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Estimates and Implications

Morris A. Davis, Jesse Gregory, and Daniel A. Hartley

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Preferences over the Racial Composition of Neighborhoods: Estimates and Implications*

Morris A. Davis
Rutgers University
mdavis@business.rutgers.edu

Jesse Gregory
University of Wisconsin and NBER
jmgregory@ssc.wisc.edu

Daniel A. Hartley
Federal Reserve Bank of Chicago
Daniel.A.Hartley@chi.frb.org

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Abstract

Using data from 197 metro areas, we estimate the parameters of a dynamic, forward-looking neighborhood choice model where households have preferences over the racial composition of the neighborhood in which they live. Using multiple metro areas in the estimation sample enables us to develop a new instrumental variables strategy to estimate the impact of the racial composition of neighborhoods on location choice that relies only on across-metro comparisons of similarly situated neighborhoods. Our neighborhood-level instrument is constructed by interacting national-average, across-neighborhood sorting patterns with respect to neighborhood-level topography with metro-level shares of households by demographic subgroup. For a given neighborhood topography, the instrument predicts variation in neighborhood-level racial shares that is attributable exclusively to variation in metro-level shares of demographic subgroups. We find that households in many different demographic subgroups have strong preferences to live in neighborhoods consisting mostly or entirely of households of the same race. These preferences are sufficiently strong that model simulations suggest that the current demographic composition of neighborhoods is not stable.

JEL Classification Numbers: D58, D59, I31, R21, R23
Keywords: segregation, neighborhood choice, equilibrium

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1 Introduction

In this paper, we propose a new method for estimating households' preferences for racial diversity in the neighborhoods in which they live. As documented by Cutler et al. (1999) and others, households in the United States continue to be racially segregated. This segregation may be the outcome of households having explicit preferences over the racial mix of the neighborhood in which they live. An alternative explanation is that households do not directly care about the racial mix of their neighborhood, but segregation occurs because households of different races differentially value or differ in their ability to pay for various neighborhood amenities. Of course, both of these forces may be present and contributing to the segregation of neighborhoods today, especially once historical dynamics including policies and other factors that restricted neighborhoods by race are taken into consideration.

There are important policy implications of understanding why segregation occurs. If households do not have strong preferences regarding the race of their neighbors, then government programs that incentivize racial integration may be able to increase neighborhood racial diversity. If some households have preferences exhibiting "homophily," the desire to live in neighborhoods with households of their same race, then government programs may shift people around in the short run, but may not increase racial diversity in the long run as households respond to the program and to the movement of other households.

To gain insight regarding the ways in which neighborhoods change due to preferences, we specify a dynamic, discrete-choice model of within-metro neighborhood choice and estimate household preferences for the racial mix of their neighborhood using a new instrumental variables (IV) strategy. We use a dynamic model in order to consider the short- and long-run impacts of hypothetical government policies on the demographic composition of neighborhoods. Our shift-share research design requires estimating a different version of the dynamic location choice model specifically tailored for each of a large number of metro areas, because the approach for identifying racial preferences involves comparisons of similarly situated neighborhoods across metro areas. For that reason, the geographic scope of our analysis needs to be substantially larger than existing studies that estimate dynamic discrete choice models of neighborhood choice using data from a single metro area. We apply our research design using panel data on neighborhood choices in nearly 200 metro areas from the New York Fed/Equifax Consumer Credit Panel and detailed topographic data in each neighborhood in these metros, a key input to our shift-share IV.

We estimate the model's parameters using a two-step, BLP-style procedure (Berry et al., 1995; Bayer et al., 2007), appropriately adapted for our dynamic modeling environment (Bishop, 2012; Davis et al., 2021). In the first step, we use GMM to obtain estimates of the indirect flow utility that each census tract ("neighborhood") provides to households from each of 54 different demographic subgroups ("types") in each metro area. In the second step, we regress these first-stage estimates of neighborhood indirect utilities on variables describing neighborhood racial composition, instrumenting for the racial share variables which are likely to be correlated with neighborhood-level unobserved amenities.

We construct the IVs for neighborhood racial shares using a shift-share strategy that harnesses the fact that topography inside a metro area is highly predictive of where households with different demographic and socio-economic characteristics tend to live (Ye and Becker, 2018; Heblich et al., 2021a; Ye and Becker, 2024) and that metro areas vary substantially in their overall demographic structure. To calculate the shift-share instrument for racial composition in every neighborhood in every metro, we interact (a) national average neighborhood-choice patterns with respect to topographic variables for each of the 54 demographic types in our data, estimated using a national sample of neighborhoods, with (b) metro-level shares of those household types. Thus, for a particular neighborhood topography, the instrument predicts variation in neighborhood-level racial shares that is attributable exclusively to variation in metro-level shares of demographic types. In estimation, we control directly for topography preferences, such that this across-metro variation in our instrument (exclusively determined by variation in metro-level type shares) is the only source of identification of preferences for racial shares.

Our IV approach is like a shift-share instrument (Bartik, 1991) in the sense that metro-level variation in the distribution of household types can be viewed as "shares" and our predictions of where household types live within a metro area (based on a nationally-estimated prediction equation using only topographic data) can be thought of as the "shifts." Thus, we can use some of the insights of the recent literature on the econometrics of shift-share instrumental variables to discuss the properties of our estimator. This literature has emphasized that either exogeneity of the shares (Goldsmith-Pinkham et al., 2020) or exogeneity of the shifts (Borusyak et al., 2022), but not necessarily both, is required for shift-share IVs to satisfy instrument exogeneity. Our approach relies on an assumption of "share exogeneity," specifically the metro-level type shares. Importantly our identification strategy allows for topography to be correlated with unobserved neighborhood amenities. To verify that our strategy is robust to such correlation, we perform Monte Carlo simulation experiments that demonstrate our approach produces consistent estimates of preference parameters in an environment where households directly sort on amenities (including topography) when making location choices.

Our estimates suggest that some, but not all, types of households have relatively strong preferences for neighborhood racial composition exhibiting homophily. The fact that households do not uniformly wish to live in more segregated neighborhoods hints that there may be some room for policy to engineer more racially integrated neighborhoods than currently observed. We use our model to predict the outcomes of one such hypothetical policy that, absent any resorting response, should mechanically increase racial integration relative to current neighborhood demographics. We simulate a policy shock in which all current low-income housing tax credit developments expand by 10 percent and the new units are populated by low-income households with the same demographic mix as the metro average for low-income households. We then compute a new steady state after the policy is implemented and all households have had a chance to resort in response to this policy and the location-choice decisions of other households.

In every metro that we simulate, the new steady state features much more racial segregation (relative to the starting point of the simulations) due to the endogenous resorting of the population that takes place over time. This resorting and the increase in segregation that results occurs because many types of households have strong preferences exhibiting homophily. When we repeat simulations of the hypothetical policy shock, but after significantly "shrinking" (but not eliminating) estimates of racial preferences for all types of households, the steady state that emerges in many metro areas is more racially integrated than the starting point of the simulations.

We also use simulations of the model to understand the relationship between household expectations and the speed at which households resort in response to implementation of this policy. If households are myopic and assume current racial shares will persist indefinitely (only updating expectations when observed shares change), then it can take decades for households to resort in response to the policy.[1] In contrast, if households expect a new steady state to emerge immediately after the policy is implemented, they act rapidly and the new steady state in fact typically emerges within 10 years.

Our paper contributes to established literatures on how the racial composition of neighborhoods affects location choices, and how this impacts the equilibrium allocation of people across neighborhoods. Kuminoff et al. (2013) provides a survey of equilibrium models with endogenous location choices, including a few papers where households have preferences over the racial composition of neighborhoods, for example Bayer et al. (2007). Focusing on estimation, some prominent recent papers have used quasi-experimental variation in geographically proximate locations to estimate how the racial composition of neighborhoods affects location choice, for example Almagro et al. (2022) and Bayer et al. (2022).[2] Almagro et al. (2022) use

[1]In the classic paper by Schelling (1971), households are assumed to solve a sequence of static models when making decisions, implying expectations are myopic over future neighborhood composition.

[2]These papers are in the spirit of Bayer et al. (2007), which uses boundaries for school attendance zones in San Francisco to generate plausibly exogenous changes in neighborhood racial composition, under the

randomness in the timing of demolitions of public housing in Chicago, under the assumption that other amenities are held fixed over time, and Bayer et al. (2022) focus on changes to the racial composition of neighbors that are geographically close (on their block) and therefore plausibly share the same bundle of amenities not related to race. Despite our use of a different model, different data, and an estimation procedure that relies on a different source of variation for identification, our results about preferences are in line with findings of Almagro et al. (2022), Bayer et al. (2022), and other studies: Many households have preferences that exhibit homophily.[3]

Our work also directly relates to other quasi-experimental studies estimating White households' migration response to inflows of Black households. Boustan (2010), who studies post-WWII White migration from central cities to suburbs, uses a shift-share approach similar to that of Card (2001) to estimate the impact of Black inflows on White migration.[4] Shertzer and Walsh (2019) use an IV approach similar to Boustan (2010), but with a prediction equation that generates within-city White migration in response to Black migration between 1900 and 1930.[5]

Finally, there is an extensive literature on the dynamics of neighborhood change. See Ellen (2000) for an overview and Ellen and Torrats-Espinosa (2019) for a discussion of racial change in the context of gentrification. An important recent study in this literature is Caetano and Maheshri (2021), which exploits the time-series structure of a dynamic location-choice decision model to develop instruments based on sufficiently lagged data that identifies exogenous components of the current racial composition of neighborhoods in San Francisco. Similar to our findings, Caetano and Maheshri (2021) estimate that household preferences exhibit homophily. Given these preferences, their model predicts that the racial composition of neighborhoods in San Francisco will change over time.[6]

assumption that unobserved amenities on both sides of the boundary are roughly the same.

[3]Additionally, in line with our findings, Aliprantis et al. (2022) find that preferences (homophily) rather than wealth explain differences in the socio-economic status of the neighborhoods in which Black and White households reside. Christensen and Timmins (2021) and Christensen and Timmins (2022) show that steering and barriers to entry may also play a role in determining the neighborhoods to which Black households have access.

[4]In related papers, Derenoncourt (2022) studies the impact of southern Black migration to northern and western commuting zones on inter-generational income mobility of households in those zones and Shi et al. (2022) study the impact of this migration on urban renewal projects at the city level. For identification, Boustan (2010), Derenoncourt (2022) and Shi et al. (2022) use southern state-level push factors interacted with historical county-level migration patterns.

[5]In Shertzer and Walsh (2019), the source of variation arises from differences in Black out-migration rates from southern states interacted with historical northern city neighborhood destinations of migrants from those states. Relative to Shertzer and Walsh (2019), we are using different shifts and shares and are estimating racial preferences within the context of a dynamic model of location choice.

[6]Almagro and Sood (2026) similarly show that even in an environment where covenants can limit where certain races may live, preferences explain a large share of observed segregation in the Minneapolis metro

2 Location-Choice and Topography Data

This section describes the data inputs used throughout the paper. We first summarize the FRBNY Consumer Credit Panel / Equifax data and how we construct annual within-metro location choices and household demographic types. We then describe the tract-level topography measures and present summary statistics that characterize the distribution of neighborhood composition and rents in the estimation sample.

2.1 FRBNY Consumer Credit Panel / Equifax Data

Our data on location choices come from the FRBNY Consumer Credit Panel / Equifax data set (CCP). The panel is comprised of a 5% random sample of U.S. adults with a social security number, conditional on having an active credit file, and any individuals residing in the same household as an individual from that initial 5% sample.[7] For years 1999 to 2019, the database provides a quarterly record of variables related to debt: Mortgage and consumer loan balances, payments and delinquencies and a few other variables we discuss later. The data do not contain information on basic demographics like race, education, or number of children. The data also includes the Equifax Risk Score^{TM} which provides some information on the financial wherewithal of the household as demonstrated in *Report to Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit* (2007).

Most important for our application, the panel data includes in each period the current census block (and therefore census tract) of residence.[8] To match the annual frequency of our location choice model, we use location data from the first quarter of each calendar year. In each year, we only include people living in metro areas – if, for example, a household moves from an eligible metro area to a rural area, that household-year observation is not included in the estimation sample. To keep estimation computationally feasible, we assume each household can only move within its metropolitan division ("metro"). If a household moves to a different metro, the household-year observation of the move is not included in the estimation sample, but the years before and after the across-metro move are included.

The panel is not balanced, as some individuals' credit records first become active after 1999. We restrict the sample to households living in one of 197 metros, each containing between 50 and 1,000 census tracts.[9] The total number of person-year observations in the

area in 1940.

[7]The data include all individuals with 5 out of the 100 possible terminal 2-digit social security number (SSN) combinations. While the leading SSN digits are based on the birth year/location, the terminal SSN digits are essentially randomly assigned. A SSN is required to be included in the data.

[8]Census block and census tract are coded using the 2000 Decennial Census tabulation geographies.

[9]We impose the limitation on the maximum number of census tracts in a metro to keep estimation feasible.

estimation sample is 142,692,072.

We sort households into 54 mutually exclusive types: by age of the head of the household (young, middle, old), by housing tenure status (renter, owner), by credit score (low, middle, high), and by race (Black, Hispanic, White/other). With the exception of race, a household's type can stochastically change over time. Borrowing a method from overlapping generations models in macroeconomics to conserve on state variables, we specify that households age up (i.e. young to middle, middle to old) or die (old to death) with a 5% probability each year. Conditional on age and race, we estimate the annual 6x6 matrix of transition probabilities of housing tenure status and credit score using the CCP data pertaining to our estimation sample.

From the CCP data, we classify a household as young if the age of the household head is between 25-44, middle aged if 45-64, and old if 65 and older. We classify the household as a homeowner if the household has a mortgage and a renter if not. Finally, we classify a household as having a low credit score if the Equifax Risk Score^{TM} of the household head is less than or equal to 599, middle credit score if between 600 and 720 inclusive, and high credit score if greater than or equal to 721.[10]

Finally, it is helpful to explain how we structure the CCP for estimation and document a shortcoming of the data. Let j represent a household's beginning-of-period location and ℓ their end-of-period location. For each type, we construct an estimate of the probability that ℓ is the end-of-period location given a beginning-of-period location of j,[11] using a procedure that allows us to observe all elements of any type τ except race. We infer information about a household's race from the census block where we first observe the primary sample person in the household.[12] Let the superscript r denote race (r equals w for White/other, b for Black, and h for Hispanic) and define ω_i^r as our estimate of the probability that household i is of race r where $\sum_r \omega_i^r = 1$. For each $r = \{w, b, h\}$, we set ω_i^r for household i equal to that race's share in the census block in which household i is first observed. We then use these probabilities to identify, for each type τ, the conditional probability that a location ℓ'

[10]We keep only households with 4 or fewer adult members. A household is defined as a homeowner based on whether anyone in the household has any type of home loan. The credit score is that of the oldest adult if the household has 2 or fewer adults, and the oldest adult under the age of 65 if there are 3 or 4 adults in the household.

[11]We compute this estimate by pooling all observations across all time periods.

[12]We define Black as non-Hispanic Black, Hispanic as Hispanic, and White/Other as everyone else. For reference, each census block has about 100 residents and a census tract has about 4,000 residents. If a household is first observed before 2010, then we use racial shares for that household for census blocks from the 2000 Decennial Census. If a household is first observed in 2010 or later, we use racial shares for census blocks from the 2010 Decennial Census. In Appendix A we derive the consequences of imputing race from the composition of the census block and show that this type of measurement error will bias our estimates away from finding homophily.

is chosen in metro m given a starting location of j' in metro m that period. Denote $r(\tau)$ as the specific race r associated with type τ. The estimate of that conditional probability is

$$P_m^{\tau}(\ell' \mid j') = \frac{\sum_t \sum_{i \in O(\tau)} \omega_i^{r(\tau)} \mathcal{I}(\ell_{i,t+1} = \ell') \mathcal{I}(j_{i,t} = j')}{\sum_t \sum_{i \in O(\tau)} \omega_i^{r(\tau)} \mathcal{I}(j_{i,t} = j')} \tag{1}$$

where $i \in O(\tau)$ indicates that household i has all the non-race characteristics of type τ households, $\mathcal{I}(j_{i,t} = j')$ is an indicator that is equal to 1 if household i starts period t in location j' in metro m and is 0 otherwise, and $\mathcal{I}(\ell_{i,t+1} = \ell')$ as an indicator that household i chooses period ℓ' in metro m in period t (or, equivalently, starts period $t+1$ in location ℓ').

2.2 Topography Data

We use 11 topography variables tabulated to census tracts from Baum-Snow and Han (2022).[13] In that study, the authors construct topographic information using the "Scientific Investigations Map 3085" derived from the US Geological Survey's National Elevation Database.[14] Baum-Snow and Han (2022) write, "This data set uses raster information on slope and elevation range for all 30X30 meter land pixels within a 0.56 km radius (1 sq. km.) of each pixel to classify it into one of nine categories that describe how flat or hilly the surrounding area is." Each of the 11 variables is the percentage of the census tract characterized by the stated topographical feature, and the sum of the variables in each tract is 1. The specific variables are *Flat Plains*, *Smooth Plains*, *Irregular Plains*, *Escarpments*, *Low Hills*, *Hills*, *Breaks-Foothills*, *Low Mountains*, *High Mountains*, *Drainage Channels* and *Everything Else*.

2.3 Summary Statistics

Table 1 reports descriptive statistics from our estimation sample of the endogenous variables we consider in estimation as affecting tract-level neighborhood choice: racial composition and rents.[15] The table reports results for the full sample (column "Overall") and separately

[13]These variables were graciously given to us by Nathaniel Baum-Snow and Lu Han. These variables are available for 195 out of the 197 metro areas in our study; only Honolulu and Anchorage (with a total of 280 tracts) are excluded. For the 195 included metros, we have complete topography data for 40,273 out of a possible 40,276 tracts (1 missing tract per metro for 3 metros). The 2 metro reduction in sample only occurs for calculations related to our IV procedure in which the topography variables are used as inputs.

[14]For reference, see USGS Land Surface Forms available at *https://pubs.usgs.gov/publication/sim3085*

[15]Our rent measure controls for observable differences in housing units measured at the census tract-level. See Table 1 note for details.

for four metro-area groups defined by whether the metro has a below- or above-median share of Black households and whether the metro is relatively small or large (columns "Low Black-share metros" and "High Black-share metros," each split into "Small" and "Large").

The table is organized into two panels that correspond to two weighting schemes. Panel A reports *population-weighted exposure* measures. In these rows, tracts are weighted by the population of a given group (Black, Hispanic, or White) living in the tract. For example, the entry 0.359 in the first row of Panel A indicates that a randomly selected Black household in our sample lives, on average, in a tract that is 35.9% Black. Analogously, the entries in the "Pct. Hisp" and "Pct. White" blocks report the average Hispanic and White tract shares experienced by each group. Panel B reports *tract-weighted* averages in which each tract receives equal weight; the means and standard deviations in Panel B therefore describe the distribution of tract characteristics in the estimation sample, rather than the distribution of experiences across households.

Three patterns stand out. First, Panel A confirms that same-race exposure is high on average. In the overall sample, Black households live in tracts that are 35.9% Black on average, Hispanic households live in tracts that are 31.1% Hispanic, and White households live in tracts that are 82.4% White. Second, exposure patterns vary systematically across metro groups. For instance, Black households in low-Black-share metros experience substantially more White neighbors than Black households in high-Black-share metros: the mean White share in the tracts where Black households live is 78.9% and 68.0% in small and large low-Black-share metros, respectively, versus 57.2% and 49.7% in small and large high-Black-share metros. Finally, Panel B shows that composition-adjusted rents are lower in smaller metros than in larger metros, both in the full sample and within the low- and high-Black-share metro groupings.

Table 2 presents summary statistics for the tract-level topography variables for the metros in our sample. The first column of Table 2 reports the means of the 11 topography variables. The next three columns report the standard deviation within metros, between metros, and overall. The statistics in this table show there is meaningful variation in topography within metro areas, a condition we exploit in estimation.

3 Estimating the Impact of Neighborhood Racial Composition on Neighborhood Choice

In this section we present the empirical object that disciplines preferences in the model and the research design used to identify the causal effect of neighborhood racial composition.

Table 1: Race and Rent in the Estimation Sample

Outcome	Weight	Overall All	Low Black-share metros Small	Low Black-share metros Large	High Black-share metros Small	High Black-share metros Large
Panel A. Population-weighted exposure (mean tract composition experienced by each group)						
Pct. Black	Black pop.	0.359	0.099	0.138	0.377	0.414
	Hisp pop.	0.105	0.037	0.063	0.189	0.162
	White pop.	0.088	0.036	0.048	0.147	0.119
Pct. Hisp	Black pop.	0.099	0.112	0.182	0.051	0.089
	Hisp pop.	0.311	0.404	0.346	0.100	0.265
	White pop.	0.089	0.079	0.121	0.050	0.075
Pct. White	Black pop.	0.543	0.789	0.680	0.572	0.497
	Hisp pop.	0.584	0.560	0.591	0.711	0.573
	White pop.	0.824	0.885	0.831	0.803	0.806
Panel B. Tract-weighted averages (each tract equal weight)						
Pct. Black	Tract	0.152	0.047	0.063	0.241	0.219
		(0.209)	(0.065)	(0.086)	(0.227)	(0.247)
Pct. Hisp	Tract	0.116	0.124	0.163	0.055	0.094
		(0.153)	(0.189)	(0.180)	(0.057)	(0.126)
Pct. White	Tract	0.732	0.829	0.774	0.705	0.687
		(0.244)	(0.198)	(0.202)	(0.231)	(0.268)
Rent ($)	Tract	928	804	1,030	762	916
		(338)	(271)	(371)	(228)	(321)
Tracts		40,556	4,478	12,932	3,256	19,890
Metros		197	57	42	42	56

Notes: "Black/Hisp/White pop." weights use the population of the indicated race in each tract, so Panel A entries can be interpreted as exposure averages for that group. "Tract" weights assign each tract equal weight. Metros are split by below/above-median metro Black share and by metro size (Small/Large). In Panel B, standard deviations are shown in parentheses beneath the corresponding mean. The row labeled "Rent" reports mean composition-adjusted rents after regression-adjusting for differences across tracts in: shares of the rental stock by numbers of bedrooms, shares by categories of number of units in the structure, and shares by category of year built and evaluating each compositional characteristic at its mean.

We begin by describing the instrument we construct and required identifying assumptions. We then document (i) strong and interpretable sorting patterns with respect to topography, (ii) first-stage relevance for tract Black and Hispanic shares, and (iii) reduced-form 2SLS estimates of how tract racial shares shift tract demand across household types.

Rather than starting from the dynamic model where the key empirical task is understanding how the racial shares of a neighborhood affect the flow utility from living in that neighborhood (which in turn affects the probability a household chooses that neighborhood), we first ask a simpler, more direct question: how do tract-level Black and Hispanic demographic shares affect the probability that households choose a tract? We treat these choice probabilities as the main outcome in this section and estimate how they are affected by

Table 2: Means and Standard Deviations of Topography Variables

Variable	Mean	Standard deviation		
		Within metro	Between metro	Overall
Flat Plains	0.410	0.276	0.320	0.423
Smooth Plains	0.221	0.222	0.139	0.262
Irregular Plains	0.203	0.211	0.160	0.265
Escarpments	0.006	0.029	0.010	0.030
Low Hills	0.000	0.001	0.000	0.001
Hills	0.032	0.081	0.050	0.095
Breaks-Foothills	0.025	0.075	0.047	0.088
Low Mountains	0.014	0.067	0.028	0.072
High Mountains	0.001	0.015	0.003	0.015
Drainage Channels	0.088	0.076	0.059	0.096
Everything Else	0.001	0.015	0.004	0.016
Tracts	40,273			
Metros	195			

changes in the racial composition of Census tracts. We estimate the impact of neighborhood racial composition on choice probabilities separately for households from each of the demographic cells that we refer to as "types" in our model. We view the IV strategy that underlies this exercise as a central contribution of the paper and the resulting patterns in choice probabilities as motivation for the structural model that follows.

Let $\hat{p}^{\tau}_{\ell,m}$ denote the empirical probability that households of type τ living in metro m choose Census tract ℓ. In this section, we consider identification and estimation of the following reduced-form specification for location choice probabilities,

$$\log \hat{p}^{\tau}_{\ell,m} = b^{\tau}_1 S^b_{\ell,m} + b^{\tau}_2 S^h_{\ell,m} + b^{\tau}_x X_{\ell,m} + \theta^{\tau}_m + A^{\tau}_{\ell,m}, \tag{2}$$

where $S^b_{\ell,m}$ and $S^h_{\ell,m}$ are the Black and Hispanic population shares of the tract, $X_{\ell,m}$ is a vector of exogenous neighborhood characteristics, θ^{τ}_m is a metro (choice set) fixed effect, and $A^{\tau}_{\ell,m}$ captures unobserved amenities valued by type τ, such as school quality, safety, environmental conditions, accessibility, and any others. The coefficients b^{τ}_1 and b^{τ}_2 summarize how racial composition is associated with location choices for each type. However, because $A^{\tau}_{\ell,m}$ is unobserved and is likely correlated with racial shares, ordinary least squares estimates of these coefficients are not valid for interpretation. This endogeneity problem motivates the instrumental-variables strategy we introduce next.

3.1 Identification Strategy

3.1.1 The instrument

To obtain unbiased estimates of b_1^τ and b_2^τ, an IV strategy is necessary. An appropriate instrument must satisfy two conditions: (i) it must be strongly correlated with the racial composition of neighborhoods; and (ii) it must be uncorrelated with unobserved neighborhood amenities (the "exclusion restriction"). Prior studies often rely on instrumental variables based on local, within-metro-area variation, for example exploiting neighborhood boundary discontinuities or policy-induced shifts in racial composition within a single metropolitan region.

In contrast, we develop an IV approach that leverages comparisons across many metropolitan areas using a new strategy. Intuitively, when we compare tracts with similar topography across metros, any difference in racial composition can be decomposed into two parts: an endogenous component that reflects how households with different racial backgrounds sort in response to unobserved neighborhood amenities, and a mechanical component implied by differences in the metro-wide racial mix. Our identification strategy is to use IV so that estimates are driven only by the mechanical, citywide component: we construct instruments based on the interaction of a predictor of within-metro sorting, local topography, with metro-level demographic composition, and use for identification only the variation in neighborhood racial shares that is predicted by this metro-level source.

This logic parallels the across-market comparisons used in IO demand estimation, where similar products are observed in many markets at different relative prices. There, demand is identified by comparing the same or very similar products across markets and exploiting only the component of price variation that is predicted by exogenous cost or mark-up shifters through the IV procedure. In our setting, tracts with the same topographic features in different metros play the role of the similar product sold in many markets, metro-level demographic composition plays the role of market conditions, and our predicted racial shares play the role of the instrumented prices.[16]

The approach requires an observed variable that is predictive of how households of different demographic subgroups sort within metro to obtain predictions of neighborhood-level demographic composition (based on metro-level demographic composition) that vary across a metro's neighborhoods. Our implementation of the IV strategy uses topographic features of neighborhoods in this role as predictor variables. The strategy involves first estimating

[16]The IV estimates are therefore based only on the component of neighborhood racial composition that is predicted by exogenous differences in metro-level demographics interacting with national sorting patterns with respect to topography.

national-level prediction equations for sorting by household demographic types across different topographic features (for example flat plains versus hills). Using the language of the shift-share literature, which we use later to discuss requirements of identification, these national sorting patterns serve as the "shift" component, which we interact with metro-level demographic shares, the "share" component, to produce tract-level predicted racial composition. To construct the shifts, we pool all metros and, for each household type τ, estimate a prediction equation for neighborhood choice probabilities that depends only on topography and metro fixed effects:

$$\log \hat{p}^{\tau}_{\ell m} \;=\; \alpha^{\tau}_{m} \;+\; b^{\tau} TOP_{\ell m} \;+\; \nu^{\tau}_{\ell m}, \tag{3}$$

where $TOP_{\ell m}$ denotes the vector of topographic variables for tract ℓ in metro m, α^{τ}_{m} is a metro-by-type fixed effect, b^{τ} are type-specific coefficients mapping relative topography to neighborhood choice probabilities, and $\nu^{\tau}_{\ell m}$ is an error term.

Denote $\hat{\hat{p}}^{\tau}_{\ell m}$ as the *predicted* choice probability in each tract ℓ of metro m that arises after estimating equation (3),[17] and let s^{τ}_{m} denote the share of the total metro population in metro m accounted for by type τ, i.e. the metro-level type share of type τ. For each tract ℓ in metro m, we then construct a predicted Black share $Z^{b}_{\ell m}$ and a predicted Hispanic share $Z^{h}_{\ell m}$ as follows:

$$Z^{b}_{\ell m} \;=\; \frac{\sum\limits_{\tau' \in \text{Black}} s^{\tau'}_{m}\; \hat{\hat{p}}^{\tau'}_{\ell m}}{\sum\limits_{\tau} s^{\tau}_{m}\; \hat{\hat{p}}^{\tau}_{\ell m}} \quad \text{and} \quad Z^{h}_{\ell m} \;=\; \frac{\sum\limits_{\tau' \in \text{Hispanic}} s^{\tau'}_{m}\; \hat{\hat{p}}^{\tau'}_{\ell m}}{\sum\limits_{\tau} s^{\tau}_{m}\; \hat{\hat{p}}^{\tau}_{\ell m}} \tag{4}$$

When the metro population is 1, the numerator of each expression is the predicted number of Black (Hispanic) households in tract ℓ in metro m, and the denominator is the predicted total number of households in that tract, where all predictions are based only on topography and metro-level type shares, i.e. predictions are all generated by equation (3) after estimating α^{τ}_{m} and b^{τ}. Once $Z^{b}_{\ell m}$ and $Z^{h}_{\ell m}$ are constructed, we use these variables as instruments for the observed racial shares $S^{b}_{\ell m}$ and $S^{h}_{\ell m}$ in estimating equation (2).

Reiterating the nature of identification, because $Z^{b}_{\ell m}$ and $Z^{h}_{\ell m}$ are built from metro-level type shares s^{τ}_{m} and predicted choice probabilities $\hat{p}^{\tau}_{\ell m}$ that depend only on topography, the variation in these instruments can be decomposed into a part coming from cross-metro differences in demographic composition and a part coming from cross-tract differences in

[17] Denote the predicted value from equation (3) as $\hat{y}^{\tau}_{\ell,m}$. We set $\hat{\hat{p}}^{\tau}_{\ell m} = \dfrac{\exp\left(\hat{y}^{\tau}_{\ell,m}\right)}{\sum\limits_{\ell' \in m} \exp\left(\hat{y}^{\tau}_{\ell',m}\right)}$.

topography. By including topography directly in the estimating equation and using the instruments to isolate the component of racial composition that is predicted by $Z^b_{\ell m}$ and $Z^h_{\ell m}$, the IV procedure bases identification on the cross-metro component.

3.2 IV Validity: History of Race, Income, and Topography

3.2.1 Historical Context

A number of historical factors have contributed to the residential sorting patterns of the present in which race and socioeconomic status are correlated with topography, providing the cross-neighborhood variation needed for first-stage relevance of our IV strategy. These factors include market-based factors, discriminatory housing policies, and decentralized discrimination. During the Great Migration from the 1910s through the 1970s, approximately six million Black people moved from the American South to Northern, Midwestern, and Western states. As the Great Migration progressed, segregation increased (Cutler et al., 1999). Housing policies such as zoning and the provision of mortgage credit played a role in the increase as well as the threat of violence, and practices possibly promulgated by real estate professional boards such as blockbusting and racially restrictive covenants. Large infrastructure projects also played a role. Increased segregation combined with amenity prices for views, and distance from industrial pollution led to topography being predictive of race and socioeconomic status.

Evidence from Chicago shows that when zoning was established in the 1920s, neighborhoods with higher shares of racial or ethnic minorities were disproportionately zoned for industrial use (Shertzer et al., 2016). In the late 1930s the Home Owners' Loan Corporation (HOLC) maps graded neighborhoods according to field agent and real estate professionals' assessment of neighborhood mortgage lending risk. However, almost all neighborhoods with Black residents received the lowest grade. Neighborhoods with environmental or industrial hazards were also likely to receive a D grade. Receiving a lower grade resulted in lower property values, presumably from reduced access to credit, and over the next three or four decades many Black migrants from southern states arriving in northern and western cities during the second wave of the Great Migration settled in D-graded neighborhoods (Aaronson et al., 2021). Violence or the threat of violence against Black households that moved to White neighborhoods (Satter, 2024) as well as racially restrictive covenants (Sood and Ehrman-Solberg, 2023) which were clauses written into real estate deeds prohibiting the sale of the property to certain racial or ethnic groups served to maintain existing segregation. Blockbusting, the practice of inducing home sales by inciting fear of neighborhood racial change in order to profit by reselling at a higher price to Black buyers, tended to occur near the boundaries of existing Black neighborhoods, meaning that even when the racial composition of a neighborhood changed, it happened quickly and segregation was maintained (Hartley and Rose, 2023).

Infrastructure decisions also contributed to the relationship between topography and segregation. Railroads may have served as natural boundaries that enhanced segregation (Ananat, 2011), and interstates were routed through minority neighborhoods, frequently along river valleys or low-lying corridors, due to lower land values and weaker political resistance (Bagagli, 2023; Valenzuela-Casasempere, 2024).

Lower wealth and income also limited housing choices for minorities, pushing them toward affordable but environmentally disadvantaged land. In New Orleans, historical development concentrated Black residents in lower-lying neighborhoods such as the Lower Ninth Ward, which suffered disproportionate damage during Hurricane Katrina (Fussell et al., 2010). Industrial and coal-fired residential pollution also followed terrain and wind patterns, influencing socioeconomic sorting. Factories and rail yards were placed in low-lying quarters near rivers, exposing residents to higher pollution levels. Heblich et al. (2021b) finds that 20% of present-day segregation in cities can be explained by historical pollution patterns.

In summary, neighborhood sorting by race and class in American cities is deeply intertwined with topography due to historical discrimination, environmental risks, infrastructure decisions, and economic constraints.

3.2.2 The Exclusion Restriction

As we noted earlier, our IV strategy can be creatively interpreted as a type of a shift-share. The recent literature on the econometrics of shift-share instrumental variables has emphasized that either the exogeneity of shares (Goldsmith-Pinkham et al., 2020) or the exogeneity of shifts (Borusyak et al., 2022), but not necessarily both, is required for the shift-share IVs resulting from the aggregation of the shift-share interactions to satisfy instrument exogeneity. Stated in these terms, we proceed under an assumption of share exogeneity, which can be stated formally as follows:

A1) Share exogeneity:

$$\text{across m:} \qquad \ddot{A}^{\tau}_{\ell,m} \;\perp\; s^{\tau'}_{m} \,\Big|\, T\ddot{O}P_{\ell,m} \quad \forall \tau, \tau' \tag{5}$$

where $\ddot{X}$ means that variable X has had metro-area fixed effects removed. In words, this equation specifies the following: Consider a given topography and a given type of household τ. Across metro areas, the amenity value (for that τ) at locations with that specific topography cannot be correlated with the realized metro-level population shares of any type of household. This lack of correlation must hold for all types τ and all possible topographies.

Under the assumption of share exogeneity, the "shift" variables – national-average predicted neighborhood choice probabilities based only on topography – can be thought of as weights that capture the idea that city-wide metro shares of particular types contribute more strongly or less strongly to predicted neighborhood-level racial makeup depending on which topographic features are present in the neighborhood. Because we control for the direct effect of topography on location choices, identification in our framework is driven only by comparisons of tracts with similar topographic configurations that have different predicted racial compositions due to the metro-wide type shares in the metro where they are located.

For share exogeneity to be violated, household types would have needed to systematically choose metros in which to locate based on the component of amenities, uncorrelated with topography, in neighborhoods in that metro with the topographic features commonly chosen by their household type. To be clear, share exogeneity is *not* violated if household types chose metros in which to locate based on metro-wide factors or amenities common to all topographies in the metro.

The most prominent historical process of voluntary metro-level location choices affecting modern metro-level racial composition was the Great Migration of 1910-1970 in which roughly 6 million Black people moved from the rural South to Northern metro areas. Therefore, understanding the factors that most strongly influenced households' choices of a Northern metro during this period provides a direct check of the plausibility of our identifying assumption. Share exogeneity would likely be violated if, during this period, Black households moved to metro areas based on the relative amenities (again, not directly driven by topography) of the topographies in each metro in which they were most likely to locate, as compared to the overall desirability of the metro area. If these considerations played a meaningful role in determining the metros to which Black households migrated, we would expect a positive correlation between $s_m^{\tau'}$ for Black household types and $\ddot{A}_{\ell,m}^{\tau}$ at the topographies where those households are most likely to live, violating share exogeneity – assumption A1 as written in equation (5).

Stuart and Taylor (2021) provides a summary of the literature on factors that influenced location decisions during the Great Migration. These factors include: 1) Labor demand and supply factors such as World War I, which increased manufacturing employment in Northern cities and the tightening of immigration restrictions which decreased labor supply from European immigrants; 2) Southern push factors such as the destruction of cotton crops by the boll weevil, labor market discrimination, racial violence, and Jim Crow laws; 3) railroad networks which channeled migration from certain regions in the South to specific Northern cities, and; 4) social networks of family, friends, and church members that had already migrated to the North. These main factors are metro-level, and not related to the amenities of the neighborhoods at the within-metro relative topographies in which Black households tend to live. For these reasons, we think it unlikely that the Great Migration led to migration flows that violate share exogeneity.

A similar logic applies to the formation of Hispanic populations across U.S. metropolitan areas. The initial growth of Hispanic communities in many metros was shaped by labor demand and migration networks: migrants were drawn to places with expanding opportunities in agriculture, construction, manufacturing, and services, and subsequent flows were reinforced by family, community, and employer networks that reduced migration costs and facilitated job finding. These determinants operate at the metro level – they influence which cities households enter – and do not naturally map into systematic selection on the relative desirability of specific within-metro neighborhood topographies.

For share exogeneity to fail for Hispanic type shares, Hispanic households would need to have disproportionately chosen metros based on unobserved amenities that are specific to the particular topographic configurations where Hispanic households tend to live within those metros, rather than on overall metro-level conditions. While it is plausible that metros differ in many amenities and in the strength of their labor markets, such differences are absorbed by metro fixed effects in our empirical specifications and do not threaten identification. The identifying concern is instead a correlation between metro-level Hispanic type shares and the within-metro, topography-residual component of neighborhood amenities; we view that channel as unlikely to be a driver of the metro-level settlement patterns that generated the Hispanic shares observed in our sample.

3.3 Estimates

3.3.1 Sorting with Respect to Topography by Demographic Groups

Table 3 provides an illustrative summary of the full set of 54 tract-type prediction equations that underlie our IV strategy. To generate the results of this table, we stack the data into a pooled sample with one observation per tract ℓ and type τ, and regress $\ln \hat{p}^{\tau}_{\ell,m}$ on tract fixed effects $\phi_{\ell m}$ plus interactions between tract topography and type characteristics.[18] The tract fixed effects absorb the baseline log choice probability for a reference type, so the estimated coefficients we show in the table describe how the relative propensity to choose a tract varies with its fraction of hills versus flat plains across types. The estimates show clear and systematic sorting patterns: relative to the reference categories (high credit, White, mortgage, and age 65+), less affluent groups are substantially less likely to choose tracts

[18] Recall $\hat{p}^{\tau}_{\ell,m}$ denotes the share of households of type τ living in metro m that choose census tract ℓ.

Table 3: Differences in Sorting with Respect to Topography by Demographic Groups

	(1) $\ln \widehat{p}^{\tau}_{\ell,m}$	
Fraction Hills × (characteristic):		
Credit categories		
Low credit	-0.597***	(0.136)
Middle credit	-0.334***	(0.0817)
High credit [ref.]	-	
Race categories		
Black	-1.182***	(0.204)
Hispanic	-0.627***	(0.100)
White [ref.]	-	
Mortgage Categories		
No Mortgage	-0.490***	(0.0850)
Mortgage	-	
Age Categories		
Age 25-44	0.152**	(0.0549)
Age 45-64	0.181***	(0.0344)
Age 65+	-	
Fraction Plains × (characteristic):		
Credit categories		
Low credit	0.563***	(0.0576)
Med credit	0.361***	(0.0356)
High credit [ref.]	-	
Race categories		
Black	0.482***	(0.0870)
Hispanic	0.474***	(0.0674)
White [ref.]	-	
Mortgage Categories		
No Mortgage	0.214***	(0.0350)
Mortgage	- -	
Age Categories		
Age 25-44	0.0275	(0.0232)
Age 45-64	-0.0379*	(0.0162)
Age 65+	-	
Observations	2,174,742	
R^2	0.653	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$\ln \widehat{p}^{\tau}_{\ell,m} = \beta_1 z^{\tau} FlatPlains_{\ell m} + \beta_2 z^{\tau} Hills_{\ell m} + \theta^{\tau}_m + \phi_{\ell m}$

with more hills (negative coefficients on *Fraction Hills* interactions for low and middle credit households, Black and Hispanic households, and households without a mortgage) and are correspondingly more likely to choose flatter tracts (positive coefficients on *Fraction Plains* interactions for the same groups). In contrast, the age interactions suggest that younger households are, if anything, relatively more likely than the 65+ group to choose tracts with more hills and are not systematically more likely to choose flatter tracts. Overall, the table makes transparent that the topography-based prediction equations embed strong and interpretable differences in tract demand across demographic types, with affluent types sorting into hills and less affluent types sorting into plains. The fact that our data show that the topography of neighborhoods is related to household race and socio-economic status is consistent with results from other papers in the literature (Lee and Lin, 2018; Ye and Becker, 2018; Heblich et al., 2021a; Ye and Becker, 2024).

3.3.2 First Stage

Table 4 reports the first-stage relationships between our two instruments, $Z^b_{\ell,m}$ and $Z^h_{\ell,m}$, and the tract-level racial shares that are endogenous, $S^b_{\ell,m}$ and $S^h_{\ell,m}$. Each column corresponds to a separate first-stage regression, with the endogenous regressor indicated at the top of the column. All specifications include tract topography controls (shares of tract area in 11 topographic categories) and metro fixed effects, so identification comes from within-metro differences in shift-share-predicted racial shares across tracts that differ in their topographic composition and related exposure measures, after controlling for the direct effect of topography. As one would expect, the shift-share-predicted Black share is the stronger predictor of tract Black share, and the shift-share-predicted Hispanic share is the stronger predictor of tract Hispanic share. The coefficients on each of these "direct" predictors are greater than one, which is consistent with the mechanical effect on a tract's racial shares predicted by the instruments being reinforced by sorting by households whose preferences on average exhibit homophily. The bottom panel reports the usual joint F-test for the excluded instruments in the baseline first stage, along with the associated p-value.

The additional F-statistics at the bottom of the table are meant to preview the instrument set we will use once we allow for quadratic terms in racial shares to affect choice probabilities, as specified in the fully dynamic model we estimate later in the paper. If preferences (or choice probabilities) depend nonlinearly on neighborhood racial shares, then the second-stage specification will include nonlinear functions of the endogenous racial shares (e.g., squared terms and interactions). In that case, it is not enough for the linear shift-share IVs to be relevant for the level of each racial share; we also want the instrument set to have predictive content for the nonlinear components that enter the second stage. Augmenting the instrument set with higher-order polynomials and interactions of the IVs is a standard way to generate excluded variation that can support these richer second-stage specifications (Notowidigdo, 2020). The reported F-statistics show that, even when the instrument set is expanded, the first-stage remains sufficiently strong in the sense that the excluded instruments are jointly relevant for the endogenous shares.

Table 4: First-Stage Estimates for Tract Racial Shares

	Endogenous regressor	
	Black Share $S^b_{\ell,m}$	Hispanic Share $S^h_{\ell,m}$
Predicted Black share, $Z^b_{\ell,m}$	1.8421	0.2134
	(0.3425)	(0.0693)
Predicted Hispanic share, $Z^h_{\ell,m}$	0.0461	1.7190
	(0.2032)	(0.1297)
Topography controls	X	X
Metro fixed effects	X	X
tracts	40,273	40,273
metros	195	195
F (excluded instruments)	19.40	88.04
p-value	0.0000	0.0000
Alternative first stage specifications, F-statistics		
5 IVs (quadratic in each IV + interaction)	17.83	66.80
15 IVs (7th order in each IV + interaction)	11.90	47.70

Notes: Each column reports a first-stage regression from the IV system. Standard errors clustered at the metro level are in parentheses.

3.3.3 Impact Estimates

Figures 1 and 2 summarize reduced-form estimates of how neighborhood racial composition predicts tract demand across our 54 demographic types. These figures show point estimates and confidence intervals of b_1^τ and b_2^τ resulting from 2SLS estimates of[19]

$$\log \hat{p}^\tau_{\ell,m} = b_1^\tau S^b_{\ell,m} + b_2^\tau S^h_{\ell,m} + b^\tau_{TOP} TOP_{\ell,m} + \theta^\tau_m + A^\tau_{\ell,m} \tag{6}$$

[19]This equation is the same as equation (2) after replacing the variable standing in for exogenous neighborhood characteristics, $X_{\ell,m}$, with topography controls.

The endogenous regressors are the tract Black share $S^b_{\ell,m}$ and tract Hispanic share $S^h_{\ell,m}$ and the instruments are the corresponding shift-share predictions $Z^b_{\ell m}$ and $Z^h_{\ell m}$ that are constructed as specified in equation (4). The coefficient b^τ_1 summarizes how a type's tract choice probability varies with the tract Black share, holding fixed the tract Hispanic share, while b^τ_2 summarizes how it varies with the tract Hispanic share, holding fixed the tract Black share. Because the dependent variable is $\log \hat{p}^\tau_{\ell,m}$, these coefficients are semi-elasticities: for example, a 10 percentage-point increase in tract Black share changes the log probability of choosing the tract by approximately $0.1\, b^\tau_1$, holding the other covariates fixed.

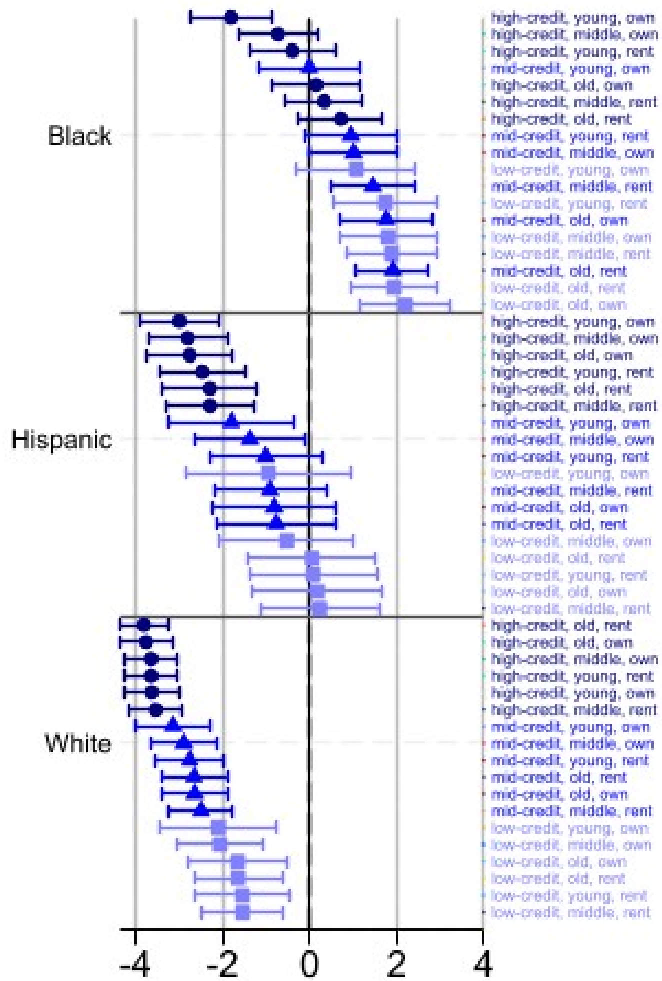
The estimates show sharp and systematic heterogeneity across types. Own-race sorting is strong: Black types tend to have positive b^τ_1 (a higher Black share raises demand), and Hispanic types tend to have positive b^τ_2 (a higher Hispanic share raises demand). Additionally, for White types the coefficients are all negative, indicating that higher Black or Hispanic shares reduce White demand for a tract. For example, the coefficient of roughly -4 for white, older, high-credit, home-owning households implies that a 10 percentage point increase in a tract's Black share reduces the probability that a household of that type chooses the tract by about 0.4 (-4 $\times$ 0.1) log units.

These reduced-form patterns motivate analyses we perform later in the paper. Many policies and shocks that are relevant for neighborhood change – for example, place-based housing programs or other interventions that directly move households across tracts – have an immediate, mechanical effect on sorting. But when households care about neighborhood racial composition, that initial impact is only the first step: households and landlords respond endogenously as the racial mix changes, and those responses feed back into subsequent neighborhood composition. The heterogeneity in Figures 1 and 2 suggests that these feedback effects can be especially important. If different demographic types value the same compositional change in opposite directions, then a small initial shock can trigger very different subsequent migration responses, further amplifying resorting dynamics or, in the extreme, possibly shifting the system toward a different long-run configuration. The fully dynamic model we estimate later provides a disciplined way to map the type-specific responses we estimate into predictions for the path of neighborhood change.

3.3.4 Racial composition and income composition

Neighborhood racial composition is strongly correlated with neighborhood socioeconomic composition, so a natural question is whether the estimated coefficients on $S^b_{\ell,m}$ and $S^h_{\ell,m}$ are capturing households' preferences over the race of their neighbors (and the bundle of endogenous neighborhood amenities that respond directly to race) or, instead, households'

Figure 1: Reduced-Form Impact of Tract Black Share on Log Choice Probabilities

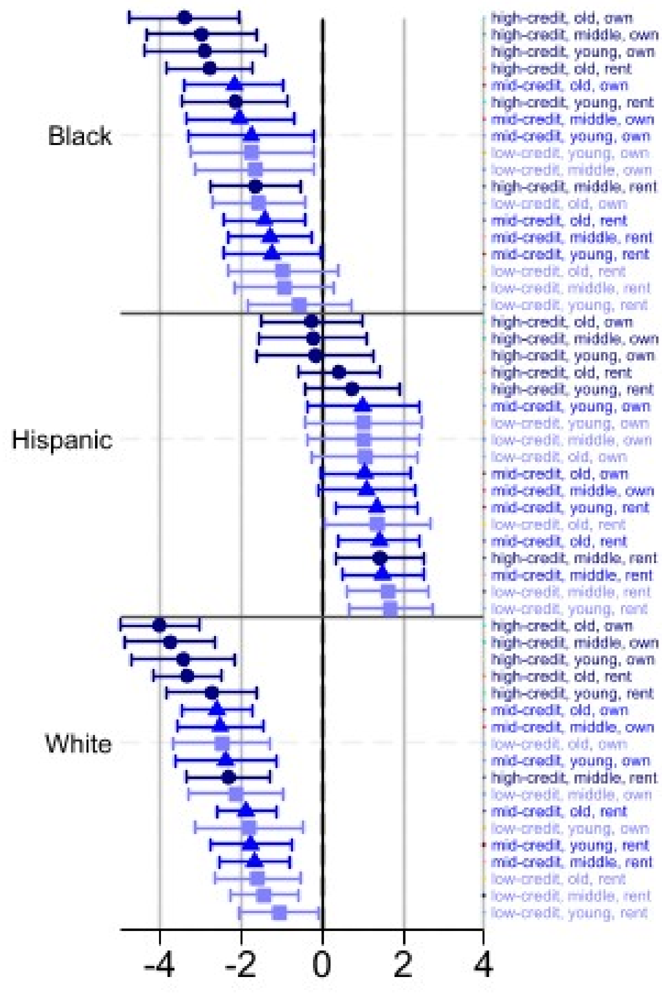


Notes: The figure plots 2SLS estimates of b_1^τ from

$$\log \widehat{p}^{\tau}_{\ell,m} = b_1^\tau S^b_{\ell,m} + b_2^\tau S^h_{\ell,m} + b^\tau_{TOP} TOP_{\ell,m} + \theta^\tau_m + A^\tau_{\ell,m},$$

where $\widehat{p}^{\tau}_{\ell,m}$ is the empirical probability that a household of type τ in metro m chooses tract ℓ, $S^b_{\ell,m}$ and $S^h_{\ell,m}$ are the tract Black and Hispanic shares, $TOP_{\ell,m}$ are controls for the direct effect of tract topography, and θ^τ_m are metro fixed effects. $S^b_{\ell,m}$ and $S^h_{\ell,m}$ are treated as endogenous and are instrumented using the IV predictions $Z^b_{\ell,m}$ and $Z^h_{\ell,m}$ constructed from national sorting patterns with respect to topography and metro-level type shares. Points show coefficient estimates and horizontal bars show 95% confidence intervals. Estimates are shown in three blocks corresponding to the race of the household type (Black, Hispanic, White). Within each block, coefficients are sorted from lowest to highest; the labels indicate the corresponding combination of age group, credit category, and tenure status.

Figure 2: Reduced-Form Impact of Tract Hispanic Share on Log Choice Probabilities



Notes: The figure plots 2SLS estimates of b_2^τ from

$$\log \widehat{p}^{\tau}_{\ell,m} = b_1^\tau S^b_{\ell,m} + b_2^\tau S^h_{\ell,m} + b^\tau_{TOP} TOP_{\ell,m} + \theta^\tau_m + A^\tau_{\ell,m},$$

where $\widehat{p}^{\tau}_{\ell,m}$ is the empirical probability that a household of type τ in metro m chooses tract ℓ, $S^b_{\ell,m}$ and $S^h_{\ell,m}$ are the tract Black and Hispanic shares, $TOP_{\ell,m}$ are controls for the direct effect of tract topography, and θ^τ_m are metro fixed effects. $S^b_{\ell,m}$ and $S^h_{\ell,m}$ are treated as endogenous and are instrumented using the IV predictions $Z^b_{\ell,m}$ and $Z^h_{\ell,m}$ constructed from national sorting patterns with respect to topography and metro-level type shares. Points show coefficient estimates and horizontal bars show 95% confidence intervals. Estimates are shown in three blocks corresponding to the race of the household type (Black, Hispanic, White). Within each block, coefficients are sorted from lowest to highest; the labels indicate the corresponding combination of age group, credit category, and tenure status.

preferences for average income in their neighborhood.

To explore this, we use IV to estimate an equation resembling equation (6) that includes as an additional regressor the tract share of low-income residents. To construct this variable, we assign each demographic type τ an imputed average income, and classify a type as low income if its imputed average annual household income is below \$50,000.[20] Let $\mathcal{T}^{INC}$ denote the set of low-income types under this definition, and define $S^{INC}_{\ell,m}$ as the share of tract ℓ's population accounted for by types in $\mathcal{T}^{INC}$. We then re-estimate equation (6) with $S^{INC}_{\ell,m}$ included as an additional regressor:

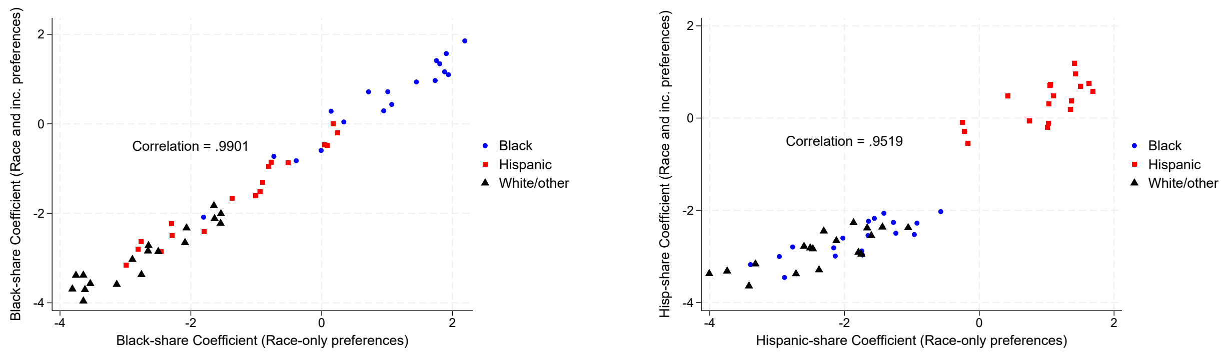
$$\log \hat{p}^{\tau}_{\ell,m} = b^{\tau}_1 S^b_{\ell,m} + b^{\tau}_2 S^h_{\ell,m} + b^{\tau}_{INC} S^{INC}_{\ell,m} + b^{\tau}_{TOP} TOP_{\ell,m} + \theta^{\tau}_m + A^{\tau}_{\ell,m} \tag{7}$$

We estimate equation (7) using the identical 2SLS approach discussed so far. With three endogenous tract shares $\left(S^b_{\ell,m}, S^h_{\ell,m}, S^{INC}_{\ell,m}\right)$, we instrument using the corresponding set of shift-share predictors $\left(Z^b_{\ell,m}, Z^h_{\ell,m}, Z^{INC}_{\ell,m}\right)$ as excluded instruments. In particular, $Z^{INC}_{\ell,m}$ is constructed by aggregating the topography-based predicted type shares (from equation 3) over low-income types: $Z^{INC}_{\ell,m} \equiv \left(\sum_{\tau' \in \mathcal{T}^{INC}} s^{\tau'}_m \, \hat{\hat{p}}^{\tau'}_{\ell,m} \right) \Big/ \left(\sum_{\tau} s^{\tau}_m \hat{\hat{p}}^{\tau}_{\ell,m} \right)$.

Figure 3 summarizes how the inclusion of $S^{INC}_{\ell,m}$ affects estimates of the key coefficients of interest, b^{τ}_1 and b^{τ}_2. Each point in the figure corresponds to a demographic type. In each panel, the x-axis plots the 2SLS coefficient from the baseline specification already reported in Figures 1-2 (race-only), and the y-axis plots the corresponding coefficient from equation (7) that includes both race and income. Panel (a) compares the coefficient on tract Black share, b^{τ}_1, across the two specifications. This panel shows the estimates are essentially unchanged when controlling for income composition: the correlation between the baseline and income-controlled coefficients is 0.990. Panel (b) reports the analogous comparison for the coefficient on tract Hispanic share, b^{τ}_2; here too the coefficients remain close (correlation 0.952), and if anything the White and Black types exhibit slightly more negative coefficients on Hispanic share once income composition is held fixed, implying slightly stronger homophily than in the baseline specification.

Taken together, this exercise suggests that the reduced-form patterns in Figures 1 and 2 are not driven solely by preferences for the income composition of tract residents that is correlated with tract racial composition. Motivated by this evidence, in the sections that

[20] Income is imputed at the type level using an auxiliary-data mapping from the observables that define our types to household income. We use the imputation procedure documented in Appendix G of Coibion et al. (2020). When implementing this procedure, we use the 2001 Survey of Consumer Finances (SCF) to impute income for CCP data from 1999-2009 and the 2010 SCF to impute income for the CCP data for 2010-2019.



(a) Black-share coefficient

(b) Hispanic-share coefficient

Figure 3: Income-composition exercise: comparing reduced-form race-share coefficients with and without controlling for tract income composition. In each panel, the x-axis reports the baseline 2SLS coefficient estimates (race-only, Figures 1-2), and the y-axis reports estimates from equation (7) that additionally controls for $S^{INC}_{\ell,m}$. Each point is a demographic type τ; markers distinguish race categories.

follow we continue to focus on how residential sorting patterns are shaped by preferences for tract racial composition, while allowing for heterogeneity of preferences across types.

4 A Simple Static Decision Model

The reduced-form evidence discussed in the previous section summarizes how tract racial composition affects tract demand across household types. The fully dynamic structural model we estimate in Sections 5 and 6 embeds the same object – type-specific neighborhood demand – in a dynamic choice problem with moving costs and expectations over future neighborhood composition. Because the estimation strategy for the fully dynamic model is a direct extension of a standard two-step (BLP-style) approach, we now present a simplified, static version of this model to make transparent the mechanics of our estimation procedure and the role of the instrument. We then run a set of Monte Carlo experiments using this model to demonstrate the ability of our proposed estimator to recover accurate estimates of racial preferences for multiple household types in a setting with a number of metros and neighborhoods similar to that of our actual sample.

4.1 The Simple, Static Model

Demand for Locations. In any given metro area m, each household (indexed by i) must choose a location in that metro (indexed by ℓ) in which to live. We assume households can freely move to any location in the metro area. We also assume households are not allowed to exit from their current metro area.

Households belong to "types" that capture differences in demographics and socio-economic status. Each type of household has its own set of parameters that determines the expected utility of living in any location. Household i of type τ living in location ℓ in metro area m receives utility of

$$u^{\tau}_{i,\ell,m} \;=\; \delta^{\tau}_{\ell,m} \;+\; \epsilon^{\tau}_{i,\ell,m} \tag{8}$$

$\delta^{\tau}_{\ell,m}$ is the portion of utility that is common to all type τ households choosing location ℓ in metro m and $\epsilon^{\tau}_{i,\ell,m}$ is a shock that is specific to household i that is drawn iid from the Type I Extreme Value Distribution. The inclusion of $\epsilon^{\tau}_{i,\ell,m}$ ensures that not every household of the same type optimally chooses the same location.

$\delta^{\tau}_{\ell,m}$ is assumed to have three components: (1) the price of a rental unit in neighborhood ℓ in metro m, $r_{\ell,m}$; (2) the fraction of neighborhood ℓ in metro m that is comprised of Black households, $S^{b}_{\ell,m}$; (3) and "amenities" in neighborhood ℓ in metro m, $\mathcal{A}^{\tau}_{\ell,m}$. We specify $\delta^{\tau}_{\ell,m}$ as

$$\delta^{\tau}_{\ell,m} \;=\; -a^{\tau}_{r}\log r_{\ell,m} \;+\; a^{\tau}_{1}S^{b}_{\ell,m} \;+\; \mathcal{A}^{\tau}_{\ell,m} \tag{9}$$

The parameters a^{τ}_{r} and a^{τ}_{1} are allowed to vary across household types. The amenity value of neighborhood ℓ in metro m, $\mathcal{A}^{\tau}_{\ell,m}$, is also allowed to vary across types. Note that in the fully dynamic model we estimate later in the paper, $\delta^{\tau}_{\ell,m}$ will also include the share of Hispanic households in neighborhood ℓ as well as quadratic terms for the shares of Black and Hispanic households.

Households are assumed to know $r_{\ell,m}$ and $S^{b}_{\ell,m}$ in every ℓ in metro m.[21] Each household optimally chooses its utility-maximizing location ℓ in metro m after observing $\epsilon^{\tau}_{i,\ell,m}$ in all locations in the metro. Suppose there are J_m possible locations in metro m, and denote $\ell^{*}_{i,m}$ as the optimal location choice for household i in metro m. This choice satisfies

$$\ell^{*}_{i,m} \;=\; \underset{\ell=1,\ldots,J_m}{\operatorname{argmax}}\left\{u^{\tau}_{i,\ell,m}\right\}$$

Given $\epsilon^{\tau}_{i,\ell,m}$ is drawn iid from the Type 1 extreme value distribution, the probability that a

[21]Formally, each household takes $r_{\ell,m}$ and $S^{b}_{\ell,m}$ as given when making decisions. In equilibrium, $r_{\ell,m}$ and $S^{b}_{\ell,m}$ must be consistent with the decisions all households have made.

household of type τ optimally chooses location k in metro m takes a multinomial logit form

$$p^{\tau}_{k,m} \;=\; \frac{\exp(\delta^{\tau}_{k,m})}{\sum_{k'=1}^{J_m}\exp(\delta^{\tau}_{k',m})} \tag{10}$$

and the probability that a household of type τ optimally chooses location k in metro m relative to the probability that same household optimally chooses another location ℓ in metro m has the simple expression

$$\log\left(p^{\tau}_{k,m}/p^{\tau}_{\ell,m}\right) \;=\; \delta^{\tau}_{k,m} - \delta^{\tau}_{\ell,m} \tag{11}$$

where $p^{\tau}_{j,m}$ is the probability that a household of type τ chooses location j in metro m for $j = \ell, k$.

Supply of Housing. We assume each neighborhood has its own housing supply curve. In simulations of this version of the model that follow, we consider two cases for all locations: Perfectly elastic provision of housing at a fixed price and perfectly inelastic and fixed supply of housing in every location. In the full dynamic model that we estimate, we allow each neighborhood to have its own housing-supply elasticity that is taken from Baum-Snow and Han (2022).

4.2 Estimating the Simple Model with IV

To estimate this model, we use the IV approach discussed in Section 3.2.2. In this static model, the IV plays the same role as in the full specification: it isolates variation in tract racial shares that is driven by metro-level type shares interacting with predicted sorting patterns based on topography, while controlling for the direct effect of topography in both stages.

4.2.1 Constructing the Estimator

To estimate the parameters of this model, we assume the following data are available:

1. *Type shares.* For each metro area, the total share of the population accounted for by each household type, denoted by s^{τ}_{m} for type τ in metro m.
2. *Neighborhood choice probabilities.* Estimates of the market share for each location ℓ in each metro area m, for many metro areas, and for all household types τ, $\hat{p}^{\tau}_{\ell,m} > 0$.
3. *Topographic data.* Topographic data for each location ℓ in each metro area m, $TOP_{\ell,m}$. In this section, $TOP_{\ell,m}$ has one dimension.

4. *Rental prices.* The constant-quality rental price of a housing unit in each location ℓ in each metro m, $r_{\ell,m}$.

Note that when items 1. and 2. are appropriately combined, we can construct the observed share of Black households in each neighborhood ℓ in each metro area m as follows:

$$S^b_{\ell,m} \quad = \quad \frac{\sum_{\tau'} \mathcal{I}\left(\tau' \in Black\right) s^{\tau'}_m \, \hat{p}^{\tau'}_{\ell,m}}{\sum_{\tau} s^{\tau}_m \, \hat{p}^{\tau}_{\ell,m}} \tag{12}$$

In this equation τ and τ' are indexes for household type and $\mathcal{I}\left(\tau' \in Black\right)$ is an indicator function that is equal to 1 if type τ' households are Black, 0 otherwise. When the population of metro m is equal to 1.0, the numerator of (12) is the total population of Black households living in tract ℓ in metro m and the denominator is the total population of households living in tract ℓ in metro m.

BLP Stage 1: Given these data, our procedure to estimate type-specific parameters of this model has two steps as in Berry et al. (1995). First, we obtain estimates of $\delta^{\tau}_{\ell,m}$ for all ℓ, m, τ. Call these estimates $\hat{\delta}^{\tau}_{\ell,m}$. To do this, for each τ in each metro m we normalize $\hat{\delta}^{\tau}_{k,m} = 0$ for one particular location $k = 1$. Given this normalization, we use equation (11) to map data on observed type-specific choice probabilities $\hat{p}^{\tau}_{\ell,m}$ to an estimate of the utility of choosing location ℓ in metro m that is common to all type τ households, $\hat{\delta}^{\tau}_{\ell,m}$. For all the $\ell \neq 1$ in metro m, we set

$$\forall \ell \neq 1, \quad \hat{\delta}^{\tau}_{\ell,m} \quad = \quad \log\left(\hat{p}^{\tau}_{\ell,m} / \, \hat{p}^{\tau}_{1,m}\right)$$

The focus of our study is the impact of racial composition on neighborhood demand. In line with this focus, and consistent with our strategy to estimate the more complicated dynamic model, we assume we know from a previous study the parameter a^{τ}_r, the sensitivity of location choices to exogenously shifting rental prices. Bayer et al. (2015) discuss why estimation of a^{τ}_r is an unusually difficult undertaking and make the case for bringing in outside evidence, as we do here.[22] Given presumed knowledge of a^{τ}_r, we define a new variable:

$$\hat{d}^{\tau}_{\ell,m} \quad = \quad \hat{\delta}^{\tau}_{\ell,m} + a^{\tau}_r \log r_{\ell,m}$$

[22] When we estimate the more complicated dynamic model, we take a^{τ}_r from Davis et al. (2021). Out of concern that our results may be sensitive to our assumed values of a^{τ}_r, we verify that the parameter estimates on racial composition in the full dynamic model that we estimate are essentially unaffected by reasonable variation (doubling or halving) of a^{τ}_r. This result occurs because the estimated coefficients of racial composition on indirect utility are orders of magnitude more important than the coefficient on rental prices.

Then we rewrite equation (9) as[23]

$$\hat{d}^{\tau}_{\ell,m} \;=\; a^{\tau}_{1} S^{b}_{\ell,m} \;+\; A^{\tau}_{\ell,m} \tag{13}$$

BLP Stage 2, Constructing the Instrument: We generate a prediction equation for location choice in each metro for each household type that only depends on the topography of a location in that metro. For each type of household we pool all data across locations and metros and estimate

$$\log \hat{p}^{\tau}_{\ell,m} \;=\; \alpha^{\tau}_{m} \;+\; b^{\tau} TOP_{\ell,m} \;+\; \nu^{\tau}_{\ell,m} \tag{14}$$

where α^{τ}_{m} is a metro-area fixed effect that can vary by τ, b^{τ} is a coefficient that maps relative topography to location choice probabilities that can also vary by τ, and $\nu^{\tau}_{\ell,m}$ is a location, metro, and type-specific error.

Once (14) is estimated for all household types, we use it to predict the probability each type lives in any location in any metro area. Denote the predicted probability for type τ in location ℓ in metro m as $\hat{\hat{p}}^{\tau}_{\ell,m}$. We then create a predicted Black share in each location ℓ in each metro m, $Z^{b}_{\ell,m}$, as

$$Z^{b}_{\ell,m} \;=\; \frac{\sum_{\tau'} \mathcal{I}\left(\tau' \in Black\right) s^{\tau'}_{m} \, \hat{\hat{p}}^{\tau'}_{\ell,m}}{\sum_{\tau} s^{\tau}_{m} \, \hat{\hat{p}}^{\tau}_{\ell,m}} \tag{15}$$

The numerator of (15) is the *predicted* total population of Black households living in tract ℓ in metro m and the denominator is the *predicted* total population of households living in tract ℓ in metro m, where all of these predictions are based only on topographic data. Restated, we use equation (14) to predict where everyone will live based only on topographic data and then, given this prediction, use metro-level household-type shares to calculate the predicted share of each location that is comprised of Black households.

BLP Stage 2, IV: Once we have created $Z^{b}_{\ell,m}$, we use 2SLS to estimate a^{τ}_{1}. Specifically, we pool data across all locations in all metros and for each type of household we estimate

$$\hat{d}^{\tau}_{\ell,m} \;=\; \theta^{\tau}_{m} \;+\; a^{\tau}_{1} S^{b}_{\ell,m} \;+\; g^{\tau}\left(TOP_{\ell,m}\right) \;+\; \upsilon^{\tau}_{\ell,m} \tag{16}$$

where $\hat{d}^{\tau}_{\ell,m} = \hat{\delta}^{\tau}_{\ell,m} + a^{\tau}_{r} \log r_{\ell,m}$, θ^{τ}_{m} is a metro-area fixed effect that varies by τ, $g^{\tau}\left(TOP_{\ell,m}\right)$

[23] Note the switch of notation for amenities, from $\mathcal{A}^{\tau}_{\ell,m}$ in equation (9) to $A^{\tau}_{\ell,m}$ in equation (13) to explicitly account for the fact that $\delta^{\tau}_{\ell,m}$ in equation (9) is replaced with $\hat{d}^{\tau}_{\ell,m}$ in equation (13).

is a flexible function of $TOP_{\ell,m}$, and $\upsilon^{\tau}_{\ell,m}$ is an error term. The first stage is

$$S^{b}_{\ell,m} \;=\; \vartheta_m \;+\; \gamma Z^{b}_{\ell,m} \;+\; g_1\left(TOP_{\ell,m}\right) \tag{17}$$

where ϑ_m is a metro-area fixed effect and $g_1\left(TOP_{\ell,m}\right)$ is a different flexible function of $TOP_{\ell,m}$.

4.3 Monte Carlo Simulations of the Simple Model

We now perform a set of Monte Carlo experiments using this simple model to demonstrate the ability of our proposed estimator to recover accurate estimates of racial preferences for multiple household types in a setting with a number of metros and neighborhoods similar to that of our actual sample. In the experiments, we repeatedly simulate decisions of 4 types of households in 200 metro areas, each with 100 possible locations. Each time we simulate the model using procedures described next, we generate a data set containing the information listed in section 4.2.1 that is required for estimation: Type shares, neighborhood choice probabilities, topographic data, and rental prices. We then estimate model parameters using that data via the IV procedure described in that section. From each simulation, we store the estimate of the model parameter of interest, a^{τ}_1, and then evaluate the mean and standard deviation of this estimate across simulations to understand the size of possible bias. In the rest of this section, we list the details of the simulation procedure and results. Note that in these experiments, the metro-level type shares are drawn independently of the component of tract-level amenities orthogonal to topography, so Assumption A1 (share exogeneity) always holds by construction.

4.3.1 Drawing Metro-Wide Type Shares and Local Amenities

We specify that type 1 and 2 households are Black and type 3 and 4 households are White. To determine the simulated share of type τ in metro m, s^{τ}_m, we first compute the variable $\tilde{s}^{\tau}_m$ as

$$\tilde{s}^{\tau}_m \;=\; \ln \mu^{\tau} + e^{\tau}_m \tag{18}$$

where e^{τ}_m is a random draw from a Normal with mean 0 and standard deviation σ^{τ}_{em}. In all simulations, we set $\mu^{\tau} = 0.25$ and $\sigma^{\tau}_{em} = 1.0$ for all household types. We then set simulated type shares in each metro as

$$s_m^\tau \;=\; \frac{\exp\left\{\tilde{s}_m^\tau\right\}}{\sum\limits_{\tau'=1}^{4}\exp\left\{\tilde{s}_m^{\tau'}\right\}} \tag{19}$$

The total population in every metro is assumed to be 1.0, implying the share of each type is also the population of that type.

Amenities for each location ℓ in each metro m for each type τ are assumed to be a linear function of a topography variable $TOP_{\ell,m}$ and 4 other common factors, $f_{n,\ell,m}$ for $n = 1, \ldots, 4$, as follows

$$\mathcal{A}_{\ell,m}^\tau \;=\; \sum_{n=1}^{4}\gamma_n^\tau f_{n,\ell,m} \;+\; \gamma_{top}^\tau TOP_{\ell,m}$$

Each of the four common factors and the topography variable can vary across locations within and across metros, but for any given location in any given metro these variables do not vary by type. The parameters $\gamma_n^\tau, n = 1, \ldots, 4$ and γ_{top}^τ can vary across types of households but for any given type of household they do not vary across locations and metros. We chose four factors to allow us to consider a scenario where each type's valuations of amenities (other than topography) are independent. In the simulations, we draw $f_{n,\ell,m}$ and $TOP_{\ell,m}$ iid from $N(0,1)$.

The parameters we use in our baseline simulations for each type are listed in Table 5. Note that we set $\gamma_{top}^\tau > 0$ for all types, implying all types value the topography variable, but by varying degrees. Note that for a_r^τ, we have in mind that Types 1 and 3 have lower income and higher budget shares on rent than Types 2 and 4. Additionally, Types 1 and 3 are less willing to pay for high values of the topography variable, the component of location-specific amenities that is common to all types.

Table 5: Baseline Set of Parameters for Monte Carlo

Type	Race	a_r^τ	a_1^τ	γ_1^τ	γ_2^τ	γ_3^τ	γ_4^τ	γ_{top}^τ
1	Black	0.5	0.5	1	0	0	0	0.25
2	Black	0.3	0.5	0	1	0	0	0.75
3	White	0.4	-0.5	0	0	1	0	0.50
4	White	0.2	-0.5	0	0	0	1	1.00

Notes: In the baseline parameterization, we assume housing in every location in every metro area is inelastically supplied. Referring to equation (18), we set $\mu^\tau = 0.25$ and $\sigma_{em}^\tau = 1.0$ for all types.

4.3.2 Finding Rental Prices and Racial Shares

For a given metro area m, we need to find market-clearing rental prices $r_{\ell,m}$ and, given these prices, the share of Black households $S^b_{\ell,m}$ in each of the locations ℓ in the metro. We employ the following algorithm to find $r_{\ell,m}$ and $S^b_{\ell,m}$ in every ℓ in every m:

a. We initialize $r_{\ell,m}$ and $S^b_{\ell,m}$ by setting $r_{\ell,m} = 1$ and $S^b_{\ell,m}$ equal to the metro-m wide share of black households $(s^1_m + s^2_m)$ for every metro. Label these initial values as $\hat{r}_{\ell,m}$ and $\hat{S}^b_{\ell,m}$.

b. Given the simulated realized values of $\mathcal{A}^\tau_{\ell,m}$ and the values $\hat{r}_{\ell,m}$ and $\hat{S}^b_{\ell,m}$, we compute

$$\hat{\delta}^\tau_{\ell,m} = -a^\tau_r \log \hat{r}_{\ell,m} + a^\tau_1 \hat{S}^b_{\ell,m} + \mathcal{A}^\tau_{\ell,m}$$

for every location ℓ and every type τ.

c. After steps a and b have been completed for every ℓ in every metro m for every household type τ, we compute for every location ℓ in metro m and type τ

$$\hat{p}^\tau_{\ell,m} = \frac{\exp\left(\hat{\delta}^\tau_{\ell,m}\right)}{\sum_k \exp\left(\hat{\delta}^\tau_{k,m}\right)}$$

where $\hat{p}^\tau_{\ell,m}$ is the probability that type τ chooses location ℓ in metro m.

d. Give the distribution of all location choices for all types in all metros as determined in step c, we compute the simulated population in each location ℓ in metro m, $\widetilde{pop}_{\ell,m}$, and the simulated Black share of the population, $\widetilde{S}^b_{\ell,m}$ as

$$\widetilde{pop}_{\ell,m} = \sum_{\tau=1}^{4} \hat{p}^\tau_{\ell,m} s^\tau_m$$
$$\widetilde{S}^b_{\ell,m} = \left(\hat{p}^1_{\ell,m} s^1_m + \hat{p}^2_{\ell,m} s^2_m\right) / \widetilde{pop}_{\ell,m}$$

e. For each ℓ, we update $\hat{S}^b_{\ell,m}$ by setting it equal to $\widetilde{S}^b_{\ell,m}$

f. When housing is inelastically supplied, we assume (i) every location ℓ has 0.01 units of housing, equal to the total population divided by 100 locations, and (ii) each household demands 1 unit of housing. We compute

$$\log \widetilde{r}_{\ell,m} = \log \hat{r}_{\ell,m} + \log \widetilde{pop}_{\ell,m} - \log 0.01$$

and then we set the updated value of $\hat{r}_{\ell,m}$ equal to $\widetilde{r}_{\ell,m}$.

g. We repeat steps b through f for all locations until expectations on the share of Black households converges to simulated Black shares in every location ($\widetilde{S}^b_{\ell,m} = \hat{S}^b_{\ell,m}$), and, $\widetilde{pop}_{\ell,m} = 0.01$ in every location.

4.3.3 Other Features and Assumptions

We simulate the model under 5 different sets of assumptions, listed below. Unless otherwise stated, each environment uses the baseline set of parameters.

1. *Baseline.* Baseline set of parameters.
2. *Elastic Supply.* In these simulations, we set and hold $r_{\ell,m} = 1.0$ everywhere; convergence (steps a-g listed above) requires only that expectations on the share of Black households is equal to simulated Black shares in every location, $\widetilde{S}^b_{\ell,m} = \hat{S}^b_{\ell,m}$.
3. *Low Variance.* $\sigma^\tau_{em} = 0.3$. This simulation helps show the relationship of the variance of estimates of a^τ_1 to the amount of across-metro variation in household type shares.
4. *Correlated Amenities.* $\gamma^\tau_{\tau'} = 0.5$ for $\tau' \neq \tau$. This simulation checks the sensitivity of estimates to assumptions about how much each household type also cares about the favorite amenity of the other household types by increasing $\gamma^\tau_{\tau'}$ from 0 in the baseline to 0.5.
5. *Imperfect Factor Measurement.* Location-specific amenities are determined as

$$\begin{aligned}\mathcal{A}^\tau_{\ell,m} &= \sum_{n=1}^{4} \gamma^\tau_n f_{n,\ell,m} \; + \; \gamma^\tau_{top} f_{5,\ell,m} \\ f_{5,\ell,m} &= TOP_{\ell,m} + f_{6,\ell,m}\end{aligned}$$

   where the topography variable is observed by the econometrician (as in the baseline) but $f_{6,\ell,m}$, also drawn from $N(0,1)$, is not observed. What we have in mind is that the topography that households value in amenities, in this case $f_{5,\ell,m}$, is only imperfectly proxied by the topography variable that an econometrician observes, $TOP_{\ell,m}$. This simulation checks that results are robust to imperfect observation of topography.

For each of the 5 environments described above, we generate 1,000 data sets and evaluate the properties of two different estimators for a^τ_1 in equation (16): OLS and our IV. For a final set of details, note that $g(TOP_{\ell,m})$ and $g_1(TOP_{\ell,m})$ are both 4th order polynomials and we use exact market shares as predicted by the model as our data for $\hat{p}^\tau_{\ell,m}$. Finally, to be explicit, we assume an econometrician observes $TOP_{\ell,m}$ for all ℓ in every m but $f_{n,\ell,m}$ for $n = 1, \ldots, 4$ and $A^\tau_{\ell,m}$ are never observed.

4.3.4 Results

The results of this exercise are shown in Table 6. The eight columns of the table report the average and standard deviation of estimates of $a_1^\tau, \tau = 1, \ldots, 4$ across all 1,000 data sets. The first column of each pair shows estimates when a_1^τ is estimated using OLS and the second shows estimates using IV. Recall the actual value of a_1^τ is 0.5 for Types 1 and 2 and -0.5 for Types 3 and 4, as shown in Table 5.

Table 6 clearly shows that the OLS estimates are biased. There is no mean OLS estimate of any parameter that can be considered "close" in any meaningful sense to the corresponding preference parameter. This highlights the challenge of identification. Household sorting based on type-specific valuations of amenities leads to correlation of the amenities in the location and the share of Black households in that location. Even though OLS controls for topography, a common component of amenities, the omission of the other factors $f_{1,\ell,m}, \ldots, f_{4,\ell,m}$ that determine amenities (along with weights in the computation of amenities $\gamma_1^\tau, \ldots, \gamma_4^\tau$ that vary by type) is sufficient to cause OLS to be severely biased.

In contrast, for each parameter we consider in all 5 simulation scenarios, the IV estimator has a mean (across the 1,000 simulations) very close to 0.5 for $\tau = 1, 2$ and -0.5 for $\tau = 3, 4$. Even though the environment changes in each of the 5 scenarios, what is common across scenarios is that the distribution of type shares in each metro area is drawn independently of the realization of all factors and topography comprising amenities in any given metro area. As shown by equation (5), this is a sufficient condition for our IV approach to be valid.

5 The Actual Dynamic Location-Choice Model

We model the system of demand for neighborhoods by considering the decision problem of a particular household head deciding where the household should live. As in Kennan and Walker (2011) Bayer et al. (2015), and Davis et al. (2021) we model location choices in a dynamic discrete choice setting. We assume each household i takes its metro area m as given. Each year, the household can choose to live in one of J_m locations in the metro. When we estimate this model, J_m will vary with the metro.

Denote j as the current location of household i in the metro and τ as that household's type. We write the value to the household, $V_{m,t}^\tau\left(\ell \mid j, \epsilon_{i,\ell,m,t}^\tau\right)$, of choosing to live in location ℓ in metro m in year t given a current location of j in the metro and current value of a shock $\epsilon_{i,\ell,m,t}^\tau$ (to be explained later) as

$$V_{m,t}^\tau\left(\ell \mid j, \epsilon_{i,\ell,m,t}^\tau\right) \quad = \quad u_{m,t}^\tau\left(\ell \mid j, \epsilon_{i,\ell,m,t}^\tau\right) + \beta \sum_{\tau'} \varphi^{\tau,\tau'} E_t\left[V_{m,t+1}^{\tau'}(\ell)\right]$$

Table 6: Monte Carlo Results

		$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
		$a_1^\tau = 0.5$		$a_1^\tau = 0.5$		$a_1^\tau = -0.5$		$a_1^\tau = -0.5$	
Sim	Name	OLS	IV	OLS	IV	OLS	IV	OLS	IV
1	Baseline	1.785	0.494	2.054	0.495	-2.367	-0.499	-2.311	-0.500
		(0.056)	(0.146)	(0.062)	(0.133)	(0.064)	(0.144)	(0.071)	(0.144)
2	Elastic Supply	2.340	0.484	2.133	0.490	-2.430	-0.493	-2.044	-0.498
		(0.057)	(0.252)	(0.058)	(0.235)	(0.055)	(0.252)	(0.059)	(0.251)
3	Low Variance	1.881	0.485	2.118	0.485	-2.505	-0.491	-2.371	-0.490
		(0.032)	(0.349)	(0.032)	(0.319)	(0.031)	(0.350)	(0.034)	(0.345)
4	Correlated Amenities	-1.429	0.493	-1.216	0.494	-4.309	-0.504	-4.165	-0.505
		(0.126)	(0.172)	(0.158)	(0.165)	(0.119)	(0.169)	(0.150)	(0.171)
5	Imperfect Factor Msmt	1.368	0.495	1.152	0.500	-2.741	-0.495	-3.098	-0.493
		(0.049)	(0.171)	(0.093)	(0.190)	(0.056)	(0.184)	(0.099)	(0.227)

In the above equation $u_{m,t}^{\tau}\left(\ell \mid j, \epsilon_{i,\ell,m,t}^{\tau}\right)$ is the flow utility in year t to household i of choosing to live in location ℓ in metro m given a current location of j in the metro and current value of a shock $\epsilon_{i,\ell,m,t}^{\tau}$; β is the discount factor on future expected utility; $\varphi^{\tau,\tau'}$ is the probability that the household becomes type τ' next year given it is type τ this year; and $E_t\left[V_{m,t+1}^{\tau'}(\ell)\right]$ is the expected value (expectation taken as of year t) in year $t+1$ of a type τ' household of having chosen to live in neighborhood ℓ in metro m in year t. The t subscripts explicitly allow that flow utility and expectations may change over time.

Flow utility depends on neighborhood racial composition, similar to assumptions made in Caetano and Maheshri (2021) and Almagro and Dominguez-Iino (2022).[24] We specify $u_{m,t}^{\tau}\left(\ell \mid j, \epsilon_{i,\ell,m,t}^{\tau}\right)$ as

$$u_{m,t}^{\tau}\left(\ell \mid j, \epsilon_{i,\ell,m,t}^{\tau}\right) \;=\; \delta_{\ell,m,t}^{\tau} \;-\; \kappa^{\tau} \cdot 1_{\ell \neq j} \;+\; \epsilon_{i,\ell,m,t}^{\tau}$$

$\delta_{\ell,m,t}^{\tau}$ is the deterministic portion of flow utility a type τ household receives in year t from living in neighborhood ℓ in metro m; this does not vary across type τ households. κ^{τ} are

[24] The utility function in Almagro and Dominguez-Iino (2022) does not depend on race but does depend on neighborhood consumption amenities which are endogenously determined.

fixed costs a household of type τ must pay when it moves to a different neighborhood in the metro i.e. when $\ell \neq j$; $1_{\ell \neq j}$ is an indicator function that is equal to 1 if location $\ell \neq j$ in metro m and 0 otherwise; and $\epsilon^{\tau}_{i,\ell,m,t}$ is a random shock that is known at the time of the location choice. $\epsilon^{\tau}_{i,\ell,m,t}$ is assumed to be iid across locations, time and people. $\epsilon^{\tau}_{i,\ell,m,t}$ induces otherwise identical households living at the same location at the same time to optimally choose different future locations.

We assume $\delta^{\tau}_{\ell,m,t}$ is comprised of disutility from log rental prices ($\log r_{\ell,m,t}$), a quadratic function of the share of neighborhood ℓ that is Black ($S^{b}_{\ell,m,t}$) and is Hispanic ($S^{h}_{\ell,m,t}$), and amenities of that neighborhood that may vary by household type, $\mathcal{A}^{\tau}_{\ell,m,t}$.

$$\begin{aligned}
\delta^{\tau}_{\ell,m,t} \quad = \quad & -a^{\tau}_{r} \log r_{\ell,m,t} && \text{rents} \\
& + a^{\tau}_{1} S^{b}_{\ell,m,t} + a^{\tau}_{2} \left(S^{b}_{\ell,m,t}\right)^{2} + a^{\tau}_{3} S^{h}_{\ell,m,t} + a^{\tau}_{4} \left(S^{h}_{\ell,m,t}\right)^{2} + a^{\tau}_{5} S^{b}_{\ell,m,t} S^{h}_{\ell,m,t} && \text{demographics} \\
& + \mathcal{A}^{\tau}_{\ell,m,t} && \text{amenities}
\end{aligned} \tag{20}$$

We do not impose a linear specification in racial shares because we do not want to impose that the marginal utility of a change in a racial share is constant with respect to the level of that racial share. A quadratic functional form is a parsimonious specification that allows for the possibility that households may like some diversity; it also allows, depending on parameters, that households may not like any diversity.

Denote $\epsilon^{\tau}_{1,m,t}$ as the shock associated with location 1 in period t, $\epsilon^{\tau}_{2,m,t}$ as the shock with location 2, and so on. In each period after the vector of ϵ are revealed (one for each location), households choose the location that yields the maximal value

$$V^{\tau}_{m,t}\left(j \mid \epsilon^{\tau}_{1,m,t}, \epsilon^{\tau}_{2,m,t}, \ldots, \epsilon^{\tau}_{J_m,m,t}\right) \quad = \quad \max_{\ell \in 1,\ldots,J_m} V^{\tau}_{m,t}\left(\ell \mid j, \epsilon^{\tau}_{i,\ell,m,t}\right) \tag{21}$$

6 Estimation and Data

To match model to data, we assume that a location (neighborhood) is a census tract. We use a 2-step procedure like Berry et al. (1995) to estimate our model of demand for locations. In the first step, we use GMM to estimate the vector of $\delta^{\tau}_{\ell,m,t}$ and the moving cost κ^{τ} for each τ. This is similar to the procedure of Neilson (2017), who uses GMM to estimate a similar first stage in a model of school choice. In the second step, we use an IV procedure to understand how exogenous changes in racial shares impact $\delta^{\tau}_{\ell,m,t}$ for each τ.

6.1 Step 1: GMM to Estimate Demand for Locations

In the first step, we use the approach of Hotz and Miller (1993) employed by Bishop (2012) and Davis et al. (2021) to set up estimating equations for $\delta^{\tau}_{\ell,m,t}$ and κ^{τ}. This approach does not require that we solve for the value functions. Instead, as we show in appendix C, the log probabilities that choices are observed are simple functions of $\delta^{\tau}_{\ell,m,t}$, κ^{τ}, β and of observed choice probabilities. Note that due to data limitations we discuss later, we combine data across multiple years when estimating probabilities and preference parameters. For this reason, going forward we remove time subscripts from value functions, expectations and elements of utility.

Define Θ^{τ}_1 as the full vector of parameters to estimate in step 1 for type τ

$$\Theta^{\tau}_1 \;=\; \left\{ \;\kappa^{\tau}, \left\{\delta^{\tau}_{\ell,m=1}\right\}^{J_1}_{\ell=1}, \left\{\delta^{\tau}_{\ell,m=2}\right\}^{J_2}_{\ell=1}, \ldots, \left\{\delta^{\tau}_{\ell,m=M}\right\}^{J_M}_{\ell=1} \;\right\} \tag{22}$$

where $\delta^{\tau}_{\ell,m}$ is the value of δ for type τ in tract ℓ in metro m, assumed fixed over the years in our estimation sample, and M is the number of metros in the sample.

The first moment we target for each household type is the unconditional probability of not moving. Define the distance between the model predicted non-moving rate and the data as

$$\begin{aligned} &G^{\tau}_1\left(\Theta^{\tau}_1\right) \\ &= \sum_{m=1}^{M}\sum_{j'=1}^{J_m} \underbrace{\hat{P}^{\tau}_m\left(j=j'\right)}_{\text{data}} \; \underbrace{\hat{P}^{\tau}_m\left(\ell=j' \mid j=j'\right)}_{\text{data}} \;-\; \sum_{m=1}^{M}\sum_{j'=1}^{J_m} \underbrace{\hat{P}^{\tau}_m\left(j=j'\right)}_{\text{data}} \; \underbrace{P^{\tau}_m\left(\ell=j' \mid j=j';\Theta^{\tau}_1\right)}_{\text{model}} \end{aligned} \tag{23}$$

In this equation, j is the location at the start of the period and ℓ is the location at the end of the period. j' indexes locations that are in metro m and there are J_m of these locations. In this equation and the next, any variable with a "hat" is computed directly from the data. $\hat{P}^{\tau}_m\left(j=j'\right)$ is the probability that a type τ household starts a period in location j' in metro m and $\hat{P}^{\tau}_m\left(\ell=j' \mid j=j'\right)$ is the probability that a type τ household that starts a period in location j' chooses to remain in location j'. The conditional probability $P^{\tau}_m\left(\ell \mid j;\Theta^{\tau}_1\right)$ for any ℓ and j is determined by the model for a given Θ^{τ}_1.

The remaining $\sum\limits_{m=1}^{M}\left[J_m-1\right]$ moments for each type are that the model matches the probability of choosing any given location in each metro. There are J_m-1 moments in each metro because the probability of choosing a location must sum to 1, and (as mentioned) households are assumed to not move outside of their metro. For any given metro m, we can write the distance for these $J_m - 1$ moments as

$$\text{for } \ell = 2, \ldots, J_m \quad G^{\tau}_{\ell,m}(\Theta^{\tau}_1) = \sum_{j=1}^{J_m} \underbrace{\hat{P}^{\tau}_m(j)}_{\text{data}} \underbrace{\hat{P}^{\tau}_m(\ell \mid j)}_{\text{data}} - \sum_{j=1}^{J_m} \underbrace{\hat{P}^{\tau}_m(j)}_{\text{data}} \underbrace{P^{\tau}_m(\ell \mid j; \Theta^{\tau}_1)}_{\text{model}} \tag{24}$$

We normalize $\delta^{\tau}_{1,m} = 0$ in each metro, which is allowable because utility is relative and adding a constant to each δ^{τ} in the choice set will not affect the probability of any choice.

For each type τ, we find the vector of parameters to minimize the sum of squared errors of the moments

$$\hat{\Theta}^{\tau}_1 = \underset{\Theta^{\tau}_1}{\operatorname{argmin}} \left\{ \left[G^{\tau}_1(\Theta^{\tau}_1)\right]^2 + \sum_{m=1}^{M} \sum_{\ell=2}^{J_m} \left[G^{\tau}_{\ell,m}(\Theta^{\tau}_1)\right]^2 \right\}$$

The model is exactly identified, so at $\Theta^{\tau}_1 = \hat{\Theta}^{\tau}_1$ the term in braces will be zero. For each type, there are $1 + \sum_m (J_m - 1)$ moments and the same number of parameters.[25]

6.2 Step 2: IV to Estimate Impact of Demographics on Demand

Once we have estimates of $\delta^{\tau}_{\ell,m}$ from the 1st stage, we wish to uncover the parameters a^{τ}_r and $a^{\tau}_1, \ldots, a^{\tau}_5$ from equation (20). We start by taking a value for the impact of rental prices on flow utility, a^{τ}_r, from Davis et al. (2021). Define $\hat{\delta}^{\tau}_{\ell,m}$ as the estimated value of $\delta^{\tau}_{\ell,m}$ from the first stage. Then we wish to estimate $a^{\tau}_1, \ldots, a^{\tau}_5$ in the following specification that is the same as equation (20), but with time subscripts removed:

$$\hat{\delta}^{\tau}_{\ell,m} + a^{\tau}_r \log r_{\ell,m} = a^{\tau}_1 S^b_{\ell,m} + a^{\tau}_2 \left(S^b_{\ell,m}\right)^2 + a^{\tau}_3 S^h_{\ell,m} + a^{\tau}_4 \left(S^h_{\ell,m}\right)^2 + a^{\tau}_5 S^b_{\ell,m} S^h_{\ell,m} + A^{\tau}_{\ell,m} \tag{25}$$

In the equation above, $\log r_{\ell,m}$ is an estimate of the log rental price for a standardized housing unit in neighborhood (census tract) ℓ of metro m that we compute from data from the 2007-2011 American Community Survey tract-level tabulations.[26] Also note, consistent with our

[25] In the event a type never chooses a given neighborhood in our data, we assume that neighborhood is not in the location choice set for that type. Sorting types by the fraction of possible locations with zero observed market shares, out of 54 types the median type has a zero market share in 1.2 percent of tracts. The inter-quartile range by type is 0.55 to 2.42 percent.

[26] Define $\bar{r}_{\ell,m}$ as the median rent of renting households for census tract ℓ in metro m and $\mathbf{X}_{\ell,\mathbf{m}}$ as a vector of tract-level housing characteristics. To compute $\log r_{\ell,m}$, we first run the regression

$$\log \bar{r}_{\ell,m} = [\mathbf{\Gamma}]' \mathbf{X}_{\ell,m} + e^r_{\ell,m}$$

where $\mathbf{\Gamma}$ is a vector of coefficients and $e^r_{\ell,m}$ is the error in this equation. Defining $\hat{e}^r_{\ell,m}$ as the estimate of the residual from this regression, we set $\log r_{\ell,m} = \left[\hat{\mathbf{\Gamma}}\right]' \bar{\mathbf{X}} + \hat{e}^r_{\ell,m}$ where $\hat{\mathbf{\Gamma}}$ is the vector of coefficient estimates practice in section 4, the switch of notation for amenities from $\mathcal{A}$ in equation (20) to A in the above equation.

Define the vector of parameters that we estimate for each type in this second step as Θ_2^τ,

$$\Theta_2^\tau \;=\; \{\; a_1^\tau, a_2^\tau, \ldots, a_5^\tau \;\}$$

Since racial shares are likely to be correlated with unobserved amenities, we use an instrumental variables approach to estimate Θ_2^τ. Our approach is nearly identical to what we describe in section 3.1.1. Briefly explaining, to generate instruments for $S_{\ell,m}^b$ and $S_{\ell,m}^h$, for each type of household we pool all data across locations and metros and estimate

$$\log \hat{p}_{\ell,m}^\tau \;=\; \alpha_m^\tau \;+\; [\mathbf{b}^\tau]' \cdot \mathbf{TOP}_{\ell,m} \;+\; \nu_{\ell,m}^\tau \tag{26}$$

where $\hat{p}_{\ell,m}^\tau$ is the estimated market share (within-metro choice probability) for location ℓ in metro m for type τ households, α_m^τ is a metro-area fixed effect that can vary by τ, and $\nu_{\ell,m}^\tau$ is an error. In comparison to the prediction equation (14) of the simple model, in equation (26) $\mathbf{TOP}_{\ell,m}$ is a vector of topographic variables for each location ℓ in metro m and $\mathbf{b}^\tau$ is a vector of coefficients that can vary by τ.

Once equation (26) is estimated for all types, we use it to predict the probability each type lives in any location in any metro area. Call this predicted probability as $\hat{\hat{p}}_{\ell,m}^\tau$. Given these predicted choice probabilities for all types in all locations in all metros, we create a predicted Black share $Z_{\ell,m}^b$ and a predicted Hispanic share $Z_{\ell,m}^h$ in each ℓ and m as

$$Z_{\ell,m}^b \;=\; \frac{\sum\limits_{\tau'} \mathcal{I}\left(\tau' \in Black\right) s_m^{\tau'}\, \hat{\hat{p}}_{\ell,m}^{\tau'}}{\sum\limits_{\tau} s_m^\tau\, \hat{\hat{p}}_{\ell,m}^\tau} \tag{27}$$

$$Z_{\ell,m}^h \;=\; \frac{\sum\limits_{\tau'} \mathcal{I}\left(\tau' \in Hispanic\right) s_m^{\tau'}\, \hat{\hat{p}}_{\ell,m}^{\tau'}}{\sum\limits_{\tau} s_m^\tau\, \hat{\hat{p}}_{\ell,m}^\tau} \tag{28}$$

As in section 3.1.1, τ and τ' are indexes for household type; s_m^τ is the share of the metro population that is accounted for by type τ households; $\mathcal{I}\left(\tau' \in Black\right)$ is an indicator function that is equal to 1 if type τ' households are Black, 0 otherwise; and $\mathcal{I}\left(\tau' \in Hispanic\right)$ is an indicator function that is equal to 1 if type τ' households are Hispanic, 0 otherwise. In both equations, the predictions are based only on the topography variables, equation (26). We use equation (26) to predict where everyone will live based only on topography and then,

of $\mathbf{\Gamma}$ and $\bar{\mathbf{X}}$ is the average value (element by element) of $\mathbf{X}_{\ell,\mathbf{m}}$.

given this prediction, use metro-level household-type shares to calculate the predicted share of each location that is Black and Hispanic.

Our five instruments are then $Z^b_{\ell,m}$, $Z^h_{\ell,m}$, $\left(Z^b_{\ell,m}\right)^2$, $\left(Z^h_{\ell,m}\right)^2$, and $\left(Z^b_{\ell,m} Z^h_{\ell,m}\right)$. With these instruments in hand, we estimate Θ^τ_2 of equation (25) using 2SLS for each type, exactly analogous to the procedure we use for the Monte Carlo of the simple model described earlier. In both the first and second stages, we include metro-area fixed effects and a set of topographic variables as controls.

7 Estimates and Implications

7.1 Estimates

Table 7 provides a summary of our estimates of preferences that household types in our data have over the racial mix of their neighborhood, $\Theta^\tau_2 = \{a^\tau_1, \ldots, a^\tau_5\}$, as described in section 6.2. We estimate Θ^τ_2 using data from 195 metros with topography data as compared to data for 197 metros we use to estimate moving costs and indirect utilities (Θ^τ_1) as well as type-transition probabilities. Based on results from Davis et al. (2021), we set a^τ_r equal to 0.243 for all low credit score household types, 0.179 for all middle credit score types, and 0.135 for all high credit score types.[27] This implies that if log rents increase by 0.3 (about a 35% increase in rental prices), that holding all else equal indirect utility declines by 0.073, 0.054 and 0.041 for low-, middle-, and high- credit score types. Keep these values in mind when evaluating the estimated magnitudes of racial preferences reported in Table 7

Column (1) of Table 7 shows the index for household type and (2) reports the percentage of the estimation sample accounted for by that type. Columns (3)-(6) show the race, age (y=young, m=middle-aged, and o=old), homeownership tenure (r=rent, o=own), and bin of credit score (l=low, m=middle, h=high) of the type. Column (7) reports the average share of Black households in the census tracts in which that type tends to live and column (8) shows 0.1 times the average derivative of utility that type would experience from an increase in the share of Black households in the census tracts in which that type tends to live (discussed two paragraphs below). Similarly, column (9) reports the average share of Hispanic households in the census tracts in which that type tends to live and column (10) shows 0.1 times the average derivative of utility that type would experience from an increase in the share of Hispanic households in the census tracts in which that type tends to live. Note that the values reported in columns (7)-(10) are computed as weighted averages over

[27] The estimates we report in Table 7 almost do not change when we double or halve the values of a^τ_r (not shown).

Table 7: Summary of Estimates of Preferences over Race

Type	Sample %	Race	Age	Tenure	Credit	Avg S^b_ℓ	$\frac{1}{10} \cdot \text{Avg}\left(\frac{\Delta\delta_\ell}{\Delta S^b_\ell}\right)$	Avg S^h_ℓ	$\frac{1}{10} \cdot \text{Avg}\left(\frac{\Delta\delta_\ell}{\Delta S^h_\ell}\right)$	$\delta^{95}_\ell - \delta^5_\ell$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	2.2		y	r	l	0.42	0.22	0.10	0.15	2.70
2	1.2		y	r	m	0.34	0.26	0.11	0.04	1.98
3	0.6		y	r	h	0.24	0.07	0.11	0.04	0.36
4	0.4		y	o	l	0.36	0.21	0.10	-0.20	2.44
5	0.5		y	o	m	0.27	0.20	0.10	-0.02	1.33
6	0.6		y	o	h	0.17	0.01	0.09	-0.01	0.50
7	1.1		m	r	l	0.45	0.13	0.10	0.03	2.25
8	0.9		m	r	m	0.39	0.17	0.10	-0.03	1.74
9	0.6	Black	m	r	h	0.29	0.05	0.10	0.02	0.36
10	0.4		m	o	l	0.43	0.08	0.09	-0.12	1.48
11	0.6		m	o	m	0.36	0.09	0.10	-0.15	0.93
12	0.9		m	o	h	0.23	0.01	0.09	-0.06	0.28
13	0.3		o	r	l	0.50	0.09	0.09	0.09	1.97
14	0.5		o	r	m	0.46	0.09	0.09	-0.12	1.47
15	1.0		o	r	h	0.36	0.05	0.08	-0.20	0.62
16	0.1		o	o	l	0.52	0.03	0.08	-0.18	1.69
17	0.2		o	o	m	0.46	0.08	0.09	-0.29	1.88
18	0.4		o	o	h	0.31	0.07	0.09	-0.23	0.75
sum	12.3				avg	0.36	0.13	0.10	-0.02	1.53
19	1.6		y	r	l	0.13	0.34	0.35	0.17	1.84
20	1.4		y	r	m	0.11	0.18	0.34	0.15	1.35
21	0.8		y	r	h	0.09	-0.00	0.28	0.08	0.97
22	0.3		y	o	l	0.12	0.30	0.33	0.11	1.65
23	0.5		y	o	m	0.10	0.07	0.30	0.12	0.94
24	0.7		y	o	h	0.08	-0.18	0.23	0.01	1.05
25	0.7		m	r	l	0.14	0.28	0.35	0.11	1.58
26	0.9		m	r	m	0.11	0.20	0.35	0.10	1.25
27	0.8	Hisp	m	r	h	0.09	-0.08	0.30	0.08	0.87
28	0.3		m	o	l	0.13	0.13	0.33	0.03	0.97
29	0.6		m	o	m	0.10	0.03	0.31	0.05	0.57
30	1.1		m	o	h	0.08	-0.13	0.24	-0.00	0.77
31	0.1		o	r	l	0.13	0.27	0.39	0.15	1.51
32	0.3		o	r	m	0.11	0.18	0.38	0.12	1.12
33	1.0		o	r	h	0.09	-0.01	0.30	0.03	0.52
34	0.0		o	o	l	0.14	0.15	0.36	-0.00	0.48
35	0.1		o	o	m	0.11	0.15	0.34	0.10	0.89
36	0.4		o	o	h	0.08	-0.01	0.25	0.07	0.67
sum	11.6				avg	0.10	0.10	0.31	0.09	1.14
37	5.6		y	r	l	0.13	0.21	0.11	0.15	0.77
38	6.1		y	r	m	0.10	0.05	0.11	0.12	0.76
39	5.4		y	r	h	0.08	-0.25	0.09	-0.03	1.63
40	1.5		y	o	l	0.11	0.20	0.10	0.06	0.83
41	3.3		y	o	m	0.09	-0.03	0.09	0.05	1.38
42	6.8		y	o	h	0.07	-0.41	0.08	-0.07	2.03
43	2.7		m	r	l	0.13	0.19	0.11	0.06	0.63
44	4.1		m	r	m	0.10	0.15	0.11	0.05	0.50
45	6.5	White	m	r	h	0.08	-0.27	0.08	-0.04	1.37
46	1.3		m	o	l	0.11	0.09	0.09	-0.04	0.55
47	3.7		m	o	m	0.09	-0.06	0.09	-0.06	0.87
48	11.5		m	o	h	0.07	-0.47	0.08	-0.19	1.73
49	0.5		o	r	l	0.13	0.16	0.11	0.08	0.54
50	1.8		o	r	m	0.10	0.04	0.10	0.07	0.29
51	10.5		o	r	h	0.08	-0.16	0.08	-0.04	1.17
52	0.2		o	o	l	0.12	0.06	0.10	-0.03	0.37
53	0.7		o	o	m	0.10	0.02	0.09	-0.01	0.42
54	4.0		o	o	h	0.07	-0.18	0.08	-0.09	1.25
sum	76.1				avg	0.09	-0.14	0.09	-0.02	1.21

For age: y = young, m = middle-aged, o = old. For tenure: r = renter, o = owner. For credit: l = low, m = middle, h = high.

all tracts in which the type may live, with the weights being the probability that the type lives in the tract.[28]

The top, middle and bottom panels of the table show results for Black, Hispanic, and White types of households, respectively. Focusing on the bottom row of each of the panels, Black households account for 12.3% of our sample, Hispanic households account for 11.6% of our sample, and White households account for 76.1% of our sample. Table 7 shows that same-race sorting is a prominent feature of our data. Columns (7) and (9) show that, on average, Black households live in census tracts that are 36% Black, Hispanic households live in census tracts that are 31% Hispanic and White households live in census tracts that are 82% White.[29]

Columns (8) and (10) show 0.1 times the derivative of utility with respect to exogenous changes in the tract-level Black share (8) or Hispanic share (10). Roughly speaking, given the tracts where each type tends to live, this is the average change in utility resulting from a 10 percentage point increase in the share of Black (column 8) or Hispanic (column 10) households living in each tract. As shown in the bottom row of each panel that summarizes all types of a given race, homophily is a prevalent feature of our data: on average Black households receive additional utility from an increase in Black shares; Hispanic households receive additional utility from an increase in Hispanic shares (as well as Black shares); and White households receive additional utility from an increase in White shares. [30] Note that our results suggest there is considerable within-race heterogeneity in preferences. For example, focusing on White types of households, Type 37 (young, low-credit score renters) accounting for 5.6 percent of the sample experience a relatively large increase in utility as the share of Black households in the neighborhoods where they tend to live increases; whereas Type 48 (middle aged, high-credit score homeowners), accounting for 11.5% of our sample, experience a large decrease in utility as the share of Black households in the neighborhoods where they tend to live increases.

Finally, column (11) illustrates the importance of racial preferences in accounting for location choice in our data. For column 11, we set $a_r^\tau = 0$ and $A_{\ell,m}^\tau = 0$ for all τ and all ℓ and m and then evaluate the level of utility for each type of household in each census tract; in this calculation, differences in Black and Hispanic shares entirely determine differences

[28]For example, suppose there are two tracts A and B; and, thinking about column 8, suppose a particular type experiences a -1.0 derivative to utility with respect to the Black share in tract A and a +1.0 derivative to utility with respect to the Black share in tract B. If the probability that that type lives in tract A is 0.20, then we would report a value in column 8 for that type of (1/10) times 0.6, computed as $0.6 = 0.2\,(-1.0) + 0.8\,(1.0)$.

[29]The total shares of Black and White households shown in this table and shown in Table 1 are different because this table uses person weights whereas the other table weights each tract equally to compute total racial shares.

[30]Specifically, utility increases for White households if either the Black or Hispanic shares decrease.

in utility across census tracts. For each type, we sort tracts by the level of utility the tract provides; we then report in column (11) the level of utility for the type at the location representing the 95th percentile less the level of utility at the location representing the 5th percentile. When compared to the estimates reported in columns 8 and 10, the average change in utility from a 10 percentage point change in the percentage of households that are Black or Hispanic, these utility differentials attributable entirely to differences in racial composition across neighborhoods are huge.

7.2 Implications: Impact of a Small Policy Shock

Next, we use simulations of the model to study the implications of a somewhat small policy change that simultaneously affects a relatively large number of locations in a metro area. Specifically, for each metro area, we simulate the long-run steady-state predicted response after local governments unexpectedly allow a one-time and immediate 10 percent expansion of all housing developments previously financed using Low Income Housing Tax Credits (LIHTC). We allow this policy to potentially increase racial integration in the new simulated steady state by initially populating the new units with low credit score tenants that have the same demographic mix as the low credit score population of the metro.[31] The thought behind this analysis was to ask if local governments could implement a relatively small place-based policy in many locations at once without causing a lot of disruption. If the policy was sufficiently small, and implemented in enough locations that already had experience with government policy via existing LIHTC developments, perhaps incumbent residents would not move in response to a small influx of new low-credit-score residents that may be of a different average racial mix than existing residents.[32]

Before continuing, we need to define a steady state. A steady state has the features that (i) the mix of household types in each tract is stable (implying shares of Black and Hispanic households in each tract are stable), (ii) the rent in each tract is stable, and (iii) expected future rents and Black and Hispanic shares in each tract are equal to realized rents and shares after all location decisions are made each period.

We implement this counterfactual policy experiment as follows. Denote ΔH as the total

[31]As the long as the tract receiving the population has a different demographic structure than the average demographic mix of the low-credit-score population of the metro, this procedure changes the racial mix of the receiving tract.

[32]Note that Cook et al. (2024) show that, in practice and unlike our assumptions in this experiment, Black households are less likely to occupy LIHTC units in "higher opportunity" neighborhoods in a metro area. The point of this experiment is not to exactly predict the racial composition of any new LIHTC units, but rather to study the behavioral response to a policy rule that mechanically tries to force a small amount of extra racial integration into a large number of locations at once.

number of new LIHTC units that will be built in the metro as a consequence of this policy. In the first step, we remove ΔH housing units (in total) from census tracts that are currently housing low-credit-score households in the metro.[33] Then, in the second step we simulate the model for 5 periods holding $\delta_{\ell,m}$ fixed and $r_{\ell,m}$ fixed for every ℓ in the metro. After these 5 periods, and before adding the new LIHTC units, in each tract and for each type we compute the number of households that need to enter or exit ("births and deaths") such that the data are in a steady state with these ΔH units removed.[34]

Finally, in the third step – the jumping-off point for finding the steady state that occurs after the policy is implemented – we add new LIHTC units in proportion to existing LIHTC units until ΔH units are added. We assume the distribution of household types in these new units is the same as the distribution of household types from the ΔH units removed in the first step. With these three steps, we preserve the metro-wide distribution of household types and maintain the metro-wide aggregate stock of housing, but move ΔH low-credit score households from census tracts without LIHTC units to census tracts with LIHTC units. Importantly, the mix of household types moving into the ΔH new LIHTC units is unlikely to be the same as the mix of household types in the tracts where those units are located.

Once we have taken the three steps listed above, we compute a new steady state for each metro. When households have strong preferences over the demographic composition of their neighborhood, we cannot rule out the possibility that there may be multiple feasible steady states in each metro. We therefore compute a new steady state that is consistent with "myopic" expectations. The steady state we consider – as well as the path to the steady state – implied by this assumption about expectations is unique.

Our algorithm to compute the new steady state with myopic expectations is as follows:

a. For each tract ℓ in metro m, denote the total number of households and the rental price in each tract in the starting steady state as $\mathcal{H}_{\ell,m}$ and $r_{\ell,m}$, respectively.
b. For each tract ℓ in metro m, denote the expected black share and expected hispanic share as $E\left[S^b_{\ell,m}\right]$ and $E\left[S^h_{\ell,m}\right]$. Set both of these equal to their values in the starting steady state.
c. Given household assumptions of $E\left[S^b_{\ell,m}\right]$, and $E\left[S^h_{\ell,m}\right]$, simulate one period of household decisions, add location- and type-specific births and deaths as computed in the jumping off point of the simulations, and find market clearing rents $r'_{\ell,m}$ and the new

[33] The housing units are removed in proportion to the low-credit score population of each tract.

[34] Recall that each household in our model faces stochastic transitions over states: age (including death), housing tenure choice, and credit score. For a stable mix of types, at a minimum we need births but also need to account for any other asymmetric type transitions.

housing stock $\mathcal{H}'_{\ell,m}$ in each tract such that the following housing-supply-elasticity holds:

$$\log \mathcal{H}'_{\ell,m} - \log \mathcal{H}_{\ell,m} = \psi_{\ell,m} \left[\log r'_{\ell,m} - \log r_{\ell,m}\right] \tag{29}$$

Where the housing supply in tract ℓ in metro m, $\psi_{\ell,m}$, is given by the estimates in Baum-Snow and Han (2022) with a floor value of 0.025.[35]

d. Given the simulated household location decisions from step [c.], update expected Black and Hispanic shares by setting them equal to realized (simulated) Black and Hispanic shares in each tract, $E\left[S^b_{\ell,m}\right] = S^b_{\ell,m}$ and $E\left[S^h_{\ell,m}\right] = S^h_{\ell,m}$.

e. Repeat steps c and d *until the distribution of types in each tract does not change with one additional iteration.*

To be completely clear, when households solve for their optimal location, they need to know utility today and in the future for all possible locations. The current and future values of $\delta^\tau_{\ell,m}$ in each period have the following as components: (i) fixed amenities $A^\tau_{\ell,m}$, (2) expected racial shares, and (3) actual current market clearing rents given those expected racial shares. At each step in the simulation path, households assume the current and expected value of $\delta^\tau_{\ell,m}$ is fixed at its current value. But, along each step of the simulation path, the value of $\delta^\tau_{\ell,m}$ changes as realized racial shares and market-clearing rents change. Thus, when the model is not in steady state, at each step along the simulation path expected racial shares are not accurate because they are backward looking.

7.2.1 Change to the Racial Composition of Neighborhoods

In the simulations, we track three statistics for each metro. The first statistic we compute is the share of tracts that "tip." We define a tract to have tipped if either the Black share or the Hispanic share changes by 5 percentage points or more in the new steady state relative to the original steady state prior to the policy change. The other two statistics we compute are Black-White and Hispanic-White dissimilarity indices. For each metro m, we compute these indices as

$$\begin{aligned}
\text{Black-White dissimilarity} &= \frac{1}{2}\sum_{\ell\in m}\left|\frac{b_{\ell,m}}{B_m} - \frac{w_{\ell,m}}{W_m}\right| \\
\text{Hispanic-White dissimilarity} &= \frac{1}{2}\sum_{\ell\in m}\left|\frac{h_{\ell,m}}{H_m} - \frac{w_{\ell,m}}{W_m}\right|
\end{aligned}$$

where $b_{\ell,m}$, $h_{\ell,m}$ and $w_{\ell,m}$ are the numbers of Black, Hispanic, and White households in tract ℓ of metro m and B_m, H_m, and W_m are the numbers of Black, Hispanic, and White

[35] In a handful of tracts, Baum-Snow and Han (2022) estimate a negative supply elasticity.

households in metro m. If there is perfect mixing of races in each tract, then these indices will equal 0; and if there is perfect segregation then the indices will equal 1.

In Table 8 below, we show the results for 20 representative metros in our sample. We chose these metros using the following process: First, we split our estimation sample of metros into 10 deciles based on number of census tracts. Then, decile by decile we find the median percentage of black households in each metro and further split the metros in each decile into above- and below-median groupings. We then randomly select two metro areas per decile, one in the grouping of below-median-share of Black households one in the above-median grouping. The metro areas in this table and others showing these same metros are sorted in the order they were chosen using this procedure.

Explaining the columns of this table, column (1) shows the (shortened) name of the metro and column (2) shows the percentage of census tracts in that metro with some LIHTC units. Columns (3), (6) and (7), and (10) and (11) show results at our baseline estimate of preferences. Column (3) shows the percentage of tracts that tip after the policy is implemented; columns (6) and (10) show the level of the Black and Hispanic dissimilarity indexes at the jumping-off steady state, respectively; and columns (7) and (11) show the change in those indexes at the new steady state, measured in percentage points. Columns (4), (5), (8), (9), (12), and (13) are discussed two paragraphs below.

The results in this table illustrate that the demographic composition of neighborhoods is not stable, in the sense that a small policy change can cause a huge reshuffling of the population that yields a new steady state that is enormously more segregated than in the current data. When measured at the median metro of the 20 we consider (penultimate row of the table), the policy generates a new steady state where 75% of tracts tip relative to the jumping-off point (column 3), the Black-White dissimilarity index changes by 60.5 percentage points (column 7), and the Hispanic-White dissimilarity index changes by 67.1 percentage points (column 11). These results reinforce the idea that households, on net, want to move to more racially segregated neighborhoods.

Ultimately, neighborhoods are not stable because a sufficient number of households have strong preferences over the racial composition of their neighborhoods. To show this, we rerun the policy experiment after "shrinking" preferences for race. In columns (4), (8) and (12) of the table, we show results after setting $\Theta_2^\tau = \{a_1^\tau, \ldots, a_5^\tau\}$ equal to 0.25 of the baseline estimates, but keep the baseline starting values of $\delta_{\ell,m}^\tau$ unchanged for all types. This keeps baseline preferences for each neighborhood unchanged, but reduces the impact of changes in demographic composition on the desirability of neighborhoods. In columns (5), (9) and (13) of the table, we shrink preferences even more and set $\Theta_2^\tau = \{a_1^\tau, \ldots, a_5^\tau\}$ equal to 0.125 of the baseline estimates. Columns (4) and (5) show that as we shrink preferences for race,

Table 8: Summary of Neighborhood Change in Response to Small Policy Shock

		% Tracts that Tip			BW Dissim.				HW Dissim.			
CBSA	LIHTC %	Base	$\frac{1}{4}$	$\frac{1}{8}$	Start	Δ	$\Delta - \frac{1}{4}$	$\Delta - \frac{1}{8}$	Start	Δ	$\Delta - \frac{1}{4}$	$\Delta - \frac{1}{8}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Springfield, IL	25	76	18	0	31	60.3	18.5	−0.1	13	72.3	3.4	0.1
Spartanburg, SC	33	100	47	0	20	69.7	28.9	0.1	13	73.0	14.9	0.1
Norwich, CT	16	50	2	0	27	63.3	−0.2	0.0	23	63.0	−0.1	0.0
Port St. Lucie, FL	18	92	20	0	27	62.9	10.0	0.0	18	66.8	4.5	0.0
Charleston, WV	29	34	5	0	30	59.2	4.5	−0.1	14	65.7	0.2	0.0
Erie, PA	21	47	3	0	36	53.4	1.5	0.0	24	56.9	0.2	0.0
Eugene, OR	36	21	0	0	12	66.6	0.0	0.0	8	69.9	0.0	0.0
Montgomery, AL	40	96	80	11	34	58.3	39.2	3.0	14	74.3	36.4	4.6
Brownsville, TX	22	97	0	0	16	54.1	0.1	−0.1	29	48.2	0.0	−0.2
Salinas, CA	30	92	5	0	26	61.7	0.9	−0.1	42	41.9	−0.8	−0.2
Utica, NY	21	27	3	0	36	53.2	5.9	−0.1	27	58.8	−2.7	0.0
Augusta, GA	22	100	86	3	27	65.1	46.3	0.0	14	76.8	28.5	0.2
Lansing, MI	30	74	12	0	33	58.8	2.7	−0.1	21	66.3	1.5	0.0
Charleston, SC	33	100	90	2	21	70.5	53.9	1.1	13	77.2	32.6	1.3
Knoxville, TN	29	49	9	0	27	64.7	8.0	0.0	11	73.5	0.5	0.1
Greenville, SC	38	96	69	0	25	65.4	32.8	0.0	15	73.5	14.7	0.1
Worcester, MA	22	45	0	0	26	60.8	−0.1	0.0	30	54.0	−0.1	0.0
Youngstown, OH	26	60	12	0	43	46.9	2.3	0.0	27	56.1	−1.2	0.0
Albany, NY	20	52	8	0	33	58.4	10.4	−0.1	19	68.9	0.5	0.0
Dayton, OH	38	81	25	0	49	42.4	16.9	−0.2	15	67.5	12.4	0.6
IQR column by column:												
25th percentile	22	49	3	0	26	58.3	1.5	−0.1	14	58.8	0.0	0.0
Median	28	75	11	0	27	60.5	7.0	0.0	16	67.1	0.5	0.0
75th percentile	33	96	25	0	33	64.7	18.5	0.0	24	73.0	12.4	0.1

the percentage of tracts that tip in the steady state after the policy is implemented falls to zero; and columns (8) and (9) and (12) and (13) show that as we shrink preferences for race, changes in the steady state black-white and hispanic-white dissimilarity indices also fall to zero.

One might wonder if the results we report are due to the nature of the policy experiment we consider. Restated, perhaps it is the case that a different policy experiment evaluated at our baseline preferences would not generate a new steady state that looks so different from the starting point that is based on current data. To investigate this, in every metro area we consider we ask if the model, when evaluated at the starting point of the policy experiments, will return to that same starting point after a tiny shock to the demographic composition of any one neighborhood. We call this evaluation our "eigenvalue analysis." Appendix D details the exact procedure we use to compute eigenvalues (measures of system stability).

In summary, in almost every metro we investigate, at least one eigenvalue is larger than 1.0, a condition for system instability. In most metros a substantial fraction of eigenvalues are much larger than 1.0. This implies that in nearly every metro we evaluate, any perturbation to demographic composition in any census tract has the potential to generate a new steady state that looks very different from the current data.

7.2.2 The Speed of Convergence to New Steady State

To understand the importance of expectations in determining the rate at which the model converges to a new steady state, we study two paths for expectations in response to the policy shock. The first assumes household expectations look backwards but are updated every period, i.e. what we have assumed so far to find the new steady state. We call this the "backward-looking path." In the second, we take the steady state arising from the backward-looking path and specify that households assume that particular steady state will occur in every period. We call this the "forward-looking path." This path is also unique, although different from the backward-looking path.

In both the backward- and forward-looking paths, the new steady states are identical but household expectations will be incorrect along the transition path to the new steady state. It turns out that the "miss" between expected and realized racial shares in both cases in each tract will be relatively small. The miss is small because realized racial shares change quite slowly along the backward-looking path and quite rapidly along the forward-looking path.

Table 9 demonstrates the importance of household expectations on the rate of convergence to the new steady state. In this table, we keep track of census tracts in which the Black or Hispanic racial share changed by at least 5 percentage points between steady states at our baseline set of parameter estimates. Columns (3) and (4) report the percentage of tracts in the metro in which the Black (column 3) or Hispanic (column 4) share changed by at least 5 percentage points. Columns (5) and (6) report the median number of years required for 80% of the total change in the tipped racial share to occur for the tracts where the Black share tips (column 5) and Hispanic share tips (column 6) along the backward-looking path. Columns (7) and (8) report the same for the forward-looking path.

This table shows that when expectations are backward looking, convergence to the new steady state occurs much more slowly than when expectations are forward looking. In the backward-looking path, at the median across all the metros we consider, for the median census tract where the Black share tips, 80% of the convergence to the new racial share occurs after 45 years and for the median Census tract where the Hispanic share tips, 80% of

Table 9: Expectations and Rate of Change Between Steady States

				Median years to 80% convergence (within CBSA)			
		% Tracts that Tip		Backward-looking		Forward-looking	
CBSA	Tracts	Black	Hispanic	Black	Hispanic	Black	Hispanic
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Springfield, IL	55	75	2	32	68	6	10
Spartanburg, SC	51	100	4	34	80	6	8
Norwich, CT	62	47	27	51	53	5	7
Port St. Lucie, FL	60	90	35	42	41	7	10
Charleston, WV	76	33	1	47	160	6	12
Erie, PA	72	46	8	35	34	5	2
Eugene, OR	78	3	18	158	148	6	14
Montgomery, AL	82	96	1	30	45	5	8
Brownsville, TX	86	1	97	82	46	5	9
Salinas, CA	83	20	89	65	36	8	8
Utica, NY	92	25	10	34	44	5	6
Augusta, GA	95	100	2	33	102	5	6
Lansing, MI	117	73	26	38	51	5	6
Charleston, SC	117	100	5	33	43	5	7
Knoxville, TN	128	48	2	29	50	5	8
Greenville, SC	126	95	6	28	40	6	7
Worcester, MA	163	20	42	51	60	5	8
Youngstown, OH	168	59	7	27	35	5	2
Albany, NY	213	48	10	29	37	5	6
Dayton, OH	208	79	3	26	46	5	8
Median				45.2	61.0	5.5	7.7

Notes: Entries report the share of tracts that tip and the median number of years required to reach 80% convergence within each CBSA under backward-looking and forward-looking expectations.

the convergence to the new racial share occurs after 61 years. In contrast, along the forward-looking path these values fall in the range of 5.5 to 7.7 years. In our view, the rate of change along the backward-looking path is so slow that it is conceivable people who are not paying attention are unlikely to notice a change in any given year, even though the change is large and significant when measured over decades.

8 Conclusion

We use a new shift-share IV approach to estimate the extent to which the racial composition of neighborhoods affects household utility and neighborhood choice in a dynamic, forward-looking location-choice model where households care about amenities of neighborhoods as well as the racial composition. We find that many households have very strong preferences for homophily. Same-race preferences are so strong that a relatively small public policy we consider generates a new steady state that involves a radical resorting of the population and even more segregation than currently observed.

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Not For Publication Internet Appendix

A Potential Implications of Imperfect Measurement of Race

The fact that we do not perfectly observe race suggests that our estimates of choice probabilities by race could be mismeasured. This may ultimately bias our estimates of $\delta^{\tau}_{\ell,m}$. That said, any bias that arises will make location choices look more similar by race than would be estimated if race were perfectly measured.

To see this, consider a simple estimate of the probability location ℓ is chosen by a White household where race is not always measured correctly.[36] This estimate can be written as

$$\hat{P}^{w}(\ell) \quad = \quad (1-\phi^{w})\,P^{w}(\ell) + \phi^{w} P^{-w}(\ell)$$

In the equation above, ϕ^{w} is the fraction of respondents labeled as "White" households that are actually nonwhite, $P^{w}(\ell)$ is the true probability White households choose tract ℓ and $P^{-w}(\ell)$ is the true probability nonwhite households choose tract ℓ. The estimated probability White households choose tract ℓ, $\hat{P}^{w}(\ell)$, will be a blended average of the probabilities White and nonwhite households choose tract ℓ. The size of the bias depends on the extent of the mislabeling and the difference of the choice probabilities of White and nonwhite households:

$$\hat{P}^{w}(\ell) \quad = \quad P^{w}(\ell) \quad - \quad \underbrace{\phi^{w}\left[P^{w}(\ell) - P^{-w}(\ell)\right]}_{\text{bias}}$$

If $P^{w}(\ell) > P^{-w}(\ell)$, then the bias is negative; estimated choice probabilities by race will appear to be more similar than would be implied if race were perfectly observed.[37]

Some simple math shows that any bias that arises due to mismeasurement is likely to be about one-third the size for White households than for either Black or Hispanic households. The reason is that White households comprise 76 percent of our sample and Black and Hispanic households each account for about 12 percent of our sample. Consider a simple example of a sample of 1000 people with 760 White, 120 Black, and 120 Hispanic. If 10% of Black and 10% of Hispanic households are incorrectly labeled as White, only 24 out of 760

[36] In this simple example we hold all aspects of a household's type other than race fixed.

[37] Obviously, other authors have discussed issues with imputing race in large data sets. One recent proposal for imputing race in administrative data suggests using both full names (or combinations of letters appearing together) and geography: See Cabreros et al. (2022). Note that we do not observe names in our data.

White-labeled households will be mislabeled – about 3 percent. For the overall racial shares in the sample to be accurate, 12 White households will be mislabeled as Black and 12 White households will be mislabeled as Hispanic, 10% each of Black and Hispanic households. Thus, ϕ for White households will be about one-third the size of ϕ for nonwhite households due to simple arithmetic.

As we show later, our current estimates imply many households make choices that suggest they prefer racially segregated neighborhoods. The bias we have discussed pushes estimates away from this finding of homophily, since it shrinks differences across race in estimated location-choice probabilities. In Appendix D, we evaluate the stability of racial shares in neighborhoods in our data by estimating the eigenvalues of our decision model. We show the hypothesis that existing neighborhood racial shares are stable can be rejected because our estimated preferences for homophily are strong. The fact that our estimates may be biased away from finding homophily makes the rejection of stability of neighborhood racial shares even more stark.[38]

[38] We discuss our analysis of eigenvalues in more detail at the end of section 7.2.1.

B Prediction Equation Estimates and Standard Errors

Coefficient Estimates and Standard Errors
Black Households

Type	Const	Smooth Plains	Irreg. Plains	Escarf- Ments	Low Hills	Hills	Breaks- Foothills	Low Mntns.	High Mntns.	Drainage Channels	All Else
1	-1.181	-0.107	-0.448	-0.113	-9.103	-1.572	-1.158	-1.873	-1.080	-1.181	-4.164
yng,rnt,low	(0.077)	(0.027)	(0.028)	(0.193)	(8.531)	(0.073)	(0.078)	(0.091)	(0.392)	(0.077)	(0.356)
2	-0.919	0.003	-0.250	-0.064	-1.675	-1.072	-0.851	-1.501	-1.015	-0.919	-3.685
yng,rnt,med	(0.066)	(0.023)	(0.024)	(0.165)	(7.283)	(0.062)	(0.067)	(0.078)	(0.334)	(0.066)	(0.304)
3	-0.404	0.194	0.077	0.007	0.241	-0.372	-0.330	-1.013	-0.919	-0.404	-2.877
yng,rnt,high	(0.061)	(0.022)	(0.023)	(0.154)	(6.800)	(0.058)	(0.062)	(0.072)	(0.312)	(0.061)	(0.284)
4	-0.477	-0.062	-0.388	-0.746	-0.796	-0.854	-0.680	-1.276	-1.044	-0.477	-4.662
yng,own,low	(0.082)	(0.029)	(0.030)	(0.207)	(9.148)	(0.078)	(0.084)	(0.098)	(0.420)	(0.082)	(0.382)
5	-0.066	0.088	-0.181	-0.750	6.138	-0.266	-0.280	-0.992	-0.950	-0.066	-3.987
yng,own,med	(0.072)	(0.025)	(0.026)	(0.181)	(7.962)	(0.068)	(0.073)	(0.085)	(0.366)	(0.072)	(0.332)
6	0.579	0.317	0.226	-0.420	7.439	0.623	0.339	-0.438	-0.727	0.579	-3.130
yng,own,high	(0.073)	(0.026)	(0.027)	(0.183)	(8.085)	(0.069)	(0.074)	(0.086)	(0.371)	(0.073)	(0.337)
7	-1.178	-0.103	-0.448	-0.139	-8.747	-1.555	-1.137	-1.622	-0.924	-1.178	-3.757
mid,rnt,low	(0.080)	(0.028)	(0.030)	(0.201)	(8.868)	(0.075)	(0.081)	(0.095)	(0.407)	(0.080)	(0.370)
8	-0.859	-0.005	-0.290	-0.242	-6.149	-1.053	-0.843	-1.235	-0.533	-0.859	-3.237
mid,rnt,med	(0.069)	(0.024)	(0.026)	(0.174)	(7.669)	(0.065)	(0.070)	(0.082)	(0.352)	(0.069)	(0.320)
9	-0.379	0.182	0.069	0.037	1.248	-0.258	-0.222	-0.641	-0.123	-0.379	-2.439
mid,rnt,high	(0.062)	(0.022)	(0.023)	(0.157)	(6.921)	(0.059)	(0.064)	(0.074)	(0.318)	(0.062)	(0.289)
10	-0.546	0.010	-0.328	-0.573	-12.456	-0.860	-0.470	-1.032	-0.752	-0.546	-4.829
mid,own,low	(0.087)	(0.031)	(0.032)	(0.218)	(9.617)	(0.082)	(0.088)	(0.103)	(0.442)	(0.087)	(0.401)
11	-0.271	0.107	-0.164	-0.608	-4.519	-0.387	-0.208	-0.777	-0.630	-0.271	-4.092
mid,own,med	(0.075)	(0.026)	(0.028)	(0.188)	(8.278)	(0.070)	(0.076)	(0.088)	(0.380)	(0.075)	(0.345)
12	0.473	0.333	0.255	-0.336	3.480	0.514	0.453	-0.170	-0.099	0.473	-2.085
mid,own,high	(0.070)	(0.025)	(0.026)	(0.175)	(7.735)	(0.066)	(0.071)	(0.082)	(0.355)	(0.070)	(0.323)
13	-1.363	-0.093	-0.450	-0.059	-24.128	-1.673	-1.117	-1.678	-0.620	-1.363	-3.767
old,rnt,low	(0.096)	(0.034)	(0.036)	(0.242)	(10.668)	(0.091)	(0.098)	(0.114)	(0.490)	(0.096)	(0.445)
14	-1.027	0.005	-0.279	-0.023	-12.208	-1.181	-0.758	-1.202	-0.480	-1.027	-3.454
old,rnt,med	(0.082)	(0.029)	(0.030)	(0.206)	(9.074)	(0.077)	(0.083)	(0.097)	(0.417)	(0.082)	(0.379)
15	-0.597	0.194	0.062	-0.047	-3.021	-0.500	-0.264	-0.746	-0.338	-0.597	-2.241
old,rnt,high	(0.070)	(0.025)	(0.026)	(0.177)	(7.818)	(0.066)	(0.072)	(0.083)	(0.359)	(0.070)	(0.326)
16	-1.034	0.010	-0.297	-0.757	-22.886	-1.039	-0.352	-1.013	-0.975	-1.034	-4.252
old,own,low	(0.109)	(0.039)	(0.040)	(0.274)	(12.065)	(0.103)	(0.111)	(0.129)	(0.554)	(0.109)	(0.503)
17	-0.727	0.098	-0.198	-0.482	-13.229	-0.734	-0.268	-0.841	-0.480	-0.727	-3.577
old,own,med	(0.094)	(0.033)	(0.035)	(0.237)	(10.445)	(0.089)	(0.096)	(0.111)	(0.480)	(0.094)	(0.436)
18	0.106	0.319	0.216	-0.118	-1.416	0.151	0.339	-0.220	-0.240	0.106	-1.638
old,own,high	(0.080)	(0.028)	(0.029)	(0.201)	(8.854)	(0.075)	(0.081)	(0.094)	(0.407)	(0.080)	(0.369)

Notes: This table shows the coefficient estimates and standard errors for the prediction equation (26) of location choice on topographic variables by household type. Legend: yng = young, mid = middle aged, old = old aged, rnt = renter, own = owner, low = low credit score, med = medium credit score, high = high credit score.

Coefficient Estimates and Standard Errors
Hispanic Households

Type	Const	Smooth Plains	Irreg. Plains	Escarf-Ments	Low Hills	Hills	Breaks-Foothills	Low Mntns.	High Mntns.	Drainage Channels	All Else
19	-0.710	-0.198	-0.529	-0.592	-2.122	-1.262	-1.464	-1.699	-1.481	-0.710	-3.811
yng,rnt,low	(0.067)	(0.024)	(0.025)	(0.168)	(7.389)	(0.063)	(0.068)	(0.079)	(0.339)	(0.067)	(0.308)
20	-0.415	-0.113	-0.353	-0.593	4.062	-0.775	-1.203	-1.396	-1.548	-0.415	-3.363
yng,rnt,med	(0.061)	(0.022)	(0.023)	(0.154)	(6.802)	(0.058)	(0.062)	(0.073)	(0.312)	(0.061)	(0.284)
21	0.070	0.064	-0.034	-0.505	11.286	-0.029	-0.649	-0.970	-1.443	0.070	-2.426
yng,rnt,high	(0.063)	(0.022)	(0.023)	(0.159)	(7.032)	(0.060)	(0.065)	(0.075)	(0.323)	(0.063)	(0.293)
22	-0.076	-0.188	-0.516	-1.310	3.385	-0.556	-0.934	-1.189	-1.784	-0.076	-4.512
yng,own,low	(0.078)	(0.028)	(0.029)	(0.197)	(8.696)	(0.074)	(0.080)	(0.093)	(0.399)	(0.078)	(0.363)
23	0.308	-0.022	-0.297	-1.120	12.192	-0.011	-0.578	-0.933	-1.664	0.308	-3.998
yng,own,med	(0.072)	(0.026)	(0.027)	(0.182)	(8.041)	(0.068)	(0.074)	(0.086)	(0.369)	(0.072)	(0.336)
24	0.762	0.177	0.114	-0.660	13.861	0.751	0.004	-0.471	-1.216	0.762	-2.821
yng,own,high	(0.076)	(0.027)	(0.028)	(0.191)	(8.400)	(0.071)	(0.077)	(0.090)	(0.386)	(0.076)	(0.350)
25	-0.664	-0.202	-0.539	-0.716	0.345	-1.159	-1.397	-1.349	-1.134	-0.664	-3.089
mid,rnt,low	(0.068)	(0.024)	(0.025)	(0.172)	(7.606)	(0.065)	(0.070)	(0.081)	(0.349)	(0.068)	(0.317)
26	-0.248	-0.134	-0.383	-0.836	3.616	-0.648	-1.125	-1.034	-1.108	-0.248	-2.698
mid,rnt,med	(0.061)	(0.022)	(0.023)	(0.154)	(6.789)	(0.058)	(0.062)	(0.072)	(0.312)	(0.061)	(0.283)
27	0.232	0.053	-0.052	-0.652	13.993	0.213	-0.505	-0.464	-0.974	0.232	-1.599
mid,rnt,high	(0.062)	(0.022)	(0.023)	(0.155)	(6.834)	(0.058)	(0.063)	(0.073)	(0.314)	(0.062)	(0.285)
28	-0.041	-0.093	-0.431	-1.289	-5.961	-0.468	-0.821	-0.836	-1.262	-0.041	-4.065
mid,own,low	(0.077)	(0.027)	(0.029)	(0.195)	(8.584)	(0.073)	(0.079)	(0.091)	(0.394)	(0.077)	(0.358)
29	0.250	-0.019	-0.243	-1.085	8.112	0.014	-0.527	-0.583	-1.149	0.250	-3.160
mid,own,med	(0.070)	(0.025)	(0.026)	(0.175)	(7.725)	(0.066)	(0.071)	(0.082)	(0.355)	(0.070)	(0.322)
30	0.827	0.204	0.145	-0.708	13.207	0.845	0.101	-0.056	-0.871	0.827	-1.427
mid,own,high	(0.071)	(0.025)	(0.026)	(0.178)	(7.870)	(0.067)	(0.072)	(0.084)	(0.361)	(0.071)	(0.328)
31	-0.838	-0.229	-0.570	-0.858	-4.361	-1.227	-1.493	-1.579	-1.209	-0.838	-3.197
old,rnt,low	(0.086)	(0.031)	(0.032)	(0.217)	(9.574)	(0.081)	(0.088)	(0.102)	(0.440)	(0.086)	(0.399)
32	-0.334	-0.135	-0.398	-0.732	2.903	-0.730	-1.058	-1.118	-0.720	-0.334	-2.377
old,rnt,med	(0.069)	(0.025)	(0.026)	(0.175)	(7.699)	(0.065)	(0.071)	(0.082)	(0.354)	(0.069)	(0.321)
33	0.193	0.046	-0.050	-0.661	10.207	0.035	-0.543	-0.542	-0.939	0.193	-1.300
old,rnt,high	(0.065)	(0.023)	(0.024)	(0.164)	(7.226)	(0.061)	(0.066)	(0.077)	(0.332)	(0.065)	(0.301)
34	-0.360	-0.096	-0.383	-0.975	16.188	-0.581	-0.833	-0.858	-1.525	-0.360	-3.695
old,own,low	(0.104)	(0.037)	(0.038)	(0.261)	(11.519)	(0.098)	(0.106)	(0.123)	(0.529)	(0.104)	(0.481)
35	-0.060	-0.015	-0.297	-1.012	4.905	-0.275	-0.634	-0.650	-0.812	-0.060	-2.938
old,own,med	(0.085)	(0.030)	(0.031)	(0.213)	(9.402)	(0.080)	(0.086)	(0.100)	(0.432)	(0.085)	(0.392)
36	0.679	0.196	0.126	-0.723	16.122	0.636	0.052	-0.018	-0.636	0.679	-0.833
old,own,high	(0.076)	(0.027)	(0.028)	(0.190)	(8.386)	(0.071)	(0.077)	(0.089)	(0.385)	(0.076)	(0.350)

Notes: This table shows the coefficient estimates and standard errors for the prediction equation (26) of location choice on topographic variables by household type. Legend: yng = young, mid = middle aged, old = old aged, rnt = renter, own = owner, low = low credit score, med = medium credit score, high = high credit score.

Coefficient Estimates and Standard Errors
White Households

Type	Const	Smooth Plains	Irreg. Plains	Escarf-Ments	Low Hills	Hills	Breaks-Foothills	Low Mntns.	High Mntns.	Drainage Channels	All Else
37	0.065	-0.060	-0.253	-0.237	5.258	-0.160	-0.648	-0.818	-0.959	0.065	-1.666
yng,rnt,low	(0.051)	(0.018)	(0.019)	(0.128)	(5.662)	(0.048)	(0.052)	(0.060)	(0.260)	(0.051)	(0.236)
38	0.415	0.073	-0.008	-0.074	8.580	0.393	-0.256	-0.386	-0.813	0.415	-1.033
yng,rnt,med	(0.053)	(0.019)	(0.020)	(0.134)	(5.900)	(0.050)	(0.054)	(0.063)	(0.271)	(0.053)	(0.246)
39	0.793	0.250	0.308	0.110	12.604	1.032	0.311	0.069	-0.592	0.793	-0.272
yng,rnt,high	(0.065)	(0.023)	(0.024)	(0.163)	(7.170)	(0.061)	(0.066)	(0.076)	(0.329)	(0.065)	(0.299)
40	0.732	-0.039	-0.216	-0.660	9.012	0.446	-0.149	-0.326	-1.169	0.732	-2.407
yng,own,low	(0.068)	(0.024)	(0.025)	(0.172)	(7.581)	(0.064)	(0.070)	(0.081)	(0.348)	(0.068)	(0.316)
41	1.033	0.129	0.040	-0.671	12.070	0.940	0.283	-0.009	-1.006	1.033	-1.620
yng,own,med	(0.069)	(0.025)	(0.026)	(0.174)	(7.679)	(0.065)	(0.070)	(0.082)	(0.353)	(0.069)	(0.320)
42	1.341	0.325	0.391	-0.310	16.693	1.550	0.832	0.420	-0.636	1.341	-0.769
yng,own,high	(0.078)	(0.028)	(0.029)	(0.197)	(8.690)	(0.074)	(0.080)	(0.093)	(0.399)	(0.078)	(0.363)
43	0.179	-0.063	-0.241	-0.300	3.642	-0.004	-0.543	-0.473	-0.499	0.179	-1.134
mid,rnt,low	(0.051)	(0.018)	(0.019)	(0.129)	(5.686)	(0.048)	(0.052)	(0.061)	(0.261)	(0.051)	(0.237)
44	0.634	0.037	-0.042	-0.275	10.530	0.544	-0.155	-0.012	-0.351	0.634	-0.446
mid,rnt,med	(0.052)	(0.018)	(0.019)	(0.131)	(5.776)	(0.049)	(0.053)	(0.062)	(0.265)	(0.052)	(0.241)
45	1.085	0.221	0.309	-0.046	18.836	1.351	0.554	0.638	0.102	1.085	0.724
mid,rnt,high	(0.066)	(0.023)	(0.024)	(0.166)	(7.299)	(0.062)	(0.067)	(0.078)	(0.335)	(0.066)	(0.305)
46	0.909	0.052	-0.088	-0.662	2.296	0.682	0.137	0.176	-0.608	0.909	-1.756
mid,own,low	(0.066)	(0.023)	(0.024)	(0.165)	(7.291)	(0.062)	(0.067)	(0.078)	(0.335)	(0.066)	(0.304)
47	1.167	0.161	0.123	-0.548	10.307	1.135	0.450	0.450	-0.390	1.167	-0.818
mid,own,med	(0.066)	(0.024)	(0.025)	(0.167)	(7.365)	(0.063)	(0.068)	(0.078)	(0.338)	(0.066)	(0.307)
48	1.550	0.356	0.468	-0.282	17.045	1.768	1.038	0.941	0.031	1.550	0.499
mid,own,high	(0.077)	(0.027)	(0.028)	(0.193)	(8.525)	(0.073)	(0.078)	(0.091)	(0.392)	(0.077)	(0.356)
49	0.191	-0.076	-0.274	-0.536	6.870	-0.121	-0.672	-0.565	-0.447	0.191	-1.078
old,rnt,low	(0.066)	(0.023)	(0.024)	(0.166)	(7.299)	(0.062)	(0.067)	(0.078)	(0.335)	(0.066)	(0.305)
50	0.642	0.057	-0.010	-0.276	10.468	0.502	-0.132	0.048	-0.175	0.642	0.027
old,rnt,med	(0.058)	(0.020)	(0.021)	(0.145)	(6.391)	(0.054)	(0.059)	(0.068)	(0.294)	(0.058)	(0.267)
51	1.085	0.238	0.336	-0.104	18.406	1.167	0.508	0.536	-0.005	1.085	1.061
old,rnt,high	(0.071)	(0.025)	(0.026)	(0.178)	(7.856)	(0.067)	(0.072)	(0.084)	(0.361)	(0.071)	(0.328)
52	0.611	0.014	-0.113	-0.740	11.761	0.483	0.074	0.108	-1.511	0.611	-1.359
old,own,low	(0.089)	(0.032)	(0.033)	(0.225)	(9.929)	(0.084)	(0.091)	(0.106)	(0.456)	(0.089)	(0.414)
53	0.919	0.141	0.090	-0.390	8.018	0.931	0.377	0.467	-0.303	0.919	-0.132
old,own,med	(0.071)	(0.025)	(0.026)	(0.179)	(7.902)	(0.067)	(0.073)	(0.084)	(0.363)	(0.071)	(0.330)
54	1.439	0.359	0.480	-0.217	18.941	1.605	0.948	0.995	0.301	1.439	1.570
old,own,high	(0.077)	(0.027)	(0.029)	(0.195)	(8.601)	(0.073)	(0.079)	(0.092)	(0.395)	(0.077)	(0.359)

Notes: This table shows the coefficient estimates and standard errors for the prediction equation (26) of location choice on topographic variables by household type. Legend: yng = young, mid = middle aged, old = old aged, rnt = renter, own = owner, low = low credit score, med = medium credit score, high = high credit score.

C Hotz-Miller Expression for Continuation Values

In our estimation sample time window, we assume that $\delta^{\tau}_{\ell,m,t}$ is fixed for each ℓ, m and τ, such that time subscripts can be removed. Also in what follows, we will hold the metro fixed such that the metro subscript m can be removed. When the ϵ are assumed to be drawn i.i.d. from the Type 1 Extreme Value Distribution, the expected value function $E\left[V^{\tau}\left(j\right)\right]$ has the functional form

$$E\left[V^{\tau}\left(j\right)\right] \;=\; \log\left\{\sum_{\ell=1}^{J}\exp\widetilde{V}^{\tau}\left(\ell \mid j\right)\right\}+\zeta \tag{30}$$

where ζ is equal to Euler's constant and

$$\widetilde{V}^{\tau}\left(\ell \mid j\right) \;=\; \delta^{\tau}_{\ell} \;-\; \kappa^{\tau}\cdot 1_{\ell\neq j} \;+\; \beta\sum_{\tau'}\varphi^{\tau,\tau'}E\left[V^{\tau'}\left(\ell\right)\right] \tag{31}$$

That is, the tilde symbol signifies that the shock ϵ_{ℓ} has been omitted.

Now, we show that the log probabilities that choices are observed are simple functions of model parameters δ^{τ}_{ℓ}, κ^{τ}, β and of observed choice probabilities. To see this, start by noting the log of the probability that location ℓ is chosen by type τ given a current location of j, call it $p^{\tau}\left(\ell \mid j\right)$, has the solution

$$p^{\tau}\left(\ell \mid j\right) \;=\; \widetilde{V}^{\tau}\left(\ell \mid j\right) \;-\; \log\left\{\sum_{\ell'=1}^{J}\exp\left[\widetilde{V}^{\tau}\left(\ell' \mid j\right)\right]\right\} \tag{32}$$

Denote ℓ_0 as a reference tract. Subtract and add $\widetilde{V}^{\tau}\left(\ell_0 \mid j\right)$ to the right-hand side of the above to derive

$$p^{\tau}\left(\ell \mid j\right) \;=\; \widetilde{V}^{\tau}\left(\ell \mid j\right)-\widetilde{V}^{\tau}\left(\ell_0 \mid j\right) \;-\; \log\left\{\sum_{\ell'=1}^{J}\exp\left[\widetilde{V}^{\tau}\left(\ell' \mid j\right)-\widetilde{V}^{\tau}\left(\ell_0 \mid j\right)\right]\right\} \tag{33}$$

Note that equation (31) implies

$$\begin{aligned}&\widetilde{V}^{\tau}\left(\ell \mid j\right)-\widetilde{V}^{\tau}\left(\ell_0 \mid j\right)\\ &=\delta^{\tau}_{\ell}-\delta^{\tau}_{\ell_0} \;-\; \kappa^{\tau}\left[1_{\ell\neq j}-1_{\ell_0\neq j}\right] \;+\; \beta\sum_{\tau'}\varphi^{\tau,\tau'}\left\{E\left[V^{\tau'}\left(\ell\right)\right]-E\left[V^{\tau'}\left(\ell_0\right)\right]\right\}\end{aligned} \tag{34}$$

But from equation (30),

$$E\left[V^{\tau'}\left(\ell\right)\right]-E\left[V^{\tau'}\left(\ell_0\right)\right] \;=\; \log\left\{\sum_{\ell'=1}^{J}\exp\widetilde{V}^{\tau'}\left(\ell' \mid \ell\right)\right\}-\log\left\{\sum_{\ell'=1}^{J}\exp\widetilde{V}^{\tau'}\left(\ell' \mid \ell_0\right)\right\}$$

Now note that equation (32) implies

$$p^{\tau'}(\ell_0 \mid \ell) = \widetilde{V}^{\tau'}(\ell_0 \mid \ell) - \log\left\{\sum_{\ell'=1}^{J}\exp\left[\widetilde{V}^{\tau'}(\ell' \mid \ell)\right]\right\}$$
$$p^{\tau'}(\ell_0 \mid \ell_0) = \widetilde{V}^{\tau'}(\ell_0 \mid \ell_0) - \log\left\{\sum_{\ell'=1}^{J}\exp\left[\widetilde{V}^{\tau'}(\ell' \mid \ell_0)\right]\right\}$$

and thus

$$\log\left\{\sum_{\ell'=1}^{J}\exp\left[\widetilde{V}^{\tau'}(\ell' \mid \ell)\right]\right\} - \log\left\{\sum_{\ell'=1}^{J}\exp\left[\widetilde{V}^{\tau'}(\ell' \mid \ell_0)\right]\right\}$$

is equal to

$$\begin{aligned} & \widetilde{V}^{\tau'}(\ell_0 \mid \ell) - \widetilde{V}^{\tau'}(\ell_0 \mid \ell_0) - \left[p^{\tau'}(\ell_0 \mid \ell) - p^{\tau'}(\ell_0 \mid \ell_0)\right] \\ = & -\kappa^{\tau'} \cdot 1_{\ell \neq \ell_0} - \left[p^{\tau'}(\ell_0 \mid \ell) - p^{\tau'}(\ell_0 \mid \ell_0)\right] \end{aligned}$$

The last line is quickly derived from equation (31). Therefore,

$$E\left[V^{\tau'}(\ell)\right] - E\left[V^{\tau'}(\ell_0)\right] = -\left[p^{\tau'}(\ell_0 \mid \ell) - p^{\tau'}(\ell_0 \mid \ell_0) + \kappa^{\tau'} \cdot 1_{\ell \neq \ell_0}\right]$$

and equation (34) has the expression

$$\begin{aligned} & \widetilde{V}^{\tau}(\ell \mid j) - \widetilde{V}^{\tau}(\ell_0 \mid j) \\ & = \delta_{\ell}^{\tau} - \delta_{\ell_0}^{\tau} - \kappa^{\tau}\left[1_{\ell \neq j} - 1_{\ell_0 \neq j}\right] - \beta\sum_{\tau'}\varphi^{\tau,\tau'}\left[p^{\tau'}(\ell_0 \mid \ell) - p^{\tau'}(\ell_0 \mid \ell_0) + \kappa^{\tau'} \cdot 1_{\ell \neq \ell_0}\right] \end{aligned} \tag{35}$$

Due to data limitations we discuss in the paper, we combine data across multiple years when estimating probabilities and preference parameters. For this reason, we assume value functions and expectations are fixed in our sample period.

D Eigenvalue Analysis

We wish to understand if our estimates imply that the current demographic composition of neighborhoods is stable. This has been studied before by Caetano and Maheshri (2021) and others, but our methods and definition of stability are going to be different. We begin by introducing some notation and defining what we mean by stability. For a given metro m with J_m total tracts, denote $\mathcal{T}$ as a $2J_m \times 1$ vector comprised of starting values of expectations of racial shares, $E\left[S^b_{\ell,m}\right]$ and $E\left[S^h_{\ell,m}\right]$ for all tracts. Let $g\left(\mathcal{T}\right)$ be an expectations-generating function produced by our model that takes as a starting input $\mathcal{T}$ and produces a different vector of expectations $\mathcal{T}'$,

$$\mathcal{T}' = g\left(\mathcal{T}\right).$$

We define a steady state of g as a vector of expectations $\mathcal{T}^*$ that generates, via g, an identical set of expectations, i.e.

$$\mathcal{T}^* = g\left(\mathcal{T}^*\right).$$

Before describing how we compute $g\left(\mathcal{T}\right)$, we now define a steady state that is consistent with the data in our estimation sample for each metro. We start with the distribution of types by tract implied by our estimation sample and then simulate the model for 5 periods, our "burn in" period. During these 5 periods, we assume each household's type stays fixed. During the burn in period, we hold $\delta^\tau_{\ell,m}$ fixed for all types and all tracts in all metros. We use a 5-period burn in to ensure all types populate all tracts in our baseline steady state implied by the data.[39] After the burn-in, we use the resulting distribution of types by tract to compute our baseline vector for $\mathcal{T}$, $E\left[S^b_{\ell,m}\right] = S^b_{\ell,m}$ and $E\left[S^h_{\ell,m}\right] = S^h_{\ell,m}$ for all ℓ and m.

Next, we compute the distribution of types across all tracts that results after running the decision model for one period such that all location choices are made and all types probabilistically evolve. For each tract, we compute the required additions ("births") or subtractions ("deaths") of the population of each type such that the resulting measures of household types in each tract after all decisions are made and all types have stochastically evolved is constant in all tracts. The addition of type-specific births and deaths to each tract guarantees that the model-predicted distribution of types across tracts is stable and the vector $\mathcal{T}^*$ reflecting our data is a steady state. That is, the decisions implied by the model are consistent with expectations households have over racial shares and rental prices in each tract.

[39] The burn-in period smoothes through sampling variability in the data.

We now describe the $g(\mathcal{T})$ function that we use to predict how expectations evolve given any starting set of expectations $\mathcal{T}$. To start, denote the total number of households and the rental price in each tract in the data as $\mathcal{H}_{\ell,m}$ and $r_{\ell,m}$, respectively. Then, we compute $g(\mathcal{T})$ as follows:

1. Denote the guess of new rental prices $r'_{\ell,m}$.
2. Using equation (20), adjust $\delta^{\tau}_{\ell,m}$ appropriately for all ℓ, m, and τ given the values of $E\left[S^{b}_{\ell,m}\right]$ and $E\left[S^{h}_{\ell,m}\right]$ from $\mathcal{T}$ and the guess $r'_{\ell,m}$, holding exogenous amenities $A^{\tau}_{\ell,m}$ fixed. Households assume this new value of $\delta^{\tau}_{\ell,m}$ is fixed forever when making decisions.
3. Simulate the model 99 periods and compute new housing demand in each tract in each metro, $\mathcal{H}'_{\ell,m}$.
4. Update the guess of rental prices and repeat steps 2-3 until rental prices in each tract clear markets to satisfy

$$\log \mathcal{H}'_{\ell,m} - \log \mathcal{H}_{\ell,m} \;\; = \;\; \psi_{\ell,m}\left[\log r'_{\ell,m} - \log r_{\ell,m}\right]$$

   The housing supply elasticity in each tract ℓ in each metro m, $\psi_{\ell,m}$, is given by the estimates in Baum-Snow and Han (2022) with a floor value of 0.025.[40]
5. Once we know rental prices $r'_{\ell,m}$ that clear housing markets given values of $E\left[S^{b}_{\ell,m}\right]$ and $E\left[S^{h}_{\ell,m}\right]$ from $\mathcal{T}$, compute simulated Black and Hispanic shares in each tract and call these $S^{b'}_{\ell,m}$ and $S^{h'}_{\ell,m}$.
6. Set the elements of $\mathcal{T}'$ equal to $S^{b'}_{\ell,m}$ and $S^{h'}_{\ell,m}$.

Given our procedure to compute $g(\mathcal{T})$, we test the stability of the steady state implied by the data by computing the eigenvalues and eigenvectors of the model at the steady state. To see why this is useful, suppose we perturb expectations of racial shares at the steady state – call these perturbed expectations as $\mathcal{T}'$ – and then measure how expectations evolve from this perturbed starting point, i.e. $T'' = g(\mathcal{T}')$. We can do this with a first-order linear approximation:

$$g(\mathcal{T}') - g(T^{*}) \;\; \approx \;\; \mathcal{G} \cdot [\mathcal{T}' - \mathcal{T}^{*}]$$

where $\mathcal{G}$ is a $2J_m$ by $2J_m$ vector of derivatives of g evaluated at $\mathcal{T}^{*}$. Once we make appropriate substitutions, we get

$$[\mathcal{T}'' - \mathcal{T}^{*}] \;\; \approx \;\; \mathcal{G} \cdot [\mathcal{T}' - \mathcal{T}^{*}]$$

We compute the elements of $\mathcal{G}$ at $\mathcal{T}^{*}$ using numerical derivatives. Specifically, define $\widetilde{\mathcal{T}}^{*}_{i}$

[40] In a handful of tracts, Baum-Snow and Han (2022) estimate a negative supply elasticity.

as equal to $\mathcal{T}^*$ in all elements except for the i^{th} element which we perturb by Δ_i units.[41] We set the i^{th} column of $\mathcal{G}$ equal to $\left[g\left(\widetilde{\mathcal{T}}_i^*\right) - \mathcal{T}^*\right]/\Delta_i$. For each metro, we repeat this computation for all $i = 1, \ldots, 2J_m$ elements of $\mathcal{T}^*$ to populate all the columns of $\mathcal{G}$.

Once we have an estimate of $\mathcal{G}$, we compute its eigenvalues to determine whether the expectations of racial shares move away from or return to the steady-state expectations implied by the data in response to a tiny perturbation to expectations. In other words, we ask if the system predicts expectations return to $\mathcal{T}^*$ if we start our model using expectations that are nearly but not exactly identical to $\mathcal{T}^*$. If all the eigenvalues of $\mathcal{G}$ are less than 1, the expectations converge back to the steady state; if at least one eigenvalue is greater than 1, expectations do not converge back to the starting point and if this is the case, we say the steady state implied by the data is not stable.

The results are shown in Appendix Table D.1 below. Summarizing results shown in column (6), every metro has at least one eigenvalue greater than 1 and the median metro has 48% of its eigenvalues greater than 1. Ultimately, the reason that the system is not stable as measured by these eigenvalues is that households have very strong preferences over the racial composition of their neighbors. Restated, the racial composition of neighborhoods at the steady state implied by the current data is unstable because many households want to live in more segregated neighborhoods. This result is not merely a statement about the direction of racial preferences; it is more of a statement about the size of these preferences. To show this, we recompute eigenvalues of $\mathcal{G}$ holding $\delta^\tau_{\ell,m}$ fixed for all tracts ℓ, metros m, and types τ, but after multiplying all coefficients on race in utility, $\Theta_2^\tau = \{a_1^\tau, \ldots, a_5^\tau\}$, by 0.25 for all types and then by 0.125 for all types. By holding $\delta^\tau_{\ell,m}$ fixed, we preserve the relative desirability of all tracts in the baseline, so any changes to eigenvalues only reflect changes in the strength of preferences for race. The bottom line is that with these scaled-down preferences for race, stability for all metros vastly improves. Measured at the median metro, as shown in column (7) with the rescaling of Θ_2^τ by 0.25, 19.3% of a metro's eigenvalues are larger than 1, and with the rescaling of Θ_2^τ by 0.125, measured at the median metro 0.2% of a metro's eigenvalues are larger than 1, shown in column (8).

[41] For each element i, we set Δ_i equal to 1.0×10^{-6}.

Appendix Table D.1

Name	Pop (000s)	Total Tracts	% Black	% Hisp	% Tracts Eigenvalues > 1 Baseline	$0.25a_k^\tau$	$0.125a_k^\tau$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Springfield, IL	201.4	55	9.6	0.9	48.2	34.5	0.0
Spartanburg, SC	253.8	51	21.0	2.7	49.0	45.1	4.9
Norwich, CT	259.1	62	6.5	5.2	51.6	12.9	0.0
Port St. Lucie, FL	319.4	60	11.8	8.0	57.5	25.0	0.8
Charleston, WV	309.6	76	5.0	0.6	42.8	9.9	0.7
Erie, PA	280.8	72	6.8	2.2	48.6	17.4	0.7
Eugene, OR	323.0	78	1.3	4.5	47.4	0.0	0.0
Montgomery, AL	346.5	82	40.7	1.1	45.1	34.1	18.3
Brownsville, TX	335.2	86	0.6	84.5	34.9	1.2	0.0
Salinas, CA	401.8	83	4.4	46.9	69.9	15.7	0.0
Utica, NY	299.9	92	5.1	2.6	45.7	4.9	0.0
Augusta, GA	499.7	95	35.6	2.4	47.4	41.6	15.3
Lansing, MI	447.7	117	9.0	4.7	48.7	31.2	0.0
Charleston, SC	549.0	117	31.0	2.4	48.7	44.4	17.5
Knoxville, TN	616.1	128	6.8	1.1	48.8	18.4	0.4
Greenville, SC	559.9	126	17.3	3.1	49.2	43.7	3.6
Worcester, MA	750.6	163	3.3	6.8	49.1	2.1	0.0
Youngstown, OH	603.0	168	11.2	1.7	44.0	20.8	0.0
Albany, NY	825.6	213	7.0	2.5	48.1	14.3	0.0
Dayton, OH	848.2	208	15.2	1.1	44.5	20.2	1.7
25th Percentile	309.6	76	5.1	1.7	45.7	12.9	0.0
Median	374.1	89	8.0	2.5	48.4	19.3	0.2
75th Percentile	559.9	126	15.2	5.2	49.0	34.1	3.6