	

FMM betas (3 submarkets)

Not much distinction; ***value/sqft & lot size*** differ more than typical

	Submarket 1	Submarket 2	Submarket 3
Pct black	-0.020*	-0.018*	-0.020*
Sqft	1.662*	0.937*	0.810*
Age	0.003*	0.003	-0.009
Age_sq	0.009*	0.034*	0.256
Total bath	0.181	0.300	1.585
Lot size	0.219	0.192*	1.639*
Math score	0.020	0.020	0.020
Crime	-0.502	-0.399	0.868
Tract cover	0.033	0.044	0.056
Above median	0.301*	0.428*	1.425*
xdist	6,592.565	6,592.578	6,592.603
xdist_Sq	-564.245	-564.280	-564.254
ydist	-39,091.666	-39,091.568	-39,091.764
ydist_sq	8,432.967	8,433.039	8,432.338
RMSE	49,132.51	70,948.29	392,189.3
Weighted RMSE	143,928.4		
AIC	25,565.62		

FMM betas (4 submarkets)

	Submarket 1	Submarket 2	Submarket 3	Submarket 4
Pct black	-0.021*	-0.021*	-0.005	-0.022*
Sqft	1.681*	1.097*	2.495	0.204*
Age	-0.003	0.011	-0.024	-0.002
Age_sq	0.057*	-0.037*	0.418	0.069*
Total bath	0.199	0.252	0.943	0.756
Lot size	0.300	0.199	1.792	0.306
Math score	0.019	0.018	0.021	0.018
Crime	-0.480	0.133	-1.539	0.420
Tract cover	0.033	0.046	0.021	0.060
Above median	0.284*	0.417*	0.624*	0.611*
xdist	6,592.590	6,592.581	6,592.593	6,592.587
xdist_Sq	-564.253	-564.233	-564.259	-564.359
ydist	-39,091.579	-39,091.833	-39,091.685	-39,091.470
ydist_sq	8,431.977	8,432.824	8,432.638	8,434.411
RMSE	46,234.50	51,738.44	317,529	79,852.36
Weighted RMSE	144,226.1			
AIC	27,603.37			

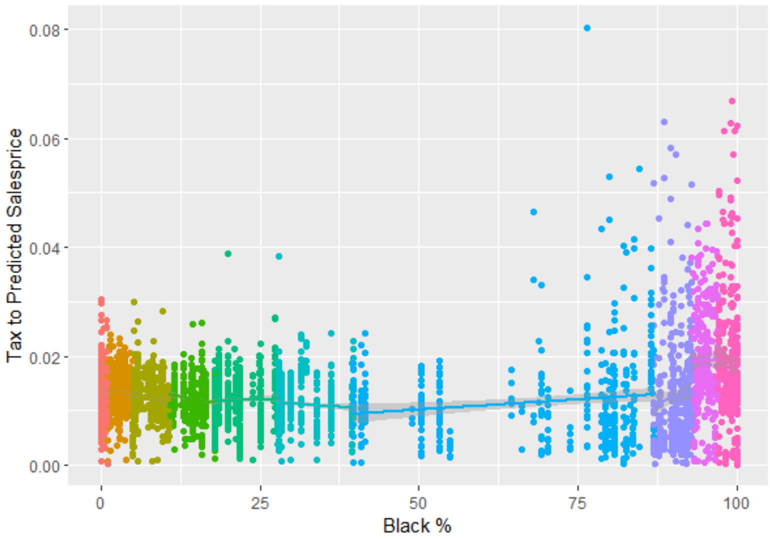
Submarket 3
most distinct

Predicted tax/sales price by %-black decile

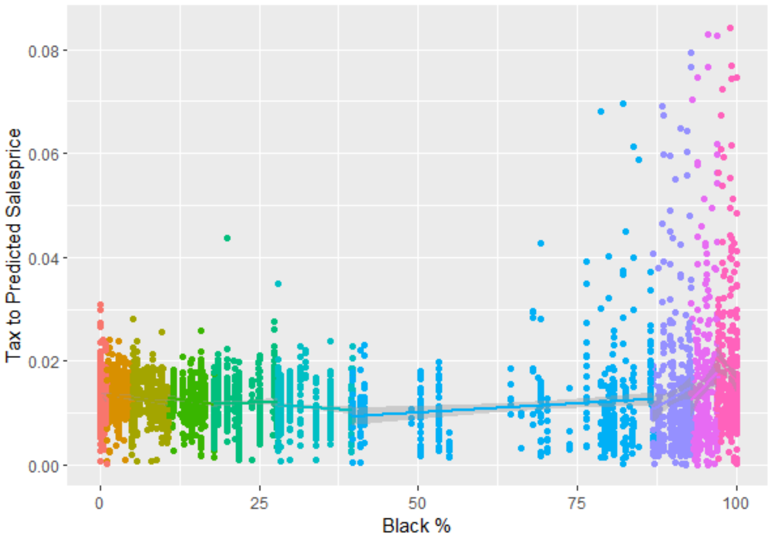
Quartile	N	Pct black	Tax/actual salesprice (%)	Tax/predicted salesprice (%) 2 submarkets	Tax/predicted salesprice (%) 3 submarkets	Tax/predicted salesprice (%) 4 submarkets
1	493	0.22	1.34	1.36	1.35	1.34
2	493	2.69	1.33	1.33	1.32	1.33
3	493	7.57	1.27	1.23	1.23	1.25
4	493	14.90	1.27	1.21	1.21	1.22
5	493	22.00	1.19	1.19	1.19	1.17
6	493	31.70	1.12	1.11	1.12	1.12
7	493	69.30	1.20	1.28	1.24	1.28
8	493	90.50	1.45	1.39	1.41	1.35
9	492	95.00	1.68	1.72	1.65	1.68
10	492	98.80	1.71	1.66	1.63	1.66

Tax by %-black decile
(higher %Black, Higher tax-to-price)

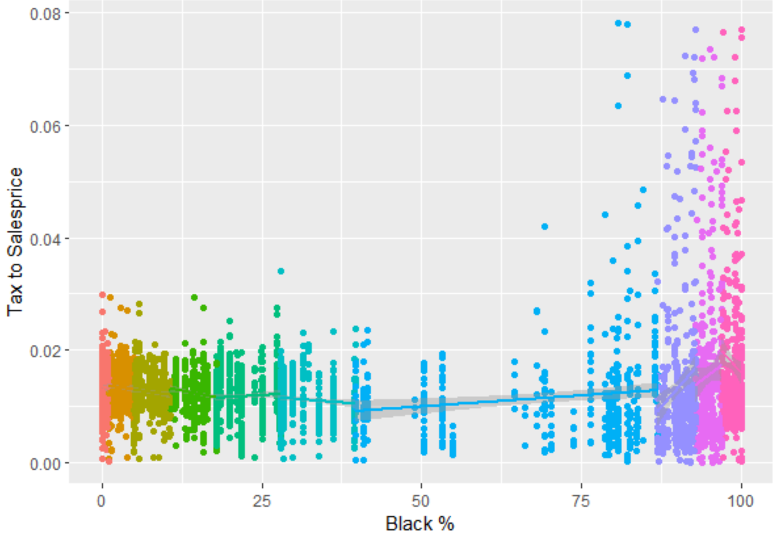
2 Submarkets
Tax-to-predicted sales price



3 Submarkets
Tax-to-predicted sales price



4 Submarkets
Tax-to-predicted sales price



Summary statistics of FMM submarkets assigned to highest probability (2 submarkets)

	N	Mean	SD
Sales price	769	890,354	605,620
Sqft	769	3,426	1,849
Math score	769	521	23.3
Lot size	769	0.451	0.45
Median income	769	122,239	66,410
Age of house	769	56.6	31.0
Pct white	769	77.3	26.0
Pct black	769	16.3	25.6
Pct over-65	769	8.40	6.50
Pct college degree	769	77.4	18.1
Tract cover	769	23.6	7.72
Crime	769	0.106	0.08
Pct renter	769	32.7	26.8

Summary statistics of FMM submarkets assigned to highest probability (2 submarkets)

	N	Mean	SD
Sales price	4,159	333,172	262,444
Sqft	4,159	1,706	972
Math score	4,159	498	27.8
Lot size	4,159	0.271	0.222
Median income	4,159	70,327	47,849
Age of house	4,159	58.3	30.1
Pct white	4,159	46.5	36.8
Pct black	4,159	48.2	38.9
Pct over-65	4,159	8.20	6.80
Pct college degree	4,159	55.6	27.3
Tract cover	4,159	21.5	7.32
Crime	4,159	0.161	0.103
Pct renter	4,159	46.7	23.9

OLS with FMM submarkets assigned to highest probability (2 submarkets)

	Submarket 1	Submarket 2
Dependent Variable: Tax/Sales price		
Pct black	-0.0895	0.0170*
R-sq	0.2869	0.3170
Depvar: Tax/FMV		
Pct black	0.0021	0.0025*
R-sq	0.1767	0.2675
Depvar: FMV/Sales price		
Pct black	-0.0068*	-0.0037*
R-sq	0.4079	0.4452
Summary stats		
N	769	4,159
Salesprice	890,354	333,172
Sqft	3,426	1,706
Income	122,239	70,327
Pct black	16.3	48.2

Summary statistics of FMM submarkets assigned to highest probability (3 submarkets)

	N	Mean	SD
Sales price	2,843	379,062	331,087
Sqft	2,843	1,554	1,077
Math score	2,843	498	28.2
Lot size	2,843	0.269	0.228
Median income	2,843	72,030	52,318
Age of house	2,843	61.0	29.3
Pct white	2,843	46.8	37.2
Pct black	2,843	48.0	39.1
Pct over-65	2,843	8.30	6.80
Pct college degree	2,843	55.7	27.7
Tract cover	2,843	21.7	7.46
Crime	2,843	0.164	0.107
Pct renter	2,843	46.9	24.7

Summary statistics of FMM submarkets assigned to highest probability (3 submarkets)

	N	Mean	SD
Sales price	1,672	354,627	255,170
Sqft	1,672	2,192	1,160
Math score	1,672	503	27.4
Lot size	1,672	0.308	0.269
Median income	1,672	77,923	49,135
Age of house	1,672	52.7	31.1
Pct white	1,672	52.2	36.2
Pct black	1,672	42.0	38.2
Pct over-65	1,672	8.00	6.80
Pct college degree	1,672	60.0	26.3
Tract cover	1,672	21.7	7.25
Crime	1,672	0.143	0.091
Pct renter	1,672	43.6	23.9

Summary statistics of FMM submarkets assigned to highest probability (3 submarkets)

	N	Mean	SD
Sales price	413	967,884	719,584
Sqft	413	3,403	2,051
Math score	413	523	23.8
Lot size	413	0.468	0.488
Median income	413	124,513	66,983
Age of house	413	59.6	30.6
Pct white	413	78.1	26.5
Pct black	413	15.6	26.1
Pct over-65	413	8.60	6.50
Pct college degree	413	78.3	18.0
Tract cover	413	23.5	7.65
Crime	413	0.108	0.083
Pct renter	413	32.2	26.5

OLS with FMM submarkets assigned to highest probability (3 submarkets)

	Submarket 1	Submarket 2	Submarket 3
Depvar: Tax/Sales price			
Binary variable	0.0156*	-0.1690	-0.0004
R-sq	0.3451	0.2619	0.3549
Depvar: Tax/FMV			
Pct black	0.0037**	0.0036*	0.0055*
R-sq	0.2809	0.2211	0.2363
Depvar: FMV/Sales price			
Pct black	-0.0041*	-0.0024	-0.0068*
R-sq	0.4185	0.4406	0.5105
Summary stats			
N	2,843	1,672	413
Salesprice	379,062	354,627	967,884
Sqft	1,554	2,192	3,403
Income	72,030	77,923	124,513
Pct black	48.0	42.0	15.6

Summary statistics of FMM submarkets assigned to highest probability (4 submarkets)

	N	Mean	SD
Sales price	2,629	381,036	342,189
Sqft	2,629	1,906	1,103
Math score	2,629	498	28.3
Lot size	2,629	0.269	0.24
Median income	2,629	71,608	51,913
Age of house	2,629	61.5	29.0
Pct white	2,629	46.6	37.3
Pct black	2,629	48.1	39.2
Pct over-65	2,629	8.30	6.80
Pct college degree	2,629	55.4	27.8
Tract cover	2,629	21.7	7.44
Crime	2,629	0.164	0.107
Pct renter	2,629	47.0	24.6

Summary statistics of FMM submarkets assigned to highest probability (4 submarkets)

	N	Mean	SD
Sales price	1,100	411,642	290,447
Sqft	1,100	2,455	1,249
Math score	1,100	505	26.7
Lot size	1,100	0.322	0.287
Median income	1,100	83,501	54,004
Age of house	1,100	50.9	32.3
Pct white	1,100	55.6	35.3
Pct black	1,100	38.5	37.2
Pct over-65	1,100	7.80	6.70
Pct college degree	1,100	62.0	26.3
Tract cover	1,100	21.9	7.42
Crime	1,100	0.142	0.091
Pct renter	1,100	42.7	24.6

Summary statistics of FMM submarkets assigned to highest probability (4 submarkets)

	N	Mean	SD
Sales price	257	1,222,571	745,874
Sqft	257	3,486	1,709
Math score	257	528	19.3
Lot size	257	0.471	0.485
Median income	257	135,354	67,393
Age of house	257	62.5	29.2
Pct white	257	83.9	18.8
Pct black	257	9.96	17.1
Pct over-65	257	9.30	6.70
Pct college degree	257	82.0	13.0
Tract cover	257	23.0	7.85
Crime	257	0.104	0.08
Pct renter	257	29.2	26.1

Summary statistics of FMM submarkets assigned to highest probability (4 submarkets)

	N	Mean	SD
Sales price	942	320,164	225,162
Sqft	942	2,528	1,461
Math score	942	503	28.5
Lot size	942	0.311	0.271
Median income	942	76,005	48,534
Age of house	942	55.6	29.9
Pct white	942	50.3	37.3
Pct black	942	44.2	39.2
Pct over-65	942	8.10	6.80
Pct college degree	942	59.5	26.2
Tract cover	942	21.90	7.20
Crime	942	0.144	0.094
Pct renter	942	44.0	24.0

OLS with FMM submarkets assigned to highest probability (4 submarkets)

	Submarket 1	Submarket 2	Submarket 3	Submarket 4
Depvar: Tax/Sales price				
Binary variable	0.1598*	-0.1379	0.0742	0.3607*
R-sq	0.3527	0.2241	0.4758	0.3133
Depvar: Tax/FMV				
Pct black	0.0036**	0.0010	0.0026	0.0023
R-sq	0.2892	0.2136	0.2014	0.2404
Depvar: FMV/Sales price				
Pct black	-0.0037*	-0.0035	-0.0029	-0.0019
R-sq	0.4109	0.4410	0.5552	0.5008
Summary stats				
N	2,629	1,100	257	942
Salesprice	381,036	411,642	1,222,571	320,164
Sqft	1,906	2,455	3,486	2,528
Income	71,608	83,501	135,354	76,005
Pct black	48.1	38.5	9.96	44.2