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

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Abstract

We estimate the parameters of a dynamic, forward-looking neighborhood choice model in 197 metro areas where households have preferences over the racial composition of neighborhoods. Our inclusion of multiple metro areas in the estimation sample enables us to develop a new, shift-share IV 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. For the "shift," we use national data to determine the probabilities different types of households live in different neighborhoods in a metro when neighborhoods are ranked only by within-metro income quantiles. The "shares" are the metro-level population shares of each household type. Thus, the instrument predicts variation in neighborhood-level racial shares, which for a given within-metro income quantile is attributable exclusively to variation in metro-level type shares. The overall IV estimate is a weighted average of the contribution from all of the income quantiles. We use the tools of Goldsmith-Pinkham, Sorkin, and Swift (2020) to analyze the comparisons that are weighted most heavily for identification and to derive appropriate balance tests. Our key finding is that many households have very strong preferences to live in same-race neighborhoods. These preferences are so strong that the current demographic composition of neighborhoods is not stable.

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1 Introduction

America is still largely racially segregated. Figure 1 shows the extent of racial segregation in the United States in 2010. Each line in this figure shows the fraction of residents of a given race, the x-axis, that live in a Census tract with less than the same-race share shown in the y-axis. The blue line shows results for non-Hispanic White households ("White"), and the black and brown lines show results for non-Hispanic Black ("Black") and Hispanic households.[1] In 2010, the median White person lived in a Census tract that was at least 88% White and 26% of White people lived in Census tracts that were at least 95% White. Nearly 30 percent of Black people lived in a Census tract that was at least 70 percent Black; this same result holds for Hispanic people.

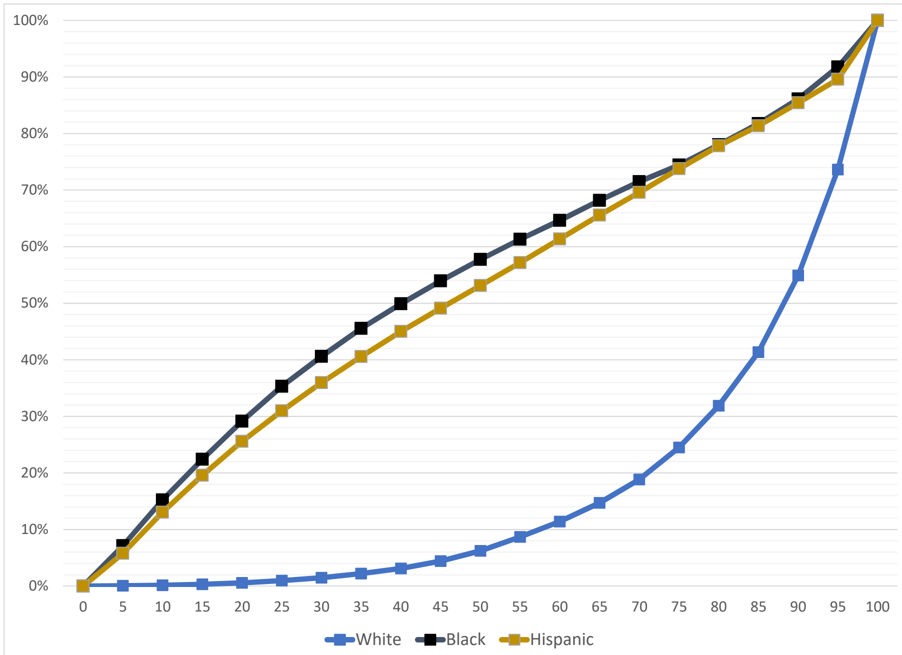
We investigate the extent to which preferences over the racial composition of Census tracts ("neighborhoods" going forward) influence where people choose to live. We estimate a dynamic, forward-looking model of neighborhood choice. In this model, households have preferences over exogenous intrinsic features and endogenous racial composition of neighborhoods. We estimate parameters of the model using data on location choices within 197 metropolitan divisions (metros) in the United States. This amounts to the estimation of 197 separate models of within-metro neighborhood choice, with some parameters held constant across metros.

The keystone of our analysis is estimation of how household preferences for a neighborhood vary with its demographic composition, and how these preferences vary by household "type," which includes race and other household characteristics. Specifically, for each type of household we want to regress indirect utility of a neighborhood, which determines the probability that neighborhood will be chosen, on the racial composition of that neighborhood. Identification of how racial composition affects preferences using location-choice data is confounded by the presence of location-specific amenities that may be unobserved, and the valuation of these amenities that may differ by household type. Therefore, identifying preferences over demographic composition of neighborhoods requires an instrument that is correlated with racial shares at the neighborhood level but uncorrelated with local amenities.

While papers that estimate dynamic models of neighborhood choice have typically focused on single metro areas, estimating households preferences over neighborhoods from a large number of metros allows us to employ a new identification strategy for recovering racial

[1] In the case of perfect racial segregation, each line would be equal to 0% until x=100, at which point each line would equal 100%. With perfect integration, each line would equal 0% until the x-axis value is equal to the mean racial percentage in the United States – 64 percent for White, 12 percent for Black, 16 percent for Hispanic – at which point the line would equal to 100%. The other categories of race that are not shown are Asian (5 percent of the population) and people identifying as two or more races (4 percent).

Figure 1: CDFs of Census Tract of Residence by Same-Race Percentage, 2010



Notes: The x-axis is the same-race racial share and the y-axis is the percentage of residents of that race living in a Census Tract that has less than the same-race racial share indicated by the x-axis. The blue line is the CDF for White residents, the black line is the CDF for Black residents and the brown line is the CDF for Hispanic residents. For example, the median White person (y-axis of 50%) lives in a Census tract that has a White racial share less than about 88 percent (x-axis); the median Hispanic person lives in a Census tract that has a Hispanic racial share less than about 46 percent; and the median Black person lives in a Census tract that has a Black racial share less than 40%.

preferences. The strategy is a new shift-share design in the style of Bartik (1991) that involves comparing households preferences for neighborhoods from different metros that are identical in terms of the rank of neighborhood income in the metro neighborhood income distribution, but that have different racial composition.

Our IV strategy works as follows. We start by ranking each Census tract within a metro area by income and then assigning to each tract its income quantile within the metro. We then pool all data across metros and estimate the probability any given household type of the 54 types of households in our data chooses to live in any particular income quantile. This gives us a "prediction equation" for where each of the 54 types of households in our data are going to live that is based only on national data. This prediction equation, for example, captures the fact that young, renting, low-credit score Black households disproportionately live in the lowest income tracts inside any given metro area and old, homeowning, high-credit score White households tend to live in higher income tracts.

Next, we use the prediction equation based on national data to assign predicted populations of each of the types of households in our data to each of the Census tracts in a given metro. Since each household type is associated with a race, the outcomes of these assignments are predicted racial shares (Black, Hispanic, White) within each Census tract. We use the same type-specific prediction equations in each metro. This implies that for each tract at a given income quantile in every metro, any variation in predicted racial shares is solely attributable to variation, across metros, in the metro population shares of household types. As long as these metro-wide type population shares are uncorrelated, across metro areas, with amenities at each within-metro income quantile, metro-wide type population shares and combinations thereof are valid instruments.

After controlling for fixed metro and income quantile effects, our IV strategy exploits comparisons across metros in the location choice probabilities and predicted racial shares at all income quantiles. According to national data, different household types tend to live in different income quantiles of a metro. This implies the impact of each type's metro-level population share is largest at the income quantiles where that household type tends to live. Thus, the predicted variation in racial shares across metros changes across income quantiles because population shares of household types vary across metros.

We use the tools of Goldsmith-Pinkham, Sorkin, and Swift (2020) to understand the key source of variation underlying our identification strategy, to discuss the requirements for consistent identification, and to motivate balance tests. Most of the variation that drives identification of the impact of the Black share of households on neighborhood choice probabilities arises from metro-level variation in the population share of Black renting households that are young or middle-aged and have a low-credit score. A similar result holds for Hispanic households. Our balance tests show that our instruments are strongly correlated with actual Black and Hispanic shares, and are not correlated with nearly all features of metros we consider related to geography, access to public transit, and distance to road networks that may be correlated with otherwise unobservable amenities.

Perhaps not surprisingly, we estimate that many – but not all – households have preferences exhibiting homophily: for many households, utility in their chosen neighborhood increases if the share of same-race households in the neighborhood increases. To give a sense of the size of these preferences, for the average Black household in our data, we find that if the share of Black households in their neighborhood increases by 1 percentage point, utility increases by approximately the same as if the price of rental housing declines by 3 percent. For the average White household in our data, if the share of Black households increases by 1 percentage point, utility declines by about the same amount as if rental prices increase by approximately 1 percent.

We believe we are the first to use a shift-share instrument to estimate preferences various types of households have over White, Black, and Hispanic racial shares of neighborhoods within the context of a dynamic location-choice model. That said, our work relates to other design-based 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.[2] Closest to us, 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.[3] While our estimation approach is new, there is an extensive literature on the racial dynamics of neighborhood change.[4] Kuminoff, Smith, and Timmins (2013) provide a survey of the literature of estimated location-choice models with endogenous amenities. Recently, in line with our findings, Aliprantis, Carroll, and Young (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.[5]

A subtle but important question is how one should interpret our estimated preferences for neighborhood racial composition, and in particular whether they should be viewed narrowly as preferences for the skin color of neighbors or broadly as preferences for both skin color and the endogenous amenities that result from the way that local retailers, employers, governments, police, and other relevant actors behave toward neighborhoods with different demographic makeups. Because our IV strategy captures variation in tract racial shares driven by variation that moves slowly over time as inputs (metro-level race shares inter-

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

[3]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.

[4]See Ellen (2000) for an overview and Ellen and Torrats-Espinosa (2019) for a discussion of racial change in the context of gentrification.

[5]Christensen and Timmins (2021) and Christensen and Timmins (2022) also show that steering and barriers to entry may also play a role in determining the neighborhoods in which Black households have access.

acted with national-average sorting predictions), we argue that a broad interpretation is appropriate, and our estimates should capture preferences for the bundle of race and the endogenous amenities that tend to come with race. For example, if certain retail establishments tend to locate more frequently in mostly White neighborhoods, the IV procedure uncovers preferences for the combination of the large fraction of White neighbors and the retail establishments locating more frequently in those neighborhoods. In some contexts understanding preferences for race separately from preferences for amenities that follow race (for whatever reason) may be important, but we do not think this distinction matters for forecasting how neighborhoods change over time in response to small shocks or changes to government policy.[6]

At the end of our analysis, we ask whether our model implies that the current racial composition of neighborhoods is stable. We first engineer the model to be in a steady state such that the shares of every type of household in our data and in every neighborhood are constant over time. Then, we take a stand on how households form expectations and make decisions in response to a small change in racial shares and evaluate the stability of the population distribution across neighborhoods in each metro by computing eigenvalues of the model. The eigenvalues determine if the model will return to its starting steady state in response to a perturbation in racial shares. The eigenvalues we compute suggest the racial composition of most neighborhoods in nearly all metros is not stable; that is, in response to a small perturbation in expected racial shares in one neighborhood in a metro, household location decisions adjust in such a way that demographic shares in many neighborhoods in that metro are predicted to move away from the current steady state rather than converge back towards it. We show this instability arises because many households have very strong preferences over racial composition and wish to live in more segregated neighborhoods.

Next, we consider the implications of a small policy, implemented simultaneously across many neighborhoods in a metro area, that mechanically should increase racial integration absent any migration in response to the policy. Specifically, we impose a policy shock in which the quantity of housing units financed by low-income housing tax credits (LIHTC) everywhere increases unexpectedly by 10%. In almost every metro, the new steady state we compute after the policy is implemented looks very different and is much more racially segregated than the starting point of the current data due to endogenous resorting of the population. Finally, we show that the rate of convergence to the new steady state resulting from the policy shock depends on how households form expectations. If households are my-

[6]In contrast, Bayer, Ferreira, and McMillan (2007) and Bayer, Casey, McCartney, Orellana-Li, and Zhang (2022) isolate preferences over race directly (as compared to the bundle of race and amenities that may accompany race over time), by focusing on comparisons that are geographically close and therefore plausibly share the same bundle of amenities not related to race.

opic, it can take decades to converge to the new steady state, consistent with the evidence of Caetano and Maheshri (2021).[7] If households are overly forward looking, that is they incorrectly believe the new steady state will happen immediately, perhaps due to "blockbusting" or any other coordination device (Hartley and Rose, 2023), then convergence to the new steady state occurs within one decade.

2 Household Decision Model

We model the system of demand for neighborhoods by considering the decision problem of a particular household head deciding where his or her family ("household") should live. As in Kennan and Walker (2011) Bayer, McMillan, Murphy, and Timmins (2015), and Davis, Gregory, Hartley, and Tan (2021) we model location choices in a dynamic discrete choice setting. We assume each household 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 bring this model to the data, J_m will vary with the metro.

Denote j as the household's current location in the metro and τ as that household's type. We write the value to the household, $V_{m,t}^{\tau}(\ell \mid j, \epsilon_{\ell,m})$, 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 $\epsilon_{\ell,m}$ (to be explained later) as

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

In the above equation $u_{m,t}^{\tau}(\ell \mid j, \epsilon_{\ell,m})$ is the flow utility in year t to the household 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 $\epsilon_{\ell,m}$; 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 in year $t+1$ of a type τ' household of having chosen to live in neighborhood ℓ in metro m today. The t subscripts explicitly allow that flow utility and expectations may change over time.

In the model, flow utility depends on neighborhood racial composition and is therefore endogenous, similar to assumptions made in Caetano and Maheshri (2021) and Almagro and Dominguez-Iino (2022).[8] We model $u_{m,t}^{\tau}(\ell \mid j, \epsilon_{\ell,m})$ as follows

[7] In the original 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.

[8] 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.

$$u^{\tau}_{m,t}(\ell \mid j, \epsilon_{\ell,m}) \;=\; \delta^{\tau}_{\ell,m,t} \;-\; \kappa^{\tau}\cdot 1_{\ell\neq j} \;+\; \epsilon_{\ell,m}$$

$\delta^{\tau}_{\ell,m,t}$ is the deterministic portion of flow utility a type τ household receives in year t from living in neighborhood ℓ in metro m. κ^{τ} are 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 $\epsilon_{\ell,m}$ is a random shock that is known at the time of the location choice. $\epsilon_{\ell,m}$ is assumed to be iid across locations, time and people. $\epsilon_{\ell,m}$ 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 exogenous amenities, $A^{\tau}_{\ell,m,t}$.

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

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 $\epsilon_{1,m}$ as the shock associated with location 1, $\epsilon_{2,m}$ 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

$$V^{\tau}_{m,t}(j \mid \epsilon_{1,m}, \epsilon_{2,m}, \ldots, \epsilon_{J_m,m}) \;=\; \max_{\ell\in 1,\ldots,J_m} V^{\tau}_{m,t}(\ell \mid j, \epsilon_{\ell,m}) \tag{2}$$

3 Estimation Overview and Data

We will use a 2-step procedure like Berry, Levinsohn, and Pakes (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 rental prices and racial shares impact $\delta^{\tau}_{\ell,m,t}$ for each τ.

3.1 Step 1: GMM to Estimate Demand for Locations

In the first step, we use the approach of Hotz and Miller (1993) and employed by Bishop (2012) and Davis, Gregory, Hartley, and Tan (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 A, 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

$$\Theta^{\tau}_1 \;=\; \left\{ \;\kappa^{\tau}, \left\{\delta^{\tau}_{\ell,m=1}\right\}_{\ell=1}^{J_1}, \left\{\delta^{\tau}_{\ell,m=2}\right\}_{\ell=1}^{J_2}, \ldots, \left\{\delta^{\tau}_{\ell,m=M}\right\}_{\ell=1}^{J_M} \;\right\} \tag{3}$$

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

$$\begin{aligned} & G^{\tau}_1\left(\Theta^{\tau}_1\right) \\ &= \sum_{m=1}^{M}\sum_{j'=1}^{J_m} \underbrace{\hat{P}^{\tau}_m\left(j=j'\right)}_{\text{data}} \; \underbrace{\hat{P}^{\tau}_m\left(\ell=j' \mid j=j'\right)}_{\text{data}} \;-\; \sum_{m=1}^{M}\sum_{j'=1}^{J_m} \underbrace{\hat{P}^{\tau}_m\left(j=j'\right)}_{\text{data}} \; \underbrace{P^{\tau}_m\left(\ell=j' \mid j=j';\Theta^{\tau}_1\right)}_{\text{model}} \end{aligned} \tag{4}$$

As before, j is the Census tract at the start of the period and ℓ is the Census tract at the end of the period. j' indexes Census tracts that are in metro m and there are J_m of these tracts.[9] 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 type a τ household starts a period in tract 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 Census tract j' chooses to remain in Census tract 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 $\sum_{m=1}^{M}\left[J_m-1\right]$ moments for each type are that the model matches the prob-

[9] We start the tract index j' at 1 within each metro, but obviously tract j' in metro m will be different than tract j' in metro m'.

ability of choosing any given tract in each metro. There are $J_m - 1$ moments in each metro because the probability of choosing a tract 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

$$\text{for } \ell = 2, \ldots, J_m \quad G^{\tau}_{\ell,m}\left(\Theta^{\tau}_1\right) = \sum_{j=1}^{J_m} \underbrace{\hat{P}^{\tau}_m(j)}_{\text{data}} \underbrace{\hat{P}^{\tau}_m(\ell \mid j)}_{\text{data}} - \sum_{j=1}^{J_m} \underbrace{\hat{P}^{\tau}_m(j)}_{\text{data}} \underbrace{P^{\tau}_m(\ell \mid j; \Theta^{\tau}_1)}_{\text{model}} \tag{5}$$

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

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

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.

3.2 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 (1). We start by taking a value for the impact of rental prices on flow utility, a^{τ}_r, from Davis, Gregory, Hartley, and Tan (2021). Define $\hat{\delta}^{\tau}_{\ell,m}$ as the estimated value of $\delta^{\tau}_{\ell,m}$ from the first stage minus $a^{\tau}_r \log \hat{r}_{\ell,m}$, where $\hat{r}_{\ell,m}$ is our estimate of the rental price for a standardized housing unit in neighborhood ℓ of metro m computed from data in the 2007-2011 American Community Survey.[10] Then we wish to estimate $a^{\tau}_1, \ldots, a^{\tau}_5$ in the following specification that is the same as equation (1), but with time subscripts removed:

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

Define the vector of parameters that we estimate for each type in this second step as Θ^{τ}_2,

$$\Theta^{\tau}_2 = \{\, a^{\tau}_1, a^{\tau}_2, \ldots, a^{\tau}_5 \,\}$$

Since racial shares are likely to be correlated with unobserved amenities, we use an instru-

[10] We regress the log of median rent of renting households, measured at the tract level, on average hedonic characteristics of housing units in the tract. We set $\hat{r}_{\ell,m}$ equal to the residuals in this regression.

mental variables approach to estimate Θ_2^τ. Our approach has two components and both components take advantage of variation across metro areas. First, we assign a label to each tract: its income quantile ranking in its metro area. By giving each tract a label (its income quantile) along a dimension that is comparable across metros, we can include income quantile fixed effects in our analysis. After including income quantile and metro fixed effects, the specification becomes

$$\hat{\delta}_{\ell,m}^\tau \;=\; a_1^\tau S_{\ell,m}^b + a_2^\tau \left(S_{\ell,m}^b\right)^2 + a_3^\tau S_{\ell,m}^h + a_4^\tau \left(S_{\ell,m}^h\right)^2 + a_5^\tau S_{\ell,m}^b S_{\ell,m}^h + \theta_{q(\ell,m),1} + \theta_{m,2} + \check{A}_{\ell,m}^\tau$$

where $\theta_{q(\ell,m),1}$ is the fixed effect appropriate for the income quantile corresponding to tract ℓ in metro m, $q(\ell,m)$, and $\theta_{m,2}$ is a metro fixed effect. After including these fixed effects, the variation in the data that drives identification is free of metro effects and free of quantile effects.[11]

The second component is our IV approach. Using a shift-share approach, we create instruments that are linear predictors of the tract level Black share, $Z_{\ell,m}^b$, and the tract level Hispanic share, $Z_{\ell,m}^h$. The instrument interacts metro-wide shares in household types with national estimates of how household types sort into neighborhoods that is based only on the within-metro income quantile of that neighborhood. This exploits across-metro variation in overall racial shares to generate an instrument that varies within income quantiles across metros, but is uncorrelated with the variation in amenities that is not accounted for by metro fixed effects or fixed effects for income quantiles.[12] Our five instruments are then $Z_{\ell,m}^b$, $Z_{\ell,m}^h$, $\left(Z_{\ell,m}^b\right)^2$, $\left(Z_{\ell,m}^h\right)^2$, and $\left(Z_{\ell,m}^b Z_{\ell,m}^h\right)$. With these instruments in hand, we estimate Θ_2^τ using 2SLS for each type.

Consistency of our estimates of Θ_2^τ requires our instruments to be uncorrelated with $\check{A}_{\ell,m}^\tau$. In section 4, we detail construction of the instruments. We then use the new tools of Goldsmith-Pinkham, Sorkin, and Swift (2020) to identify the sources of variation in our instruments and derive appropriate balance tests to show that the instruments are uncorrelated with observable proxies for $\check{A}_{\ell,m}^\tau$.

[11]Explaining, there may be certain metros that have a relatively large Black population and therefore the share of Black households in every tract in that metro might be relatively high. The metro fixed effects will account for the fact that the share of Black households will tend to be high in all tracts in those metros; and, the variation that remains reflects the relatively desirability of tracts in those metros to Black households. Similarly, there may be certain income quantiles that disproportionately attract Black households in every metro. The income-quantile fixed effects account for the fact that the Black share will tend to be high at that income quantile in all metros. The variation that remains after accounting for the income-quantile fixed effects reflects the relative desirability of the neighborhoods at that income quantile in certain metros relative to other metros.

[12]Blair (2023) also exploits across-metro variation to understand how differences in the nature of outside options affect tipping points.

3.3 Data

3.3.1 FRBNY Consumer Credit Panel / Equifax

We estimate the model using panel data 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.[13] 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 some other variables we discuss later. The data does not contain information on basic demographics like race, education, or number of children and it does not contain information on income or assets although it does include the Equifax Risk Score^{TM} which provides some information on the financial wherewithal of the household as demonstrated in Board of Governors of the Federal Reserve System (2007).

Most important for our application, the panel data includes in each period the current Census block of residence.[14] 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.[15] The total number of person-year observations in the 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). Referring to $\phi^{\tau,\tau'}$, with the exception of race a household's type can stochastically change over time. Borrowing a method from

[13]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 and we do not capture the experiences of illegal immigrants.

[14]We match Census block to Census tract using the year-2000 definition of Census tracts.

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

overlapping generations models in macroeconomics to conserve on state variables, we assume that households assume they age up (i.e. low to middle, middle to high) or die (high 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.[16]

Before we show how we estimate parameters, we first need to explain how we structure the CCP for estimation and document a shortcoming of the data. 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. We compute this estimate by pooling all observations across all time periods in a way we describe later.

Additionally, while we observe most of the elements of any type τ, we do not directly observe race. We infer information about a household's race from the Census block where we first observe the primary sample person in the household.[17] 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' 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

$$P_m^\tau(\ell' \mid j') = \frac{\sum_t \sum_i \omega_i^{r(\tau)} \mathcal{I}(\ell_{i,t+1} = \ell') \mathcal{I}(j_{i,t} = j')}{\sum_t \sum_i \omega_i^{r(\tau)} \mathcal{I}(j_{i,t} = j')} \tag{6}$$

[16]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 of there are 3 or 4 adults in the household.

[17]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 year-2000 Census. If a household is first observed in 2010 or later, we use racial shares for Census blocks from the year-2010 Census.

where $\mathcal{I}(j_{i,t} = j')$ 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').

3.3.2 Potential Implications of Imperfect Measurement of Race

The fact that we do not perfectly observe race suggests our estimates of choice probabilities by race may 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.[18] This estimate can be written as

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

In the 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:

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

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.[19]

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

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

[19] 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, Agniel, Martino, Damberg, and Elliott (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. One of the applications of our structural exercise is a test of the stability of existing racial shares in neighborhoods. 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.

4 A Detailed Discussion of the IVs

4.1 Background

Since racial shares of neighborhoods are endogenous, instruments are required to identify preferences households have over the racial composition of neighborhoods. Finding valid instruments has proven to be difficult. A few recent approaches used to identify preferences over race include Bayer, Ferreira, and McMillan (2007) who use variation arising from sorting around school-zone boundaries, Almagro, Chyn, and Stuart (2022) who use past exogenous public housing demolitions and BLP-style instruments, and Caetano and Maheshri (2021) who use long lags of racial shares after controlling for inflows in a model-consistent way, just to name a few.[20] These studies use variation entirely within one metro, whereas our approach uses variation across metros for identification.[21]

4.2 Creating the Instruments

To start, note that the total population of Census tract ℓ in metro m can be written as $\sum_k pop^k_{\ell,m}$, where k is an index of household type and $pop^k_{\ell,m}$ is the population of type k living

[20] Card, Mas, and Rothstein (2008) estimate tipping points on racial shares using a regression discontinuity approach.

[21] Conceptually similar, Baum-Snow, Hartley, and Lee (2019) and Baum-Snow and Han (2022) also use a within-metro Bartik IV approach. Baum-Snow and Han (2022) estimate local housing-supply elasticities and Baum-Snow, Hartley, and Lee (2019) measure the impact of exogenous increases in high-skill labor demand into a neighborhood on affluence in adulthood of children in that neighborhood.

in tract ℓ in metro m.[22] Thus the Black share in tract ℓ in metro m, $S^b_{\ell,m}$, can be written as

$$S^b_{\ell,m} = \frac{\sum_k \mathcal{I}\left(k \in Black\right) pop^k_{\ell,m}}{\sum_{k'} pop^{k'}_{\ell,m}}$$

In this section we focus on the Black share, but the Hispanic share is computed analogously throughout. Note that

$$pop^k_{\ell,m} = N^k_m \rho^k_{\ell,m}$$

where N^k_m is the total number of type k households living in metro m and $\rho^k_{\ell,m}$ is the probability that a type k household living in metro m chooses to live in tract ℓ. Make that substitution and divide both the numerator and the denominator by the total metro population:

$$S^b_{\ell,m} = \frac{\sum_k \mathcal{I}\left(k \in Black\right) s^k_m \rho^k_{\ell,m}}{\sum_{k'} s^{k'}_m \rho^k_{\ell,m}} \tag{7}$$

In equation (7), s^k_m is the share of the metro population that is accounted for by type k households.

To construct the instrument, we replace $\rho^k_{\ell,m}$, the actual probability a type k household chooses tract ℓ in metro m, with a predicted probability density *that only varies with the income quantile of the tract in that metro.*[23] Denote the income quantile associated with tract ℓ in metro m as $q\left(\ell, m\right)$ and denote the predicted probability density that specific tract is chosen by type k as $\hat{\rho}^k_{q(\ell,m)}$. Given this, our predicted Black share in tract ℓ of metro m is

$$Z^b_{\ell,m} = \frac{\sum_k \mathcal{I}\left(k \in Black\right) s^k_m \hat{\rho}^k_{q(\ell,m)}}{\sum_{k'} s^{k'}_m \hat{\rho}^{k'}_{q(\ell,m)}} \tag{8}$$

To construct predicted probability densities, we regress the log of $\rho^k_{\ell,m}$ on metro fixed effects[24] and a 7th order polynomial in the income quantile associated with tract ℓ in metro

[22] In the notation that follows, we will use k to index household types when discussing the construction of and properties of the instrument and we will use τ to index household types when discussing parameter estimates associated with a particular type.

[23] For notation reasons, we switch from probabilities to probability densities to handle the fact that different metros have different numbers of tracts.

[24] We include metro fixed effects to account for the fact that metros vary in the total number of tracts, so metros with fewer tracts will by construction have higher choice probabilities in every tract. The fixed effect

m. We run this regression separately for each type, but for each type we pool all tracts in all metros. Thus, for any type and any income quantile of a tract, the predicted probability density based on this regression does not vary across metros, except for the metro fixed effects.[25] Denote the predicted value arising from the regression used to predict probability densities as $\hat{x}^k_{\ell,m}$. We compute the predicted probability to be used in equation (8) as

$$\hat{\rho}^k_{q(\ell,m)} = \frac{\exp \hat{x}^k_{\ell,m}}{\sum_{\ell' \in m} \exp \hat{x}^k_{\ell',m}} \tag{9}$$

4.3 A Simple Example

To give some intuition on how instrument construction works, we provide a simple example. Suppose there are three types of households in our data – Black, Hispanic, and White – and that each metro in our sample has exactly three tracts: low-income, middle-income, and high-income. In the first step, we use national data to estimate the probability that each type of household lives in one of the three tracts. Estimates from our data for each of the three types of households in each of the low- middle- and high-income tracts are shown in the top panel of Table 1.

Now consider predicting the Black, Hispanic, and White shares of each of the three tracts in two of the metros in our sample. The first metro shown in the middle panel, York-Hanover, PA, has a population that is 2% Black, 3% Hispanic, and 95% White; and the second metro (Trenton, NJ) shown in the bottom panel has a population that is 8% Black, 18% Hispanic, and 74% White. Given these overall metro type shares, the first three columns of the middle and bottom panels show the predicted racial shares and, for comparison, the final three columns show the actual racial shares. By construction, the variation in predicted shares at the tract level is driven only by variation in metro racial shares; the predicted probability that any given race lives in the low-, middle-, or high-income tract is fixed across metros and is shown in the top panel of Table 1. As the middle and bottom panels of the table illustrate, both the predicted and actual racial shares vary considerably, and the predicted racial shares are correlated with the actual racial shares. For example, in York-Hanover, PA, the predicted Black share of the low-income tract is 4% (actual is 11%), whereas in Trenton, NJ, the predicted Black share of the low-income tract is 15% (actual is 38%). In both metros, the share of Black households in the lowest-income tracts is higher than predicted, but the

scales probabilities in all tracts by a common factor but does not otherwise affect the relative probabilities of any two tracts in the same metro.

[25] Note that we construct overall racial shares in each metro and racial composition within Census tracts using only data from our estimation sample.

Table 1: A Simple Example of the Shift-Share Instrument

Probabilities over Locations using National Data

	Black	Hispanic	White
Low Income Tract	42%	35%	19%
Middle Income Tract	32%	34%	35%
High Income Tract	26%	30%	46%

Racial Shares by Tract: York-Hanover, PA

	Predicted			Actual		
	Black	Hispanic	White	Black	Hispanic	White
Overall	2%	3%	95%	2%	3%	95%
By Tract:						
- Low Income	4%	5%	91%	11%	7%	82%
- Middle Income	2%	3%	95%	4%	2%	94%
- High Income	1%	2%	97%	4%	2%	94%

Racial Shares by Tract: Trenton, NJ

	Predicted			Actual		
	Black	Hispanic	White	Black	Hispanic	White
Overall	8%	18%	74%	8%	18%	74%
By Tract:						
- Low Income	15%	26%	59%	38%	18%	44%
- Middle Income	8%	17%	75%	18%	8%	74%
- High Income	5%	13%	82%	6%	6%	88%

instrument exploits the fact that Trenton, NJ has more Black households than York-Hanover, PA to predict that the share of Black households in low-income tracts is higher in Trenton than in York.

4.4 Comparison to Bartik (1991)

The original shift-share IV strategy of Bartik (1991) was used to estimate the impact of employment growth on wages. The dependent variable was the growth in the metro-level prevailing wage and the regressor of interest was the growth in local employment over the same time period. In this framework, OLS estimation will yield biased estimates if the change in employment is correlated with changes in non-wage location amenities that may also affect wages. The Bartik shift-share instrument is a forecast of local employment computed as an average of national industry-specific employment growth ("shift"), weighted by the local share of employment belonging to each industry in a base time period ("share"). When this strategy is applied using data from one time period, the regression includes one observation per metro, and the Bartik IV takes on one value per metro. When this strategy is applied using data from multiple time periods, the regression includes one observation per metro per time period. The Bartik IV is also specific to the metro by time period, since the national industry employment growth rates are time-period specific.

The shares in our shift-share forecast are household-type shares of overall metro population and the shifts are the type-specific probabilities of choosing to live in a tract in a metro area at specific income quantiles, computed using national data. Similar to how the Bartik employment instrument can be computed for multiple time periods, our shift-share tract-racial-share forecasts are computed for multiple income quantiles. In the Bartik IV, each industry share in each metro is weighted by different national growth rates, one national growth rate per time period. In our application, each household type share (which varies by MSA) is weighted by different national probabilities of choosing neighborhoods, where there is one probability per income quantile of a neighborhood.

4.5 Identification

We now use tools from the work of Goldsmith-Pinkham, Sorkin, and Swift (2020), hereafter GSS, to understand the nature of identification of estimates of $\Theta_2^\tau = a_1^\tau, \ldots, a_5^\tau$. GSS clarify the source of identifying information in a Bartik instrument and suggest several procedures for investigating the validity of the instrument. In this section, we derive that our 2SLS estimator can be written as a weighted sum of individual IV-regression estimates. Each IV regression estimate comes from a comparison across metros of indirect utilities at the same point in the within-metro income distribution and the instrument is the metrowide population share of a single household type. There are multiple benefits from expressing our estimator like this. First, we can document what is required for consistent estimation. Second, we can compute which of the individual IV regressions receives the highest weight in determining the overall estimate. Finally, and relatedly, these both guide our choice of diagnostic balance tests.

In this section, we consider a simplified model with one endogenous variable, the tract Black share, and one instrument, the shift-share-predicted Black share. We do this to make the intuition transparent. We also assume that each metro area in the sample has the same number of tracts. This allows us to conserve on notation: Instead of writing $q(\ell, m)$, we will simply write q to denote both the tract and the income quantile of the tract. In this setup, in the first stage of estimation, the actual tract- and metro-level Black share, $S_{q,m}^b$, is regressed on the shift-share-predicted Black share, $Z^b_{q,m}$, quantile fixed effects, $\theta_{q,1}$, and metro fixed effects, $\theta_{m,1}$. Denote the estimated coefficients from this regression as $\hat{\gamma}$, $\hat{\theta}_{q,1}$, and $\hat{\theta}_{m,1}$ and the residual from this regression as $\hat{e}^b_{q,m}$. We construct the predicted Black share for each tract in each metro as

$$\hat{S}^b_{q,m} = \hat{\gamma} Z^b_{q,m} + \hat{\theta}_{q,1} + \hat{\theta}_{m,1}$$

Once the predicted Black share is constructed, the second-stage estimating equation to uncover the impact of the Black share on preferences is

$$\delta^\tau_{\ell,m} = a^\tau_1 \hat{S}^b_{q,m} + \theta_{q,2} + \theta_{m,2} + \mathcal{A}^\tau_{\ell,m} \tag{10}$$

where $\theta_{q,2}$ and $\theta_{m,2}$ are fixed effects for income quantiles and metros in the second stage. Denote $X^\perp$ as the residual of a regression of variable X on the fixed effects $\theta_{q,2}$ and $\theta_{m,2}$. The estimating equation for a^τ_1 can be rewritten as

$$\delta^{\tau\perp}_{\ell,m} = a^\tau_1 \hat{S}^{b\perp}_{q,m} + \mathcal{A}^{\tau\perp}_{\ell,m} \quad \text{where} \quad \mathcal{A}^{\tau\perp}_{\ell,m} = a^\tau_1 \hat{e}^{\tau\perp}_{\ell,m} + A^{\tau\perp}_{\ell,m} \tag{11}$$

4.5.1 An Illustration of the Comparisons that Drive Identification

To understand how the different income quantiles contribute to identification, use $\hat{S}^{b\perp}_{q,m} = \hat{\gamma} Z^{b\perp}_{q,m}$ and start with the expression

$$\hat{a}^\tau_1 = \frac{\sum_q \sum_m \delta^{\tau\perp}_{q,m} \hat{\gamma} Z^{b\perp}_{q,m}}{\sum_{q'} \sum_{m'} \left(\hat{\gamma} Z^{b\perp}_{q',m'}\right)^2}$$

Now multiply and divide by $\sum_{m''} \left(\hat{\gamma} Z^{b\perp}_{q,m''}\right)^2$ in the numerator

$$\hat{a}^\tau_1 = \frac{\sum_q \sum_m \sum_{m''} \left(\hat{\gamma} Z^{b\perp}_{q,m''}\right)^2 \left(\frac{\delta^{\tau\perp}_{q,m} \hat{\gamma} Z^{b\perp}_{q,m}}{\sum_{m''} \left(\hat{\gamma} Z^{b\perp}_{q,m''}\right)^2} \right)}{\sum_{q'} \sum_{m'} \left(\hat{\gamma} Z^{b\perp}_{q',m'}\right)^2}$$

Rearrange terms to get

$$\hat{a}_1^\tau = \sum_q \underbrace{\left(\frac{\sum_{m''}\left(Z^{b\perp}_{q,m''}\right)^2}{\sum_{q'}\sum_{m'}\left(Z^{b\perp}_{q',m'}\right)^2}\right)}_{w_q} \underbrace{\left(\frac{\sum_{m}\delta^{\tau\perp}_{q,m}\hat{\gamma}Z^{b\perp}_{q,m}}{\sum_{m''}\left(\hat{\gamma}Z^{b\perp}_{q,m''}\right)^2}\right)}_{\hat{a}^\tau_{1,q}}$$

The estimate of a_1^τ can be written as the sum over quantiles of the product of an income quantile specific weight, w_q, and an estimate of a_1^τ using only information from that income quantile, $\hat{a}^\tau_{1,q}$.

Figure 2: A Picture Depicting Identification

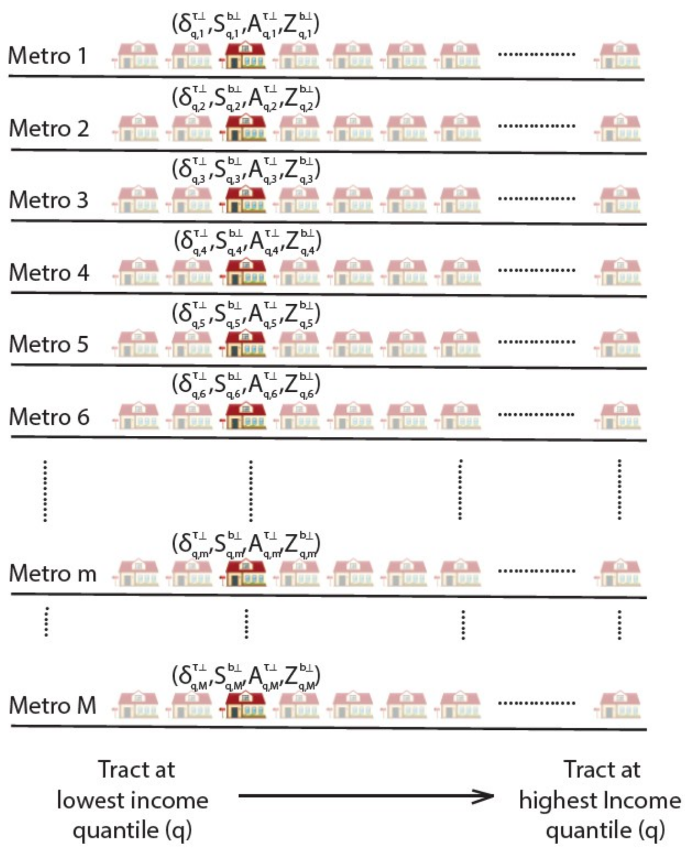


Figure 2 illustrates how identification operates in our framework for one type of household. In that figure, each row corresponds to one metro and each metro consists of a set of neighborhoods, where each neighborhood is pictured as a house. Inside each metro, neighborhoods are ranked left to right from lowest income to to highest income. For a given type τ, each neighborhood has associated an indirect utility $\delta^{\tau\perp}_{q,m}$ that is a function of endogenous neighborhood composition (Black share in the picture, $S^{b\perp}_{q,m}$) and exogenous amenities relevant to that type, $A^{\tau\perp}_{q,m}$. At the location corresponding to that income quantile, the instrument $Z^{b\perp}_{q,m}$ is correlated with the Black share and uncorrelated with the type-specific amenities. To estimate the impact of the Black share on indirect utility from IV, data from only one income quantile in each metro is needed[26] – in the picture, this is shown as the bolded 3rd income quantile in all metros. The full estimator aggregates contributions from all quantiles using weights that are proportional to the share of the overall variation in the instrument accounted for by variation in that quantile.

4.5.2 Linear approximation of $\hat{S}^{b\perp}_{q,m}$

So far, we have shown how each income quantile contributes to identification. The prediction at each income quantile is itself a function of the metro-level type shares weighted by national-average sorting patterns. Our goal now is to use the tools of GSS to understand how the metro-level type shares contribute to identification.

To exactly map our work to that of GSS, we need to be able to write our estimator as a linear combination of the instruments. Equation (8) shows that the predicted Black share is a non-linear function of the type shares s^k_m: the denominator is the total fraction of *all* households in the metro predicted to choose the tract and the numerator is the total fraction of all *Black* households in the metro predicted to choose the tract. To directly relate our results to the work of GSS, we need to take a linear approximation to $\hat{S}^{b\perp}_{q,m}$. The correlation of the linear approximation to the actual instrument is very high. This suggests the decomposition of contribution to identification of the linearized instrument that we report later on is very close to that of the actual instrument.

Note that the derivative of $Z^b_{q,m}$ with respect to s^k_m is equal to

$$\frac{\partial Z^b_{q,m}}{\partial s^k_m} = \frac{I\left(k = Black\right)\hat{\rho}^k_q}{\sum\limits_{k'} s^{k'}_m \hat{\rho}^{k'}_q} - \frac{\hat{\rho}^k_q \sum\limits_{k''} I\left(k'' = Black\right) s^k_m \hat{\rho}^{k''}_q}{\left(\sum\limits_{k'} s^{k'}_m \hat{\rho}^{k'}_q\right)^2} = \left(\frac{\hat{\rho}^k_q}{\sum\limits_{k'} s^{k'}_m \hat{\rho}^{k'}_q}\right)\left[I\left(k = Black\right) - Z^b_{q,m}\right]$$

Now define $\bar{s}^k$ as the national average share of type k in a metro, and define $\bar{Z}^b_q$ as the shift-share-constructed Black share in income quantile q when all type shares in a metro are equal to their national average, i.e.

$$\bar{Z}^b_q \equiv \frac{\sum\limits_k I\left(k \in Black\right)\bar{s}^k \hat{\rho}^k_q}{\sum\limits_{k'} \bar{s}^{k'} \hat{\rho}^{k'}_q}$$

[26] With the caveats that $\hat{\gamma}$ is the first-stage coefficient when using the entire sample in estimation and quantile and metro fixed effects have been removed.

Given this notation, a first-order Taylor series approximation of $Z^b_{q,m}$ around $\bar{Z}^b_q$, call it $\tilde{Z}^b_{q,m}$, is equal to

$$\begin{aligned} \tilde{Z}^b_{q,m} &= \bar{Z}^b_q + \sum_k \left.\frac{\partial Z^b_{q,m}}{\partial s^k_m}\right|_{\bar{s}^k \forall k} \left(s^k_m - \bar{s}^k\right) \\ \text{where} \quad \left.\frac{\partial Z^b_{q,m}}{\partial s^k_m}\right|_{\bar{s}^k \forall k} &= \left(\frac{\hat{\rho}^k_q}{\overline{pop}_q}\right)\left[I\left(k = Black\right) - \bar{Z}^b_q\right] \end{aligned}$$

$\overline{pop}_q$ is the predicted population of the tract with income quantile q when all type shares in a metro are equal to the national average: $\overline{pop}_q = \sum_{k'} \bar{s}^{k'} \hat{\rho}^{k'}_q$. After simplification, this reduces to

$$\begin{aligned} \tilde{Z}^b_{q,m} &= \bar{Z}^b_q + \sum_k g^k_q s^k_m \\ \text{where} \quad g^k_q &= \left(\frac{\hat{\rho}^k_q}{\overline{pop}_q}\right)\left[I\left(k = Black\right) - \bar{Z}^b_q\right] \end{aligned} \tag{12}$$

Equation (12) gives an approximation of $Z^b_{q,m}$ that is linear in type shares. This implies a first-order linear approximation to $\hat{S}^b_{q,m}$, call it $\tilde{\hat{S}}^b_{q,m}$, can be written as

$$\begin{aligned} \tilde{\hat{S}}^b_{q,m} &= \hat{\gamma}\tilde{Z}^b_{q,m} + \hat{\theta}_{q,1} + \hat{\theta}_{m,1} \\ &= \hat{\gamma}\left(\bar{Z}^b_q + \sum_k g^k_q s^k_m\right) + \hat{\theta}_{q,1} + \hat{\theta}_{m,1} \end{aligned} \tag{13}$$

In appendix B we show that

$$\tilde{\hat{S}}^{b\perp}_{q,m} = \hat{\gamma} \sum_k g^{k\perp}_q s^{k\perp}_m \tag{14}$$

where $g^{k\perp}_q$ and $s^{k\perp}_m$ are equal to g^k_q and s^k_m after subtracting fixed effects for metro area m and income quantile q.

To check the quality of this approximation, we regress $\hat{S}^{b\perp}_{q,m}$ on the linear approximation $\tilde{\hat{S}}^{b\perp}_{q,m}$ shown in equation (14) for 100 income quantiles for our 54 types of households. The slope is 0.90 and the R^2 of 0.99. The results for the Hispanic share are similar.

4.5.3 Sources of Identification of a_1^τ

Returning to equation (11), and after replacing $\hat{S}_{q,m}^{b\perp}$ with its linear approximation $\tilde{\hat{S}}_{q,m}^{b\perp}$, the estimate of a_1^τ, call it $\tilde{\hat{a}}_1^\tau$ is equal to

$$\tilde{\hat{a}}_1^\tau = \frac{\sum_q \sum_m \delta_{q,m}^{\tau\perp} \tilde{\hat{S}}_{q,m}^{b\perp}}{\sum_{q'} \sum_{m'} \left(\tilde{\hat{S}}_{q',m'}^{b\perp}\right)^2} = \frac{\sum_q \sum_m \delta_{q,m}^{\tau\perp} \hat{\gamma} \sum_k g_q^{k\perp} s_m^{k\perp}}{\sum_{q'} \sum_{m'} \tilde{\hat{S}}_{q',m'}^{b\perp} \hat{\gamma} \sum_{k'} g_{q'}^{k'\perp} s_{m'}^{k'\perp}} = \frac{\sum_q \sum_m \sum_k \delta_{q,m}^{\tau\perp} \, g_q^{k\perp} s_m^{k\perp}}{\sum_{q'} \sum_{m'} \tilde{\hat{S}}_{q',m'}^{b\perp} \sum_{k'} g_{q'}^{k'\perp} s_{m'}^{k'\perp}}$$

Multiply and divide by $\sum_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} g_q^{k\perp} s_{m''}^{k\perp}$ in the numerator

$$\tilde{\hat{a}}_1^\tau = \frac{\sum_q \sum_k \left(\sum_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} g_q^k s_{m''}^k\right) \left(\frac{\sum_m \delta_{q,m}^{\tau\perp} \, g_q^{k\perp} s_m^{k\perp}}{\sum_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} g_q^{k\perp} s_{m''}^{k\perp}}\right)}{\sum_{q'} \sum_{m'} \tilde{\hat{S}}_{q',m'}^{b\perp} \sum_{k'} g_{q'}^{k'\perp} s_{m'}^{k'\perp}}$$

Rearrange terms and simplify

$$\begin{aligned}
\tilde{\hat{a}}_1^\tau &= \sum_q \sum_k \left(\frac{\sum_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} g_q^{k\perp} s_{m''}^{k\perp}}{\sum_{q'} \sum_{m'} \tilde{\hat{S}}_{q',m'}^{b\perp} \sum_{k'} g_{q'}^{k'\perp} s_{m'}^{k'\perp}}\right) \left(\frac{\sum_m \delta_{q,m}^{\tau\perp} \, g_q^{k\perp} s_m^{k\perp}}{\sum_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} g_q^{k\perp} s_{m''}^{k\perp}}\right) \\
&= \sum_q \sum_k \left(\frac{\sum_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} g_q^{k\perp} s_{m''}^{k\perp}}{\sum_{q'} \sum_{m'} \tilde{\hat{S}}_{q',m'}^{b\perp} \sum_{k'} g_{q'}^{k'\perp} s_{m'}^{k'\perp}}\right) \left(\frac{\sum_m \delta_{q,m}^{\tau\perp} s_m^{k\perp}}{\sum_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} s_{m''}^{k\perp}}\right) \\
&= \sum_q \sum_k w_{qk} \tilde{\hat{a}}_{1,qk}^\tau \qquad (15)
\end{aligned}$$

The second term in equation (15), $\tilde{\hat{a}}_{1,qk}^\tau$, is an IV estimate of a_1^τ from equation (11), once $\hat{S}_{qk}^b$ has been replaced with its linear approximation $\tilde{\hat{S}}_{qk}^b$ and (i) when the estimation sample only includes the tract (ℓ) in each metro area exactly at income quantile q and (ii) the instrument is the share of type k households living in metro m. The first term, w_{qk}, is the Rotemberg weight for neighborhoods with income quantile q and households of type k: it is the share of the overall variation of the shift-share-generated Black share attributable to the city-level share of type k households in neighborhoods at income quantile q.

4.6 Rotemberg Weights

To better understand the source of variation in the instrument, we compute Rotemberg weights associated with the linear approximation of the shift-share-predicted Black and Hispanic shares, shown by w_{qk} in equation (15). Equation (15) shows exactly how to construct Rotemberg weights when every metro has exactly the same number of tracts and (therefore) exactly the same number of income quantiles. In our data, the number of tracts varies across metro areas. To account for this, we slightly adjust the computation.

We construct weights for each of our 54 types of households for 100 income quantiles, and compute these weights as follows.[27] First, using equation (8) we create a value of $Z^b_{\ell,m}$ for every tract ℓ in every metro m in our sample. Next, we sort each tract into its closest income-quantile bucket. Let $q(\ell, m)$ denote the closest income quantile, out of 100, for tract ℓ in metro m. This means that metros with more than 100 tracts will have multiple tracts in some income buckets, and metros with less than 100 tracts will have some income buckets without any tracts.

Once tracts have been sorted this way, we create the ingredients to the linear approximation to $Z^b_{q(\ell,m)}$ in equation (12): $\bar{Z}^b_{q(\ell,m)}$, $\hat{\rho}^k_{q(\ell,m)}$, $\overline{pop}_{q(\ell,m)}$, and therefore $g^k_{q(\ell,m)}$. Since at this point we have sorted all tracts into income quantiles, going forward we will replace the notation $q(\ell, m)$ with q and let $\mathcal{W}_{q,m}$ denote the number of tracts grouped in metro m into income quantile q. We construct Rotemberg weights for the Black share in our sample – the Hispanic share is constructed analogously – as[28]

$$w_{qk} = \frac{\sum_{m''} \mathcal{W}_{q,m''} \tilde{Z}^{b\perp}_{q,m''} g^{k\perp}_q s^{k\perp}_{m''}}{\sum_{q'} \sum_{m'} \mathcal{W}_{q',m'} \tilde{Z}^{b\perp}_{q',m'} \sum_{k'} g^{k'\perp}_{q'} s^{k'\perp}_{m'}} \tag{16}$$

where to compute $X^\perp$ for any variable X in the above equation, we regress that variable on a full set of metro and income-quantile controls.[29]

The top panel of table 2 summarizes the Rotemberg weights for predicting the Black

[27]Note that when we estimate preferences over Black and Hispanic shares, we need to generate a value of $\hat{S}^b_{q(\ell,m),m}$ appropriate for each tract in each metro. For the purposes of computing Rotemberg weights to understand the source of variation in the predicted Black and Hispanic shares, it is acceptable to divide all tracts in a metro into a fixed number of quantiles based on tract income.

[28]Including $\mathcal{W}_{q,m}$ reflects the fact that metros with more tracts have a larger influence on coefficient estimates. Also, note that we have replaced $\hat{\tilde{S}}^{b\perp}_{q,m''}$ with $\tilde{Z}^{b\perp}_{q,m''}$ in constructing w_{qk}. This is allowable because $\hat{\tilde{S}}^{b\perp}_{q,m''} = \hat{\gamma}\hat{\tilde{Z}}^{b\perp}_{q,m''}$ as we show in appendix B. $\hat{\gamma}$ drops out of equation (16) because it appears in both the numerator and denominator.

[29]Specifically, we include a full set of metro dummy variables and a 7th order polynomial in income quantile. We use a 7th order polynomial rather than a full set of income dummy variables because this is our control function for income quantiles in our full model that does not use linear approximations.

share. Black households account for 84.5% of these Rotemberg weights. Hispanic households account for 12.0% and White households account for only 3.5%. About 40% (740/1,800) of the Rotemberg weights for predicting the Black share of neighborhoods attributable to White households are negative, but the sum of these negative Rotemberg weights is quite small at -1.4%; the other, positive Rotemberg weights for White households sums to 4.9%. The bottom two rows of this panel show that the Rotemberg weights for predicting the Black share for Black renting households is 65.7% and for Black home-owning households it is 18.9%.

Table 2: Distribution of Rotemberg Weights

Predicted Black Share

Race	Owner/Renter	Sum of Rotemberg Weights
Black		0.845
Hispanic		0.120
White*		0.035
Black	Renter	0.657
Black	Owner	0.189

Predicted Hispanic Share

Race	Owner/Renter	Sum of Rotemberg Weights
Black		0.046
Hispanic		0.883
White		0.071
Hispanic	Renter	0.673
Hispanic	Owner	0.211

* White types have 740 (out of 1800) negative Rotemberg weights for predicted Black shares. The average weight when negative is -1.86×10^{-5} and the sum of these negative weights is -0.014.

The bottom panel of table 2 summarizes the Rotemberg weights for predicting the Hispanic share. All Rotemberg weights for predicting the Hispanic share are nonnegative. Hispanic households account for 88.3% of these weights, with White households accounting for 7.1% and Black households accounting for 4.6%. The bottom two rows of this panel show that the Rotemberg weights for predicting the Hispanic share for Hispanic renting households is 67.3% and for Hispanic home-owning households it is 21.1%. Overall, both panels of table 2 show that the Rotemberg weights of renting households for predicting own-race racial shares sum to about 2/3rds.

The top panel of Figure 3 shows the Rotemberg weights of Black renting households for predicting the Black share.[30] To keep the graph clean, we show the sum of the weights in

[30] We do not graph the Rotemberg weights for Black homeowning households because these weights are

5 percentile income bins, i.e. income percentiles 1-5, 6-10, and so forth. We do not show results between the 61st and 100th income percentiles since there is minimal variation in that range. There are 9 lines on this graph, one for each type of Black renting household. The different colors correspond to different credit bins – black for lowest, blue for middle, and red for highest – and the different markers refer to different ages – square for youngest, circle for middle aged, and triangle for oldest. The figure shows that a disproportionate amount of variation in predicted Black shares is accounted for by young- and middle-aged Black renting households with low credit scores locating in lower-income tracts, the black lines with square and circle markers.

The bottom panel of Figure 3 shows the Rotemberg weights for predicting the Hispanic share for Hispanic renting households. The formatting of the bottom panel is identical to the top panel. The panel shows that four types of Hispanic households account for a disproportionate amount of variation in predicted Hispanic shares: young- and middle-aged Hispanic renting households with low and middle-tier credit scores, the black and the blue lines with square and circle markers.

4.7 Balance Tests

Equation (15) highlights that a sufficient condition for consistent estimation of a_1^τ for a given type τ is that $\tilde{\hat{a}}_{1,qk}^\tau$ is a consistent estimator at every value of q and and every type k. To see this, for each type τ write:

$$\begin{aligned}\tilde{\hat{a}}_{1,qk}^\tau &= \frac{\sum\limits_m \delta_{q,m}^{\tau\perp} s_m^{k\perp}}{\sum\limits_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} s_{m''}^{k\perp}} = \frac{\sum\limits_m a_1^\tau \tilde{\hat{S}}_{q,m}^{b\perp} s_m^{k\perp}}{\sum\limits_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} s_{m''}^{k\perp}} + \frac{\sum\limits_m \tilde{\mathcal{A}}_{q,m}^{\tau\perp} s_m^{k\perp}}{\sum\limits_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} s_{m''}^{k\perp}} \\ &= a_1^\tau + \frac{\sum\limits_m \tilde{\mathcal{A}}_{q,m}^{\tau\perp} s_m^{k\perp}}{\sum\limits_{m''} \tilde{\hat{S}}_{q,m''}^{b\perp} s_{m''}^{k\perp}}\end{aligned} \tag{17}$$

where we have added the tilde character to $\mathcal{A}_{q,m}^{\tau\perp}$ to explicitly note that we are working with the linear approximation. Again, adding the tilde character to $\tilde{\hat{e}}_{q,m}^{\tau\perp}$, equation (11) implies

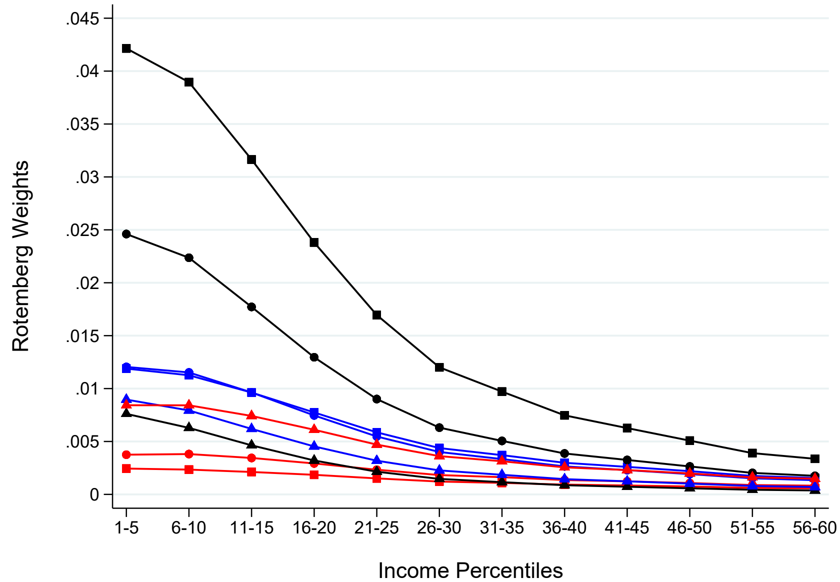
$$\tilde{\mathcal{A}}_{q,m}^{\tau\perp} s_m^{k\perp} = a_1^\tau \tilde{\hat{e}}_{q,m}^{\tau\perp} + A_{\ell,m}^{\tau\perp}$$

For consistent estimation,[31] as the number of metro areas gets very large $\hat{\gamma}$ will converge

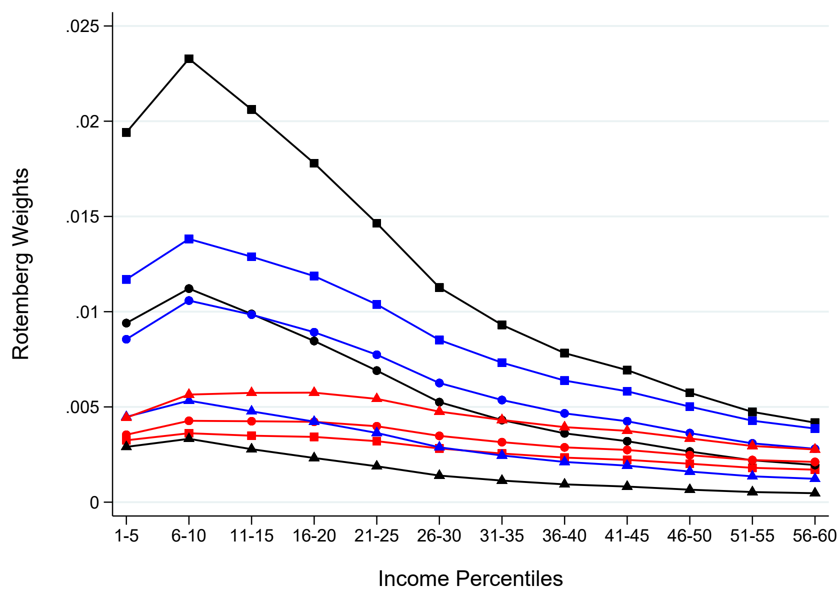
relatively very small compared to Black renting households.

[31] We focus on the requirement for consistent estimation because IV estimates are biased in small samples as shown by Bound, Jaeger, and Baker (1995).

Figure 3: Rotemberg Weights



(a) Weights for Predicted Black Share, Black Renters



(b) Weights for Predicted Hispanic Share, Hispanic Renters

Notes: The black line is for the lowest credit score, the blue line is for the medium credit score, the red line is for the highest credit score, the square marker is for the youngest age, the circle marker is for the middle age, and the triangle marker is for the oldest age.

to γ which means that $\tilde{\hat{e}}^{\tau\perp}_{q,m}$ will converge to $\tilde{e}^{\tau\perp}_{q,m}$. Thus, as the number of metros gets large

$$\text{plim } \tilde{\hat{a}}^{\tau}_{1,qk} \;=\; a^{\tau}_1 \;+\; a^{\tau}_1 \left[\frac{\text{cov}\left(\tilde{e}^{\tau\perp}_{q,m}, s^{k\perp}_m\right)}{\text{cov}\left(\tilde{\hat{S}}^{b\perp}_{q,m}, s^{k\perp}_m\right)} \right] \;+\; \frac{\text{cov}\left(A^{\tau\perp}_{q,m} s^{k\perp}_m\right)}{\text{cov}\left(\tilde{\hat{S}}^{b\perp}_{q,m} s^{k\perp}_m\right)}$$

The 2nd term is zero by construction since $s^{k\perp}_m$ is a linear input to $\tilde{Z}^b_{q,m}$. Thus, for each type τ, and for any quantile q and type k, consistency of $\tilde{\hat{a}}^{\tau}_{1,qk}$ requires the third term – the covariance, across metros, of the share of type k households living in metro m and the amenities valued by type τ at quantile q in metro m – to be zero.

We cannot directly test whether $\text{cov}\left(A^{\tau\perp}_{q,m}, s^{k\perp}_m\right) = 0$ because $A^{\tau}_{q,m}$ is not observable for any q, m or τ. Instead we try to find variables that may proxy for amenities, and test if the covariance of these proxies and Black or Hispanic share predicted by our instruments is zero. To the extent that certain amenities are associated with certain racial groups, and our estimates for preferences for the Black and Hispanic shares of neighborhoods bundle both preferences for race and amenities associated with race, we do not want to include proxies for $A^{\tau\perp}_{q,m}$ that may be influenced by household or government choices potentially related to racial shares.

To proxy for amenities, we consider seven variables: (1) tract distance to the nearest river in miles, (2) tract distance to the nearest lake in miles, (3) tract distance to the coast in miles, (4) the fraction of the tract that is a flat plain, (5) a dummy variable if the tract is within 0.25 miles of public transit, (6) a dummy variable if the tract is within 0.50 miles of public transit, and (7) an estimate of the road network density of the tract.[32] The top panel of Table 3 shows results of these balance tests for predicted Black shares. The bottom panel of the table shows results for predicted Hispanic shares.

Columns (1) and (2) of Table 3 show the means and standard deviations of these variables. Columns (3) and (5) show estimates from two different regressions of the outcome variable (i.e. distance to river) on our instrument after controlling for metro fixed effects and a 7th order polynomial in income; columns (4) and (6) show the standard errors; and columns (7) and (8) show p-values for the null hypothesis that the coefficient is zero. The column marked "IV" is for our actual instrument (which can be thought of as the sum of the Rotemberg-weighted individual instruments) and the column marked "IV2" is the linear approximation of our instrument from equation (12), but only including Black or Hispanic households that rent, the source of most of the variation of the instrument according to the Rotemberg

[32]In the regressions with distance to nearest river, distance to nearest lake, and distance to nearest coast as the dependent variables, we require that at least one tract in the metro lie within 5 miles of the relevant body of water for that metro to be included in the analysis.

weights.

Table 3: Balance Test Results

Panel A: Predicted Black Share

Outcome	Num. Metros	mean (1)	sd (2)	Coefficient on $\widehat{S}^{b\perp}_{\ell,m}$ IV (3)	SE (4)	IV2 (5)	SE (6)	p-values IV (7)	IV2 (8)
Distance to river (mi)	192	3.316	3.562	0.712	(1.105)	1.321	(1.649)	0.520	0.423
Distance to lake (mi)	24	26.019	29.416	-6.323	(6.237)	-5.878	(6.485)	0.311	0.365
Distance to coast (mi)	66	6.916	9.882	-10.053	(3.158)	-9.300	(3.454)	0.001	0.007
Fraction flat planes	197	0.410	0.423	-0.167	(0.113)	-0.174	(0.102)	0.141	0.089
Public transit < .25 miles	197	0.023	0.103	0.053	(0.057)	0.033	(0.048)	0.354	0.495
Public transit < .5 miles	197	0.059	0.189	0.085	(0.094)	0.054	(0.084)	0.369	0.522
Road network density*	197	2.895	6.165	0.675	(1.402)	0.885	(1.644)	0.630	0.591
S^b_j	197	0.156	0.250	1.221	(0.021)	1.226	(0.024)	0.000	0.000
S^h_j	197	0.112	0.179	-0.426	(0.058)	-0.411	(0.054)	0.000	0.000

Panel B: Predicted Hispanic Share

Outcome	Num. Metros	mean (1)	sd (2)	Coefficient on $\widehat{S}^{h\perp}_{\ell,m}$ IV (3)	SE (4)	IV2 (5)	SE (6)	p-values IV (7)	IV2 (8)
Distance to river	192	3.316	3.562	1.029	(1.761)	2.015	(1.994)	0.559	0.312
Distance to lake (mi)	24	26.019	29.416	16.084	(40.526)	-7.103	(41.569)	0.691	0.864
Distance to coast (mi)	66	6.916	9.882	9.380	(6.418)	6.352	(13.301)	0.144	0.633
Fraction flat planes	197	0.410	0.423	0.517	(0.199)	0.246	(0.235)	0.009	0.294
Public transit < .25 miles	197	0.023	0.103	-0.017	(0.063)	-0.091	(0.066)	0.786	0.163
Public transit < .5 miles	197	0.059	0.189	0.041	(0.120)	-0.116	(0.130)	0.731	0.374
Road network density*	197	2.895	6.165	-3.845	(2.089)	-5.097	(2.863)	0.066	0.075
S^b_j	197	0.156	0.250	-1.518	(0.177)	-1.397	(0.256)	0.000	0.000
S^h_j	197	0.112	0.179	1.383	(0.022)	1.373	(0.034)	0.000	0.000

* Road network density is the intersection density in terms of auto-oriented intersections per sq. mile.

With two exceptions, columns (4), (6), (7) and (8) show that we systematically fail to reject the null that our instrument is uncorrelated with these variables. We reject the null that the instrument for Black share is uncorrelated with the distance to coast variable, although we note this variable does not include two-thirds of the metros from our sample. Additionally, the instrument predicts Black households live closer to the coasts, which a-priori may be believed to be a desirable amenity. We also reject the null that the full instrument for Hispanic share (column 7) is correlated with the fraction of flat plains.

Columns (3) - (8) of the last two rows of the top and bottom panels show the results from regressing actual Black or Hispanic shares on either predicted Black share (top panel) or predicted Hispanic share (bottom panel). As before, these regressions also include metro fixed effects and control for tract income quantile.[33] Shown in the top panel, the predicted Black share strongly positively predicts the actual Black share and strongly negatively predicts the actual Hispanic share. Conversely, the bottom panel shows the predicted Hispanic share strongly negatively predicts the actual Black share and strongly positively predicts the actual Hispanic share.

5 Estimates and Implications

Table 4 provides a summary of our estimates of preferences that household types in our data have over the racial mix of their neighborhood, $\Theta_2^\tau = \{a_1^\tau, \ldots, a_5^\tau\}$, as described in section 3.2. As we mentioned in the introduction, we interpret our estimates of preferences as for the bundle of racial shares and any amenities that tend to accompany racial shares, for example retail establishments targeted towards certain groups. Column (1) of Table 4 shows the type index 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 credit score bin (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 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. Similarly, column (9) reports the average share of Hispanic households in the Census tracts in which which that type tends to live and column (10) shows 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 all tracts in which the type may live, with the weights being the probability that the type lives in the tract.[34]

The top, middle and bottom panels of the table show results for Black, Hispanic, and White types, 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 4 shows that same-race sorting is a prominent feature of our data. Columns (7) and (9) show that, on average, Black house-

[33] These regressions are not our actual first stages (which have five instruments), but we find the results in this table to be informative on the relevance of the instruments.

[34] 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 0.6 which we compute as $0.2\,(-1.0) + 0.8\,(1.0)$.

Table 4: Summary of Estimates of Preferences over Race

Type (1)	Sample % (2)	Race (3)	Age (4)	Tenure (5)	Credit (6)	Avg S_ℓ^b (7)	Avg $\Delta\delta_\ell/\Delta S_\ell^b$ (8)	Avg S_ℓ^h (9)	Avg $\Delta\delta_\ell/\Delta S_\ell^h$ (10)	$\delta_\ell^{95}-\delta_\ell^5$ (11)
1	2.2%		y	r	l	0.47	1.22	0.10	2.32	1.54
2	1.2%		y	r	m	0.37	1.11	0.11	1.31	1.06
3	0.6%		y	r	h	0.26	0.41	0.10	-0.01	0.47
4	0.4%		y	o	l	0.38	1.21	0.09	1.16	1.19
5	0.5%		y	o	m	0.28	0.59	0.09	0.96	0.58
6	0.6%		y	o	h	0.17	-0.21	0.08	0.37	0.94
7	1.1%		m	r	l	0.50	0.89	0.09	1.64	1.36
8	0.9%		m	r	m	0.43	0.89	0.10	0.46	1.05
9	0.6%	Black	m	r	h	0.31	0.42	0.09	-0.51	0.35
10	0.4%		m	o	l	0.47	0.69	0.08	-0.19	1.04
11	0.6%		m	o	m	0.38	0.48	0.08	-0.42	0.58
12	0.9%		m	o	h	0.23	0.38	0.08	-0.42	0.53
13	0.3%		o	r	l	0.56	0.60	0.08	0.90	1.46
14	0.5%		o	r	m	0.52	0.58	0.08	0.04	1.10
15	1.0%		o	r	h	0.39	0.25	0.07	-0.71	0.34
16	0.1%		o	o	l	0.58	1.03	0.07	0.31	1.81
17	0.2%		o	o	m	0.51	0.88	0.07	0.19	1.33
18	0.4%		o	o	h	0.33	0.42	0.07	-0.47	0.41
Sum	12.3%				Avg	0.39	0.73	0.09	0.70	0.97
19	1.6%		y	r	l	0.14	1.61	0.37	1.55	1.42
20	1.4%		y	r	m	0.11	0.78	0.36	1.49	1.40
21	0.8%		y	r	h	0.09	-0.85	0.29	1.11	1.74
22	0.3%		y	o	l	0.12	1.21	0.33	1.35	1.23
23	0.5%		y	o	m	0.10	-0.28	0.31	1.29	1.70
24	0.7%		y	o	h	0.07	-1.82	0.22	0.82	1.82
25	0.7%		m	r	l	0.14	1.50	0.37	1.09	1.10
26	0.9%		m	r	m	0.11	0.88	0.38	0.93	0.92
27	0.8%	Hisp	m	r	h	0.09	-0.37	0.32	0.93	1.25
28	0.3%		m	o	l	0.13	0.72	0.35	0.79	0.76
29	0.6%		m	o	m	0.10	0.27	0.32	0.77	1.10
30	1.1%		m	o	h	0.07	-0.30	0.23	0.58	1.34
31	0.1%		o	r	l	0.14	1.43	0.41	1.13	1.18
32	0.3%		o	r	m	0.11	0.74	0.40	0.99	0.94
33	1.0%		o	r	h	0.08	-0.47	0.31	0.65	1.08
34	0.0%		o	o	l	0.14	1.94	0.38	1.67	1.38
35	0.1%		o	o	m	0.12	0.54	0.36	1.04	0.96
36	0.4%		o	o	h	0.08	-0.26	0.25	1.16	1.19
Sum	11.6%				Avg	0.10	0.31	0.33	1.07	1.30
37	5.6%		y	r	l	0.13	1.05	0.11	1.03	0.81
38	6.1%		y	r	m	0.09	0.50	0.10	0.87	1.40
39	5.4%		y	r	h	0.07	-1.19	0.08	-0.23	2.23
40	1.5%		y	o	l	0.10	1.03	0.09	0.65	1.29
41	3.3%		y	o	m	0.08	-0.86	0.08	0.57	2.07
42	6.8%		y	o	h	0.06	-2.90	0.06	0.08	2.67
43	2.7%		m	r	l	0.13	1.12	0.11	0.52	0.55
44	4.1%		m	r	m	0.09	0.87	0.10	0.25	0.92
45	6.5%	White	m	r	h	0.06	-0.22	0.07	-0.35	1.63
46	1.3%		m	o	l	0.10	1.04	0.08	-0.11	0.94
47	3.7%		m	o	m	0.08	0.76	0.08	-0.18	1.44
48	11.5%		m	o	h	0.05	-0.31	0.06	-0.22	2.04
49	0.5%		o	r	l	0.13	1.10	0.11	0.41	0.49
50	1.8%		o	r	m	0.09	0.86	0.09	0.20	0.67
51	10.5%		o	r	h	0.06	-0.27	0.07	-0.51	1.49
52	0.2%		o	o	l	0.12	1.05	0.09	-0.01	0.73
53	0.7%		o	o	m	0.09	1.04	0.08	-0.10	0.95
54	4.0%		o	o	h	0.06	0.26	0.06	-0.37	1.75
Sum	76.1%				Avg	0.08	-0.15	0.08	0.05	1.61

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

holds live in Census tracts that are 39% Black, Hispanic households live in Census tracts that are 33% Hispanic and White households live in Census tracts that are 84% White.

Columns (8) and (10) show the derivative of utility with respect to exogenous changes in the tract-level Black share (8) or Hispanic share (10). Shown in the bottom row of the top and middle panels, on average both Black and Hispanic households receive additional utility from an increase in Black and Hispanic shares. The bottom panel shows that White households are roughly indifferent to an increase in Hispanic shares and, on average and with considerable heterogeneity, White households experience disutility from an exogenous increase in the share of Black households living in their Census tracts. The White type experiencing the largest disutility are young, homeowning, high-credit score households, type 42, accounting for 6.8% of our sample. The average derivative of utility of this type with respect to the Black share of the population is -2.90, such that if the Black share increases by one percentage point, on average utility falls by -0.029. For comparison, a twenty percent increase in rental prices generates approximately the same decline in utility.

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 the level of utility for each type in each tract; in this calculation, differences in Black and Hispanic shares entirely determine differences in utility across 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. These utility differentials attributable entirely to differences in racial composition across neighborhoods are huge: 0.97 for Black households, 1.30 for Hispanic households, and 1.61 for White households. On average, there is essentially no change to rent that can compensate types sufficiently to induce households to move from neighborhoods with their most desired demographic composition to neighborhoods with their least desired demographic composition.

5.1 Implications

So far, we have generated estimates of how the indirect utility of neighborhoods varies with racial shares in a dynamic model of neighborhood choice. We wish to use the model to study whether the current allocation of household types to neighborhoods is stable, and, relatedly, the consequences of location-based public policies on neighborhood sorting and selection. Ultimately, we find that the current demographic composition of neighborhoods is not stable; and, that small place-based policies can cause a metro-wide shuffling of the population. Both these results occur because a large measure of household types strongly prefer to live in racially segregated neighborhoods. Ultimately, we need to take a stand on how households adjust expectations of the racial composition of neighborhoods in response to shocks, and much of the discussion that follows is related to assumptions we make when computing how households update expectations.

5.1.1 Stability of Demographic Composition of Neighborhoods

To start, 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. A simple look at the data suggests that the racial composition of neighborhoods has not been stable for many decades. Figure 4 shows the percentage of all Census tracts experiencing a change in the White, Black, or Hispanic share of residents of at least 5 percentage points (black line), 15 percentage points (red) or 25 percentage points (blue line) between decades, starting in 1960. The figure shows that in every decade, at least 40 percent of all Census tracts experienced a 5 percentage point or larger change to at least one racial share. From 1960 to 1980 about 15 percent of all tracts experienced at least a 25 percentage-point change in at least one racial share; even after 1980, about 4 percent of all tracts experienced a 25 percentage-point or larger change in at least one racial share in any given decade.[35]

In our framework, stability ultimately depends on the process by which expectations of neighborhood composition change. 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 $\mathcal{T}'$,

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

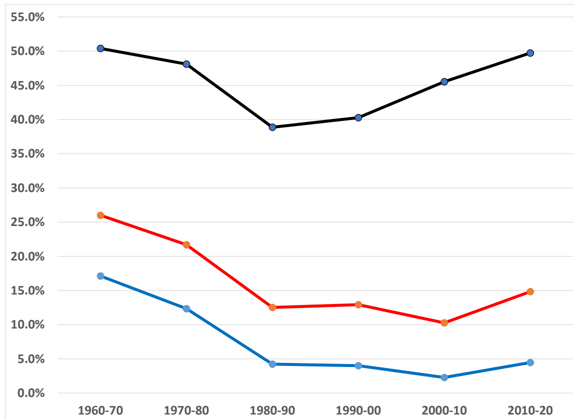
We define a steady state of g as a vector of expectations $\mathcal{T}^*$ that generates, via g, an identical set of expectations, i.e.

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

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

[35] Results are nearly identical when we restrict the set of Census tracts such that 99 percent of the land area of a tract in the later decade overlaps with the land area of the tract in the earlier decade (not shown).

Figure 4: Share of Census Tracts with a Change in Black, Hispanic or White Share of at least 5, 15, or 25 Percentage Points



Notes: The black line shows the percentage of all Census tracts with changes in at least one racial share above 5 percentage points, the red line shows changes above 15 percentage points and the blue line shows changes above 25 percentage points.

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.[36] 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.

Recall that our model has deaths and other type transitions, for example renter to owner.

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

So, for a stable population mix of types, at a minimum we need births but also need to account for any other asymmetric type transitions. A question then arises of how to allocate any new households (to neighborhoods) required to keep the distribution of types stable after one period has elapsed. Any such allocation is arbitrary; we choose the allocation that guarantees that the current data are in steady state after all choices have been made. We view this as a conservative choice, since in the absence of any aggregate or neighborhood-level shocks, the current data will be in steady state, by assumption.[37]

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 (1), 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

$$\log \mathcal{H}'_{\ell,m} - \log \mathcal{H}_{\ell,m} \quad = \quad \psi_{\ell,m}\left[\log r'_{\ell,m} - \log r_{\ell,m}\right] \tag{18}$$

   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.[38]
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

[37]Even after this, our analysis rejects that this steady state implied by the data is stable, in a way we precisely define next.

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

approximation:

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

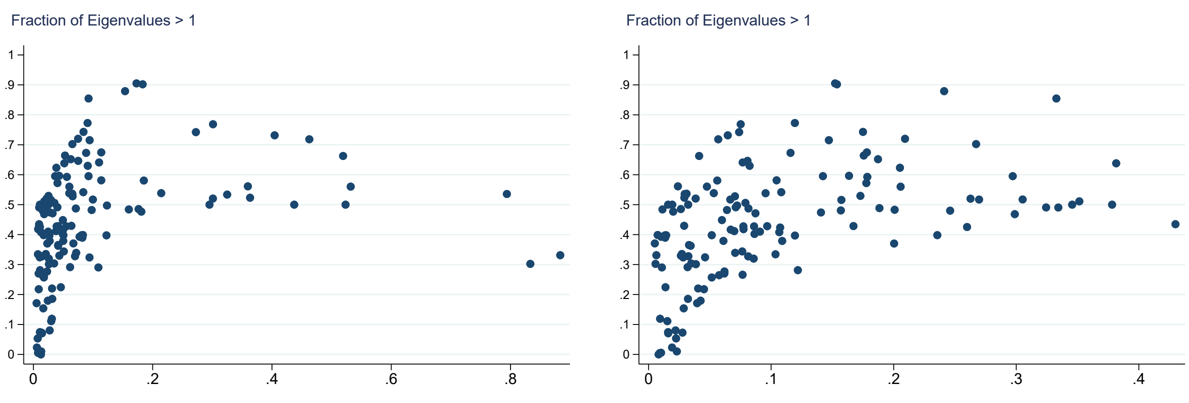
where $\mathcal{G}$ is a $2J_m$ by $2J_m$ vector of derivatives of g evaluated at $\mathcal{T}^*$. Once we make appropriate substitutions, we get

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

We compute the elements of $\mathcal{G}$ at $\mathcal{T}^*$ using numerical derivatives. Specifically, define $\widetilde{\mathcal{T}}_i^*$ as equal to $\mathcal{T}^*$ in all elements except for the i^{th} element which we perturb by Δ_i units.[39] 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.

Figure 5: Fraction of Metro Eigenvalues > 1



(a) Black Share of Metro

(b) Hispanic Share of Metro

Summarizing results, only one metro out of 197 in the sample, Rockingham County-

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

Strafford County, NH, has zero eigenvalues greater than 1. Every other metro has at least one eigenvalue greater than 1 and the median metro has 47% of its eigenvalues greater than 1.[40] Ultimately, the reason that the system is not stable is that households have very strong preferences over the racial composition of their neighbors. To show the impact of the presence of nonwhite households in a metro on our estimates of eigenvalues, Figure 5 graphs the share of eigenvalues of $\mathcal{G}$ that are larger than 1 in each metro on the y-axis against the percentage of Black households (left panel) or percentage of Hispanic households (right panel) in each metro on the x-axis. As shown in the left panel, on average the share of eigenvalues larger than 1 increases rapidly with the Black share of the metro population until the Black share is about 20%, at which point the share of eigenvalues larger than 1 stabilizes at about 50%. Nearly the exact same relationship holds with respect to the percentage of Hispanic households, shown in the right panel.

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, $\Theta^{\tau}_2 = \{a^{\tau}_1, \ldots, a^{\tau}_5\}$, by 0.25 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, with this rescaling only 3.2% of a metro's eigenvalues are larger than 1.

5.1.2 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 tracts. Specifically, for each metro, we simulate the long-run steady-state predicted response if 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).[41] 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

[40] Appendix table C.1 lists results for the full set of metros. Rockingham County-Strafford County, NH, is stable because the population is almost entirely White; the Black share is 1.3% and the Hispanic share is 0.8%. The other metros that have a only a few eigenvalues larger than 1 are also almost entirely White.

[41] As we show in Appendix Table C.2, in many metros LIHTC developments are located in about 20-35 percent of Census tracts.

government policy via LIHTC developments, perhaps incumbent residents would not move in response to a small influx of low-credit-score new residents that may be of a different average racial mix than existing residents.

We implement this counterfactual policy as follows. Denote ΔH as the total 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 tracts that are currently housing low-credit-score households in the metro.[42] Then, in the second step we simulate the model for 5 periods holding $\delta_{\ell,m}$ fixed and $r_{\ell,m}$ fixed. After these 5 periods, we compute births and deaths needed to keep the data (with these ΔH units removed) in a steady state, before adding the new LIHTC units. Finally, in the third step we add new LIHTC units in proportion to existing LIHTC units until ΔH units are added. We assume the distribution of types in these new units is the same as the distribution of types from the ΔH units removed in the first step. With these three steps, we preserve the metro-wide distribution of types and maintain the metro-wide aggregate stock of housing, but move ΔH low-credit score households from tracts without LIHTC units to tracts with LIHTC units. Importantly, the mix of household types moving into the ΔH new LIHTC units is unlikely 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. 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. 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 – 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. Set $\mathcal{H}_{\ell,m}$, $r_{\ell,m}$, $E\left[S^{b'}_{\ell,m}\right]$, and $E\left[S^{h'}_{\ell,m}\right]$ equal to their starting values.

b. 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 and find market clearing rents and the new housing stock in each tract such that the housing-supply-elasticity equation (18) holds. This generates new simulated Black and Hispanic shares, $S^{b'}_{\ell,m}$ and $S^{h'}_{\ell,m}$.

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 $E\left[S^{h}_{\ell,m}\right] = S^{h'}_{\ell,m}$.

d. Repeat steps b and c *until the distribution of types in each tract does not change with*

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

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 backwards looking.

5.1.2.1 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 baseline steady state. 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 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.

Appendix Table C.2 lists all of the results for each metro in our sample. Summarizing results here, at the median metro, 83% of tracts tip when racial preferences are at our baseline estimates. When we redo the policy simulations after setting racial preferences $\Theta^{\tau}_2 = \{a^{\tau}_1, \ldots, a^{\tau}_5\}$ equal to 0.25 of the baseline estimates (but keeping the baseline starting values of $\delta^{\tau}_{\ell,m}$ unchanged for all types), only 2% of tracts tip. This confirms intuition from the eigenvalue analysis that the current racial composition of neighborhoods is not stable, and the lack of stability arises from strong preferences over racial composition.

At the median metro in our data, the Black-White dissimilarity index is 37% and the Hispanic-White dissimilarity index is 27%. The simulations suggest metros become enormously more segregated after the policy is implemented. Measured at the median metro, in the new steady state the Black-White dissimilarity index increases by more than 41 percentage points and the Hispanic-White dissimilarity index increases by nearly 48 percentage points. The result reinforces the idea that households, on net, want to move to more racially segregated neighborhoods. When we set parameters determining racial preferences equal to 0.25 of the baseline estimates and redo simulations, for most metros the dissimilarity indexes do not change very much: the median change is 0 percentage points in the Black-White and 0.1 percentage points in the Hispanic-White.

5.1.2.2 The Speed of Convergence to New Steady State:

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

In both the backwards- and forwards-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 backwards-looking path and quite rapidly along the forwards-looking path.

To illustrate the importance of expectations on the rate of convergence to the new steady state, we consider two metros, one small and one large: Trenton, NJ and Seattle, WA. In each case, for Census tracts in which the Black or Hispanic racial share changed by at least 5 percentage points between steady states, Table 5 below reports the median number of years for those tracts in which 80% of the total change in the racial share occurs. The first two columns of this table report the metro and that metro's total number of tracts; the fourth column reports the number of tracts with a change of at least 5 percentage points in the racial share of the race reported in the third column; and the final two columns report the median number of years for 80% of the change in racial share to occur for the tracts that change in the fourth column. The fifth column reports years for the backwards-looking path and the sixth column reports years for the forward-looking path.

The top panel of this table reports results when preferences for race are set to our baseline estimates. Two facts jump out from this panel. First, when expectations are

Table 5: Expectations and Rate of Change Between Steady States

Metro	Total Tracts	Race	# Tracts w/ ≥5 ppt. Chg. in Given Race	Median Years for 80% of Change to Occur: Backwards Looking	Forwards Looking
		Preferences over Race as Estimated			
Seattle, WA	506	Black	407	32 years	9 years
		Hispanic	198	29.5 years	5 years
Trenton, NJ	72	Black	67	36 years	5 years
		Hispanic	38	40.5 years	6 years
		Preferences over Race Multiplied by 0.25			
Seattle, WA	506	Black	11	174 years	14 years
		Hispanic	11	168 years	16 years
Trenton, NJ	72	Black	29	187 years	22 years
		Hispanic	8	184.5 years	19 years

backwards looking, convergence to the new steady state occurs much more slowly than when expectations are forwards looking. In the backwards-looking path, for the median Census tract with a large demographic change, 80% of the convergence occurs between 30 and 40 years; in the forwards-looking path, it only takes 5-9 years. Second, a large percentage of tracts in both metros experience a large change in Black and Hispanic racial shares after the policy is implemented. This arises in part because the racial composition of tracts in these metros is not stable, as we have shown so far.

The bottom panel of this table reports results when preferences for race are set to our baseline estimates multiplied by 0.25. The panel shows that the number of tracts where at least one racial share changes by more than 5 percentage points is much smaller when preferences are rescaled. When household preferences are multiplied by 0.25, household utility is less sensitive to changes to neighborhood demographics, households optimally move less frequently, and change occurs more slowly. However, as before, change occurs much more slowly along the backwards-looking path than along the forwards-looking path.

6 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 exogenous amenities of neighborhoods as well as the endogenous racial composition. Using the tools of GSS, we document the source of identification of our estimates of preferences over race and discuss the key requirement for consistent estimation of preferences. We find that many households have very strong preferences for homophily. Same-race preferences are so strong that the model predicts the current racial composition of neighborhoods is not stable and that relatively small public policies can cause a radical resorting of the population.

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