Racial Sorting, Restricted Choices, and the Origins of Residential Segregation in U.S. Cities

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Abstract

This paper quantitatively decomposes forces driving Black-White segregation in major U.S. cities in 1940. It estimates models of neighborhood demand, identifying race-specific preferences governing price and racial composition using exogenous neighborhood variation in both Black and White rural migrant inflows. The results confirm that White families had a high willingness-to-pay to avoid Black neighbors. However, a decomposition of cities' segregated equilibria attributes about half of racial segregation across cities to implicit or explicit constraints on Black families' choices. The early constraints on Black households' neighborhood choices explain the persistence in segregation across cities between 1960–2010.

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1 Introduction

Higher rates of residential segregation are associated with a variety of negative outcomes from worse educational attainment in childhood to lower employment and earnings in adulthood.[1] Segregation's modern persistence can be traced to two factors: the endurance of White preferences for White neighborhoods and the long shadow of non-market institutions that historically restricted housing supply to minorities (Cutler, Glaeser, and Vigdor 1999). Historically, researchers have documented the former in "White Flight" following school desegregation and rapid neighborhood "tipping" of neighborhood racial shares throughout the twentieth century. The latter took the form of housing covenants that prohibited sales to minority buyers; racial zoning laws that codified separation between White and minority neighborhoods; and even threatened and realized violence (see e.g. Rothstein 2017).

There is little doubt that both sorting and constraints had a historical effect on Black-White segregation. However, to the best of my knowledge, there has been no study that has quantified or compared their relative contributions. Quantifying sorting and constraints' effects on segregation has two requirements: (1) identifying variation that can credibly distinguish preferences over neighborhood racial composition from local amenities; and (2) a model that can reliably predict Black choices in an unconstrained counterfactual. Neither requirement is satisfied by an individual program evaluation of a specific restriction, whose analysis cannot predict Black choices absent the plethora of other restrictions. Neither requirement is satisfied by existing state-of-the-art models of housing demand such as Bayer, Ferreira, and McMillan (2007), which rationalize segregated equilibrium choices in cross-sectional data. Bayer, McMillan, and Rueben (2004) carefully note that their estimates "[combine] the difference that results from decentralized preferences... as well as any centralized discrimination that causes black households to appear as if they prefer black versus white neighborhoods."

Credibly identifying racial preferences is particularly difficult because racial preferences are endogenous peer effects and generate a "reflection problem" (Angrist 2014; Manski 1993). The reflection problem arises because choices and racial composition are mechanically related. Consequently, homophily and race-specific preferences for local amenities are observationally equivalent. Uncoincidentally, virtually all papers estimating racial preferences find homophily. The reflection

[1] See e.g., Cutler and Glaeser 1997; Massey and Denton 1993; the 1966 Coleman Report; Chetty and Hendren 2018a; Chetty and Hendren 2018b; Chetty et al. 2014. Chyn and Katz (2021) provide a useful review of evidence on neighborhoods' effects more broadly.

problem can lead one to erroneously conclude that households prefer to live with members of the same race; to systematically overstate the role of racial sorting in driving segregation; and to systematically understate the role of external factors such as non-market constraints.

This paper credibly estimates racial preferences in order to quantitatively measure the contributions of sorting and non-market constraints driving the patterns of racial segregation in large US cities in 1940. To satisfy the two requirements, the paper estimates a neighborhood choice model using (1) instruments that capture external perturbations induced by large influxes of White and Black rural migrants and (2) panel data. First, rural migrant instruments approximate an experiment where neighbors of different races are randomly assigned to neighborhoods. Intuitively, variation from rural migrants addresses the reflection problem and is not subject to peer effect reflection because migrants are not initially "peers:" they do not live in cities at baseline. Second, cross-sectional analyses cannot distinguish constraints from unobservable disamenities. I use panel data methods to infer amenities' unobserved demand effects by measuring the serial persistence in choice; to compare Black and White preferences for amenities; and to predict how amenities affect Black demand in restricted neighborhoods. The bulk of the paper is devoted to quantifying racial preferences in simple structural models of neighborhood choice. In the last part of the paper, I use the estimates to quantitatively decompose observed segregation into components reflecting (1) the differential preferences of Blacks and Whites that are mediated through prices and (2) the non-price constraints faced by Black residents across cities. I conclude by using the quantitative variation in these measures across cities to revisit explanations for racial segregation's long-run persistence.

The paper is organized around a multinomial logit structural model of neighborhood choice where families have preferences over three factors: the local price, the Black share of the neighborhood, and local amenities. I partition the demand analysis into two parts. The first part estimates how households tradeoff between the local price and racial composition of the neighborhood holding amenities constant. The identifying variation comes from the tendency of migrants to move to specific enclaves (Altonji and Card 1991; Card 2001). The conceptual framework formalizes the identifying assumptions, addressing concerns about "endogenous shares." One innovation of the paper is to use the clustering of surname distributions of non-migrant families to measure immigrant enclaves at baseline. In contrast to other research designs of structural housing demand models, the model produces intuitive reduced form predictions that corroborate the findings.

The second part of the demand analysis measures differences in how Black and White families value local amenities using correlated random effects (CREs). The principal insight of Bayer, Ferreira, and McMillan (2007) is that local amenities' demand effects reflect their hedonic value. My approach extends this logic to unobservables. CREs measure cross-decadal dependence in residual determinants of demand, essentially "shrunken" neighborhood fixed effects. The CREs provide an estimate of Black and White residents' valuation of the same unobservable amenities. Importantly, they provide an estimate of the relationship between the two. I use the relationship to predict how Black residents would value amenities in restricted, all-White neighborhoods. The approach is infeasible in cross-sectional demand analyses, which attribute unobservables' effects to residuals. Cross-sectional residuals cannot distinguish constraints from disamenities; cannot predict amenities' effects on Black demand in restricted neighborhoods; and consequently, cannot predict counterfactual Black demand absent constraints.

The last part of the paper uses the neighborhood demand model to make aggregate predictions. Unlike other measures of segregation, the Kullback-Liebler (1951) relative entropy can be decomposed with the predicted logit odds of the structural Black and White demand models. I decompose the KL divergence distance metric into two separate distances generated from the model's predictions. First, I compare Black families' actual neighborhood choices to the counterfactual choices that would arise if neighborhood constraints had been removed—quantifying the contribution of non-market constraints to segregation. Second, I compare counterfactual Black demand to actual White demand—quantifying the contribution of divergent neighborhood preferences and decentralized choices. Rather than simply showing that each qualitatively mattered in isolation, the decomposition is the first analysis that shows that market forces and non-market constraints had quantitatively similar effects on segregation.

The paper has three main findings. First, the empirical strategy quantifies White racial preferences as a unit compensated semi-elasticity—a one percentage point increase in the Black share of the neighborhood must be compensated by a one percent decrease in the local price of housing to keep White households indifferent. The result is broadly consistent with previous findings of White homophily, notwithstanding others' potential contamination by reflection. However, I also find that Black residents exhibit at most weak homophily, a conclusion impossible in the presence of the reflection problem. The disparity in Black and White racial preferences is corroborated by migrants' reduced form effects. Second, intense White and weak Black racial preferences together imply that White neighborhoods must be very expensive to keep Black residents out via purely market forces. This is not what the data show. The decomposition analysis shows that the distribution of prices within cities is incompatible with sorting alone. Noting that only a fifth of the neighborhoods in the data have meaningful numbers of Black households, the amount of sorting predicted by the estimated model explains only half of observed segregation across cities in 1940, attributing the quantitatively important remainder to constraints.

One implication of intense White racial preferences is the existence of multiple equilibria inherent in models of social interactions (Brock and Durlauf 2001). Multiplicity of equilibria implies that moving from the segregated cities from prior to the Second World War toward more racially integrated ones is path dependent. Widespread improvements in both attitudes and institutions may not lead to integration, and segregation today may be a legacy of historical constraints rather than purely a product of enduring, modern racism. To assess this possibility, I use variation in segregation and the measure of constraints from the decomposition across cities. I show that while the serial correlation in segregation is initially driven by both sorting and constraints, the former decays with the passage of time while the latter persists.

This paper contributes to several strands of literature. Primarily, it (1) addresses methodological shortcomings of equilibrium sorting models following Bayer, Ferreira, and McMillan (2007) (henceforth, BFM) to (2) resolve the ecological tension that arises from linking constrained choices at the neighborhood-level to segregation at the city-level and its long-run consequences. First, the research design confronts two simultaneity issues—upward sloping supply and the reflection problem driven by endogenous social interactions (Manski 1993). Even randomly assigned cost shifters (e.g. Galiani, Murphy, and Pantano 2015) cannot solve both.

Whereas I use migrant perturbations, most structural housing demand papers use characteristics of own or adjacent neighborhoods as instruments for price and racial composition (BFM; Caetano and Maheshri 2021; Davis, Gregory, and Hartley 2019; Galiani, Murphy, and Pantano 2015; Wong 2013). Cross-sectional neighborhood demand instruments face steep requirements to overcome the reflection problem. A suitable instrument must be related to the preferences of one race—instrument relevance—but unrelated to the preferences of other races—instrument exclusion. To resolve reflection in the cross-section, each demand equation requires different excluded instruments.[2] For instance, suppose parks were randomly as-

[2]In many housing demand applications, including this paper, preferences are parameterized as functions of the local minority share. Both the numerator and the denominator are functions

signed to neighborhoods. The effect of randomly-assigned parks on White neighborhood choices identifies White racial preferences only if *minority residents do* have preferences for parks (relevance) and *White residents do not* have preferences for parks (exclusion). If parks are valid instruments for White racial preferences, they are not valid instruments for minority racial preferences. The identification requirements become only steeper when candidate instruments are correlated with other unobservable local amenities. To the best of my knowledge, no other housing demand paper directly engages with the reflection problem by using instrument sets that satisfy cross-equation exclusion restrictions. In contrast, the identifying assumptions in my longitudinal setting are weaker and more intuitive. Some migrant enclaves attract more Black or White migrants (relevance). *Changes* in local amenities in migrant enclaves that did receive migrants do not systematically differ from migrant enclaves that did not (exclusion). Formalized in the paper, conditional independence does not require finding neighborhood variables that matter for some races but not others.

Second, the paper decomposes a measure of observed segregation using a choice model. From Fisher's ANOVA to Oaxaca-Blinder, economics has a long tradition of using decompositions to link conditional patterns in microdata to unconditional aggregate statistics. Racial segregation is a macro city-level phenomenon. Neighborhood choices and constraints occur at the micro neighborhood level. Linking the two is not immediate. For example, suppose racial restrictive covenants were randomly assigned to neighborhoods in a city. How would analysts estimate their effect on the city's segregation? Convenants' effects on demand are related but distinct from their effects on segregation. However, just as one can decompose observed racial wage gaps using observed (or structural) estimates of the returns to education using an Oaxaca decomposition of a linear wage model, one can decompose observed segregation using estimates of convenants' effects on demand using a KL divergence decomposition of a logit choice model.

Without a decomposition methodology, studies of segregation have varied in even their units of observation. Cross-city analyses study institutions' effect on segregation indirectly using ecological regression models, ignoring whether and how much institutional constraints may bind because of their location (Ananat 2011; Andrews et al. 2017; Cutler, Glaeser, and Vigdor 1999). Neighborhood-level studies of segregation consider residents with counterfactual preferences,

of the structural equations of interest. Relevant instruments that shift the minority share in cross-sectional data must shift the numerator or denominator. They cannot also be excluded from both the White and minority demand equations.

but largely ignore how much observed segregation is affected by the prevalence and location of specific institutions (e.g. Caetano and Maheshri 2021; Kucheva and Sander 2018; Wong 2013). A notable exception is Christensen and Timmins (2021). In a novel application of a rental audit experiment, the paper uses race-specific callback rates to weight a pooled logit demand model, capturing granular variation in discriminatory search frictions as consideration probabilities. However, because they treat price and racial composition as exogenous, their welfare conclusions using counterfactual White callback rates may be subject to reflection. This paper's identification strategy and decomposition of the KL divergence consider both institutions and sorting simultaneously. The decomposition of the KL divergence allows a microeconometric analysis of neighborhood choice to directly inform drivers of observed segregation. The exercise generates a city-specific measure of the constraining effect of segregating institutions, which I show predicts long-term segregation.

This paper also relates to the expansive literature studying localized effects of migrants on labor markets, particularly those which utilizes the Card (2001) "past settlement" instrument.[3] Most of the research in immigration has focused on labor market effects, but two studies in particular, Saiz (2003) and Saiz (2010), utilize the housing demand variation driven by large inflows of immigrants to trace out housing supply curves. The bulk of these papers exploit the tendency of migrants to follow the paths of past migrants and utilize variation in migrant flows from different countries of origin, or in the case of internal U.S. migration, the subject of this paper, different states of origin (Boustan 2010; Shertzer and Walsh 2016). Recent work by Stuart and Taylor (2019) has shown that these tendencies are defined for very granular origins, reflecting the importance of social networks. This paper contributes to this literature by showing that migrants that share the same origin county are drawn to very granular destinations—the same census tracts.

Finally, this paper connects to the tradition across the social and biological sciences that investigates the signals hidden in one's name. The focal points of interests have diverged across disciplines: social scientists have taken particular interest in how names, often first names, are connected to labor market success (see e.g. Bertrand and Mullainathan 2004; Clark 2014; Olivetti and Paserman 2015; Goldstein and Stecklov 2016), while biologists and physical anthropologists trace divergences in gene distributions from the hereditary nature of surnames (see e.g. Zei et al. 1983; Piazza et al. 1987; Zei et al. 1993). This paper utilizes the latter to

[3]For an inventory of such papers, see Jaeger, Ruist, and Stuhler (2018).

explore how highly localized nature of social networks transmits correspondingly into highly localized housing demand pressure by neighborhood.[4]

This paper is organized as follows. Section 2 presents the conceptual framework. The organization of its subsections mirrors the empirical analysis of the paper. Section 3 defines concepts in the full count census data that are crucial for the analysis and how I construct geography-consistent 1940 census tracts using street addresses. Section 4 estimates how households trade off between the local price of housing and the neighborhood racial composition using surname-predicted migrant demand shocks. Section 5 models the residual variation to see whether Black and White households value similar amenities. It then uses the model predictions to estimate Black demand in all-White neighborhoods. Section 6 uses counterfactual predicted demand to decompose segregation across cities. Finally, Section 7 concludes.

2 Conceptual Framework for Neighborhood Choice

2.1 Overview

Any measure of a city's racial segregation can be aggregated from race-specific neighborhood choice probabilities. Thus, for a city c characterized by a collection of neighborhoods $\mathcal{J}_c^*$, an empirical analysis of racial segregation is an analysis of the probability π_{rjt} that individuals of race r choose to live in neighborhood j in time t. This paper analyzes π_{rjt} directly before aggregating and comparing segregation across cities.

In my setup, householders' decisions over neighborhoods $j \in \mathcal{J}_c^*$ are governed by preferences that are represented by indirect utilities$v_{ijt} \equiv \delta_{r(i),jt} + \varepsilon_{ijt}$,where δ_{rjt} is a race-specific mean and ε_{ijt} are individual deviations.

During the period of my analysis (1930–1940), there is extensive documentary evidence that certain neighborhoods in most cities were off-limits to Black residents via formal prohibitions (e.g., restrictive covenants) and also via de facto constraints such as actual and threatened violence.[5] $\mathcal{J}_{rc} \subseteq \mathcal{J}_c^*$ denotes the set

[4]Massey et al. (1987) and Munshi (2003) explore the strong ties that migrants retain with origin communities within states in Mexico.

[5]Cutler, Glaeser, and Vigdor's (1999) taxonomy separately considers three types of forces driving segregation:

> the "port of entry" theory, where blacks prefer to live among members of their own race, particularly when they are new migrants to an urban area; the "centralized" or "collective action racism" theory, where whites use *legal, quasi-legal, or violent, illegal barriers* [emphasis added] to keep blacks out of white neighbor-

of neighborhoods "available" to a particular race. Black families choose from a restricted choice set. Households choose from available neighborhoods that maximize their utility $D_{it} \equiv \arg\max_{j \in \mathcal{J}_{rc}} v_{ijt}$, and corresponding neighborhood choice probabilities are given by $\pi_{rjt} \equiv \Pr\left[D_{it} = j | r(i), c(j), t\right]$. Segregation may arise from systematic differences in preferences between races δ_{rjt} (e.g., different price elasticities, preferences over the local racial composition, race-specific local amenities) or from restrictions in Black households' choice sets $\mathcal{J}_{Bc}$.

How segregated would cities be if location choices only reflected market forces? Separately determining how constraints shaped segregation requires predicting counterfactual choices of Black residents $\hat{\pi}^{CF}_{Bjt}$ in their absence, $\mathcal{J}_{Bc} = \mathcal{J}^*_c$. Black preferences for restricted, all-White neighborhoods depends crucially on their racial preferences.

To predict counterfactual choices, I make two simplifying assumptions about preferences:

Assumption 1 (Individual idiosyncratic preferences and mulitnomial logit)**.** *ε_{ijt} is an i.i.d. draw from a standard extreme-value type I distribution*

Assumption 2 (Linearity in parameters)**.** *Race-specific mean utilities can be written linearly as $\delta_{rjt} = \beta_r \ln P_{jt} + \gamma_r s_{jt} + \xi_{rjt}$ where P_{jt} is the local price of housing in neighborhood j,[6] s_{jt} is the Black share of the neighborhood, and ξ_{rjt} is a residual that summarizes preferences over local amenities (e.g. parks or good schools) and disamenities (e.g. pollution).*[7]

The choice shares follow the convenient and well-known functional form of a multinomial logit $\pi_{rjt} = \frac{\exp \delta_{rjt}}{\sum_{j' \in \mathcal{J}_r} \exp \delta_{rj't}}$ for $j \in \mathcal{J}_{rc}$ and 0 otherwise. Substituting and taking logs yields a linear regression model (Berry 1994):

$$\ln \pi_{rjt} = -\theta_{rct} + \beta_r \ln P_{jt} + \gamma_r s_{jt} + \xi_{rjt}, \tag{1}$$

hoods; and the "decentralized racism" theory, where whites segregate themselves by paying more to live with members of their own race.

Their distinction between non-market constraints ("collective action racism") and market forces ("ports of entry" and "decentralized racism") is not meant to suggest that non-market constraints do not also reflect White preferences. Rather, the classification implies that only some of segregation is mediated through prices. "Constraints" are how Whites get segregation for free. Teasing apart those forces is the objective of the paper.

[6] See section 3 for a discussion of how the price of a neighborhood is defined. See appendix D for an alternative choice model defined for houses instead of neighborhoods.

[7] The model presented in this section is related to the one presented by Bayer and Timmins (2005) and Brock and Durlauf (2002) but with a specific functional form for the social interactions.

where the city- and race-specific intercept $\theta_{rct} = \ln \sum_{j' \in \mathcal{J}_{rc}} \exp \delta_{rj't}$ is the inclusive value, the population mean utility of households of race r living in a city c given the choices available to them.

The remainder of the section is organized around addressing two key issues:

2.2 identifying how households trade off between the local price of the neighborhood β_r and the racial composition γ_r of the neighborhood by using migrant shocks; and

2.3 predicting how Black households value unobserved characteristics of neighborhoods ξ_{Bjt} where essentially no Black residents lived using correlated random effects.

2.2 Identifying how households trade off between price and neighborhood racial composition

This section discusses identification of β_r and γ_r in equation 1.

Through the lens of the simple model, the reflection problem in identifying racial preferences occurs because s_{jt} is a function of π_{Wjt} and π_{Bjt} and thus also a function of ξ_{Wjt} and ξ_{Bjt}. In cross-sectional data, White instruments must be correlated with ξ_{Bjt} (relevance), but uncorrelated with ξ_{Wjt} (exclusion), and analogously for Black instruments. Since ξ_{rjt} captures race-specific preferences for amenities, it is difficult to imagine cataloguing amenities that one race cares about that the other race does not in observational data. An ideal experiment that randomly assigned "dosages" of Black residents to some neighborhoods and randomly assigned dosages of White residents to others would satisfy the requirement—the treatment arms are equivalent to race-specific amenities. Such an experiment also puts pressure on local housing supply, providing identifying variation for price.

Migrants and longitudinal data offer an opportunity to approximate this experiment. To facilitate exposition, I decompose ξ_{rjt} into a permanent component ($\bar{\xi}_{rj}$) and a transitory component ($\tilde{\xi}_{rjt}$) so $\xi_{rjt} = \bar{\xi}_{rj} + \tilde{\xi}_{rjt}$. First differencing equation 1 yields:

$$\Delta \ln \pi_{rj} = -\Delta\theta_r + \beta_r \Delta \ln P_j + \gamma_r \Delta s_j + \Delta\tilde{\xi}_{rj}, \tag{2}$$

absorbing static unobservable amenities that make neighborhoods more attractive (Nevo 2001).

This section is divided into two parts. First, I formally define Black and White migrant shocks and the exclusion restriction. Second, I examine how exogenous migrant shocks theoretically shift neighborhood equilibria.

2.2.1 Definition of the past settlement instrument and instrument exclusion

If migrants chose neighborhoods randomly, then inmigrant doses M_{rjt} would be identical to the ideal experiment. However, migrants may choose neighborhoods based on their local amenities ξ_{rjt} like incumbent residents. Following Card (2001) and the literature on the wage effects of immigrants on native workers, exogenous variation can be obtained by isolating immigrant inflows from shocked origins. Immigrant enclaves connect origin shocks (e.g. drought, racial violence) to destination outcomes. This section formalizes this idea through the lens of the structural demand model.

To formally link migrant choices to the model, I assume the following about preferences for enclaves of migrants of race r from origin g:

Assumption 3 (Group idiosyncratic preferences and decomposition of multinomial logit variance components)**.** *The i.i.d. extreme value error ε_{ijt} can be decomposed into $\varepsilon_{ijt} = \eta_{r(i),g(i),jt} + \tilde{\varepsilon}_{ijt}$, where $\tilde{\varepsilon}_{ijt}$ is i.i.d. extreme value type I and η_{rgjt} is i.i.d. according to the appropriately scaled and parameterized distribution formalized in Cardell (1997).*

It follows immediately that $\ln \pi_{rgjt} = \ln \pi_{rjt} + \eta_{rgjt}$: migrants' decisions are just as "endogenous" as non-migrants'.[8] Assumption 3 extends the standard multinomial logit assumption. Under Assumption 1, one individual's choices are not more or less endogenous than another's. Under Assumption 3, one group's choices are not more or less endogenous than another's.

Define each race-specific shift-share instrument $Z_{rj} \equiv \sum_g \pi_{rgj0} \times \hat{M}^c_{rg}$, mirroring an accounting inflow relationship.[9] The first "shares" component π_{rgj0} are past migrant choices π_{rgj0}, which proxy for ethnic enclaves and capture migrants' tendencies to follow in the footsteps of past migrants. The identifying assumptions come

[8] Assumption 3 is stronger than Proposition 1 requires for expositional purposes. The proof simply requires that $\pi_{rgjt}|\pi_{rjt}$ are i.i.d. The distributional assumption aids exposition because additive separability ensures that the group-specific model mirrors the race-specific model: migrants' choices are just as "endogenous" as non-migrants'.

[9] Consider individuals that share the same race that also come from the same rural county of origin, social network groups indexed by g. One can decompose immigrant inflows into group-specific flows $M_{rjt} = \sum_g M_{rgjt}$ which in turn is a function of the group-specific probability of choosing a neighborhood $\sum_g M_{rgjt} = \sum_g \pi_{rgjt} \times M^c_{rgt}$, where $\pi_{rgjt} \equiv \Pr\left[D_{it} = j | r(i), g(i), c(j), t\right]$ and the immigrant inflow to the city $M^{c(j)}_{rgt}$.

from π_{rgj0}. The second "shift" component $\hat{M}^c_{rg}$ proxies for push factors that shift the probability that migrants leave their origins.[10] $\hat{M}^c_{rg}$ is the product of (1) the probability that past migrants chose *city c*, $q_{rgjc0} = \Pr\left[c\left(D_{it}\right) = c | r\left(i\right), g\left(i\right), t\right]$, and (2) the total contemporaneous migrant outflows from origin g leaving out destination c, M^{-c}_{rg}. Together, $\hat{M}^c_{rg} = q_{rgc0} M^{-c}_{rg}$ and $Z_{rj} = \sum_g \pi_{rgj0} \times q_{rgc0} \times M^{-c}_{rg}$.

Each instrument measures the degree to which a neighborhood is connected to origins facing large outflows to all other cities. The exclusion restriction is satisfied if shocked neighborhoods—those connected to shocked origins—are conditionally independent of neighborhoods experiencing changes in amenities, $Z_{rj} \perp \Delta\xi_{rj} | \boldsymbol{X}_j$. By construction, the instrument is derived from past settlement decisions, which ameliorates concerns that migrants are intentionally deviating toward neighborhoods with improving amenities.

However, threats to identification may remain because the instrument is constructed using baseline group choices π_{rgj0}. Baseline shares partially reflect baseline amenities, which could be correlated with changes in amenities, raising concerns about "endogenous shares." For a concrete example, note that neighborhoods without any past migrants cannot be shocked. A violation arises if amenities systematically improve in migrant enclaves relative to neighborhoods without migrants.

Through the lens of Assumption 3, remedying this threat requires isolating the variation in π_{rgj0} arising from idiosyncratic preferences η_{rgj0} rather than amenities ξ_{rj0}. Intuitively, both shocked and unshocked enclaves have information about baseline amenities ξ_{rj0}. Neighborhoods with better baseline amenities are likely to attract migrants from *all* locations and thus are likely to be more connected. In contrast, only shocked enclaves have information about contemporaneous migrants. I introduce a measure of overall connectedness—the sum of shares—as a control. Conditional on connectedness, the instrument's identifying variation reflects comparisons between equally connected migrant enclaves rather than enclaves to non-enclaves. Exclusion holds so long as shocked enclaves experience no more or less changes in amenities than unshocked enclaves. With this control, Assumption 3 is sufficient to establish instrument validity.

Proposition 1 (Conditional independence)**.** *Under Assumption 3, if* $\boldsymbol{X}_j$ *includes the sum of shares then* $Z_{rj} \perp \Delta\xi_{r'j} | \boldsymbol{X}_j \quad \forall r, r'$.

The proof is in the appendix. I include a Black migrant and White migrant sum of shares control in all the neighborhood regressions. Notably, identification

[10] $\hat{M}^c_{rg} = q_{rgc0} M^{-c}_{rg}$ is the shift-share instrument typically used in cross-city analyses.

does not rely on an "exogenous shares" assumption: past migrant choices can be correlated with contemporaneous changes in amenities so long as the correlation does not differ based on the origin.[11] Under the model's assumptions, the design resolves three threats to identification: (1) static unobserved amenities, (2) migrants intentionally deviating to neighborhoods with improving unobservables, and (3) migrant destinations differing from non-migrant destinations in unobservable changes.

The identification strategy is threatened if Assumption 3 fails to hold: that idiosyncratic preferences of migrants from specific counties are correlated with changes in amenities that all residents value. The most plausible way this could happen is if migrants *cause* changes in local amenities. Recall that IV interprets migrants' causal effects on neighborhood choices exclusively via price and the neighborhood racial composition. However, this violation is not exclusive to my design: even instruments derived from randomly assigned migrants would be subject to such a violation. Inseparability of racial shares from amenities would threaten not only all existing neighborhood demand estimates, but the entire research agenda devoted to better understanding neighborhood choice. The bar to identification would be insurmountable.

However, if migrants cause changes in amenities, then local population and price effects should be more or less uniform. Everyone likes better amenities, and no one likes worse amenities. If instead migrants' effects come from racial preferences responding to shifts in the neighborhood racial composition, then the corresponding behavioral responses are complex. Empirically, the results in Section 4 are consistent with the sorting predictions of the model, laid out in the next subsection.

2.2.2 Instrument relevance: reduced form equilibrium effects of migrants in the presence of sorting

The theory generates reduced form predictions of migrants' equilibrium effects that guide the estimation of the first stage relationships. For example, Black

[11] Recent theoretical research has explored the underlying assumptions of "shift-share" instruments in the spirit of Bartik (1991), a weighted *average* of industry-specific shocks. In particular, Goldsmith-Pinkham, Sorkin, and Swift (2020) argue that identification is derived from assumptions about the shares, which themselves may be a source of omitted variable bias. The weights should sum to one. When they do not (e.g. when the weights are *specific* manufacturing employment shares), Borusyak, Hull, and Jaravel (2018) recommend controlling for the sum of shares (e.g., the *overall* manufacturing employment share). In contrast, this paper uses a version of the Card (2001) past settlement instrument, a weighted *sum* of origin-specific shocks. The weights may sum to zero or exceed one *by design*.

migrants' first order effect increases local demand, which increases prices. But, the first order effect may be partially or more than offset by second order White flight. A Black migrant shock may in fact *decrease* local neighborhood prices. This intuitive ambiguity is borne out in the model, which provides a lens to formalize such effects. The simple demand relationship in equation 1 predicts that the reduced form price effects of migrant shocks vary heterogeneously depending on the pre-existing racial composition of the neighborhood.

I make three mild structural assumptions to generate equilibrium predictions; I do not impose them through coefficient restrictions when estimating equation 2. However, the intuitive predictions provide a foundation for the empirical analysis.

Assumption 4 (Equilibrium assumptions)**.**

1. *All else constant, an (inverse) neighborhood housing supply relationship slopes upward with respect to the local population*
2. *Demand slopes downward:* $\beta_W, \beta_B \leq 0$.
3. *White residents weakly prefer White neighborhoods* $\gamma_W \leq 0$*, and Black residents weakly prefer Black neighborhoods* $\gamma_B \geq 0$.

Note that I do not assume homogeneity in housing supply—each neighborhood can have its own positive supply elasticity. I also do not place other restrictions on how housing can vary with other factors.

Proposition 2 in Appendix C formally derives the first-stage reduced form relationships in terms of structural parameters. I summarize the predictions in two remarks.

Remark 1. Under assumptions 1–4, migrants' population effects are always offsetting.

1. A Black migrant increases the local Black population and decreases the local White population.
2. A White migrant increases the local White population and decreases the local Black population.

Remark 2. Under assumptions 1–4, if White preferences for White neighborhoods are particularly strong $\gamma_W \leq -1$, the total population and price declines in response to a Black migrant in White neighborhoods and increases in Black neighborhoods. Similarly, if Black preferences for Black neighborhoods are particularly strong $\gamma_B \geq 1$, the total population and price declines in response to a White migrant in Black neighborhoods and increases in White neighborhoods. However, population and price effect heterogeneity crosses from positive to negative at most once.

Migrants' offsetting effects have separate implications for using migrant shocks as instrumental variables. One implication of remark 1 is that White population declines in the face of Black inmigration are not necessarily indicative of White preferences for White neighborhoods $\gamma_W < 0$. White population declines may be a result of upward pricing pressure alone. The model predicts, reassuringly, that Black migrant shocks increase the neighborhood Black share, and White migrant shocks decrease the neighborhood Black share. The offsetting forces make migrants' population and price effects ambiguous averaged over all neighborhoods. The theory attributes the ambiguity to different responses in neighborhoods with more or less Black share.

Proposition 2 in Appendix C shows that a simple monotonic, linear specification approximates this heterogeneity. I operationalize the predictions with simple mean effects specifications,

$$\Delta \ln P_j = a_{1c(j)} + \sum_r b_{1r} Z_{rj} + c_{1r} Z_{rj} \times s_{j0} + \boldsymbol{d}_1' \boldsymbol{X}_j + e_{1j} \tag{3}$$

$$\Delta s_j = a_{2c(j)} + \sum_r b_{2r} Z_{rj} + c_{2r} Z_{rj} \times s_{j0} + \boldsymbol{d}_2' \boldsymbol{X}_j + e_{2j}. \tag{4}$$

The first difference specifications utilize within-neighborhood variation, absorbing static unobservable characteristics. City fixed effects $a_{\cdot c}$ capture city-specific trends. In addition to the sum of shares, the vector of controls $\boldsymbol{X}_j$ includes baseline 1930 Black share, price, and population. Consequently, the remaining variation in both the main Z_{rj} and interacted $Z_{rj} \times s_{j0}$ terms is driven by the instruments. This variation is the basis for identification and excluded from the second stage regressions. The reduced form errors terms $e_{\cdot j}$ reflect unspecified higher order non-linearities in migrants' effects, measurement error, and heterogeneity in the local supply elasticity (see the derivation of Proposition 2 in Appendix C).

If racial preferences are homophilic, then Proposition 2 predicts that Black migrants decrease the price in White neighborhoods, $b_{1B} < 0$, an effect canceled out in increasingly Black neighborhoods, $c_{1B} > 0$. Similarly, White migrants' positive price effect in White neighborhoods, $b_{1W} > 0$, is offset in Black neighborhoods $c_{1W} < 0$. The relative size of the effects depends on the intensity of each groups' respective racial preferences.

With controls, equation 2 is operationalized empirically as

$$\Delta \ln \hat{\pi}_{rj} = -\Delta\theta_{rc} + \beta_r \Delta \ln P_j + \gamma_r \Delta s_j + \boldsymbol{d}'_{0r}\boldsymbol{X}_j + e_{0rj}. \tag{5}$$

$\Delta\tilde{\xi}_{rj} + (\Delta \ln \hat{\pi}_{rj} - \Delta \ln \pi_{rj}) = \boldsymbol{d}'_{0r}\boldsymbol{X}_j + e_{0rj}$ captures changes in sampling error associated with measuring the choice probabilities $\Delta \ln \hat{\pi}_{rj}$ from finite populations and predictable changes in local amenities. I estimate equation 5 via 2SLS using equations 3 and 4 as my first stage regressions.

2.3 Household valuations of local amenities and correlated random effects

The previous section discussed how migrant shocks identify racial preferences. Predicting Black demand in restricted neighborhoods also requires measuring amenity preferences. The principal insight of BFM is that mean utilities adjusted for price effects—residualized choice probabilities—reflect amenties' demand effects and correspondingly, their hedonic values.[12] I apply this insight to unobservables. The challenge associated with interpreting residualized choices as amenities is estimation error. The structural residual $u_{rjt} \equiv -\theta_{rct} + \bar{\xi}_{rj} + \tilde{\xi}_{rjt}$ differs from the measured residual $\hat{u}_{rjt} = \ln \hat{\pi}_{rjt} - \hat{\beta}_r \ln P_{jt} - \hat{\gamma}_r s_{jt}$ because of estimation error $\tilde{u}_{rjt} = \hat{u}_{rjt} - u_{rjt}$. The residuals are incidental parameters and using them for prediction suffers from overfitting (Neyman and Scott 1948). Fitting neighborhood dummies as fixed effects suffers the same problem.[13]

CREs are essentially shrunken fixed effects. I project $\bar{\xi}_{rj}$ onto the instrument and covariate set, yielding

$$\hat{u}_{rjt} = -\theta_{rct} + \underbrace{\boldsymbol{F}'_r \left[\boldsymbol{Z}'_j, \boldsymbol{X}'_j\right]' + \psi_{rj}}_{\bar{\xi}_{rj}} + \tilde{\xi}_{rjt} + \tilde{u}_{rjt}, \tag{6}$$

a linear regression model where the inclusive value θ_{rct} is absorbed by city-time

[12]Whereas BFM adjust only for price effects and treat local race shares as an exogenous amenity, I adjust mean indirect utilities by both price and race effects. The approach is related to methods that link selection-corrected treatment estimates to choices (see e.g. French and Taber (2011); Abdulkadiroglu, Pathak, Schellenberg, and Walters). In those cases, selection-corrected estimates are regressors in unconditional choice equations. In my setting, the utility measure of local amenities is the objective.

[13]Because there are thousands of neighborhoods and only two time periods, "unshrunk" fixed effects are overfit, incidental parameters. This approach is similar to empirical Bayes approaches used to recover estimates of teachers' test score value-added. Just as teacher value-added estimates rely on adequately accounting for non-random student selection, estimating amenity preferences relies on adequately accounting for racial preferences.

fixed effects, and instruments and controls are used as linear predictors. To predict the value of unobservables ψ_{rj}, I make the following assumption

Assumption 5 (Correlated random effects)**.**

1. *$\tilde{\xi}_{rjt}+\tilde{u}_{rjt}$ is conditionally, serially independent, $\tilde{\xi}_{rj1}+\tilde{u}_{rj1} \perp \tilde{\xi}_{rj0}+\tilde{u}_{rj0}|\boldsymbol{Z}_j, \boldsymbol{X}_j$*
2. $\begin{pmatrix} \psi_{Bj} \\ \psi_{Wj} \end{pmatrix} \sim \mathcal{N}\begin{pmatrix} 0 & \sigma_B^2 & \sigma_{BW} \\ 0 & , & \sigma_B^2 \end{pmatrix}$

Crucially, if the estimates of racial preferences are biased due to e.g. reflection, then the correlated random effects cannot be interpreted as index for amenity values.[14] However, because they do not impose assumptions that would affect identification β_r and γ_r (see e.g. Chamberlain 1980; Chamberlain 1982; Mundlak 1978), I can estimate (rather than assume) whether White amenity preferences correlate with Black amenity preferences.

Importantly, CREs measure preference heterogeneity across races for the *same* amenities: do amenities drive segregation? The between-race correlation structure of the CREs allows me to use White choice probabilities to predict Black demand in restricted neighborhoods. Subsequently, the cross-decade, cross-race correlation in the residuals reflect the correlation in Black and White residents' preferences for amenities. Normality is not strictly required, but Assumption 5 is sufficient to produce a simple linear prediction, $\boldsymbol{E}\left[\psi_{Bj}|\psi_{Wj}\right] = \frac{\sigma_{BW}}{\sigma_W^2}\psi_{Wj}$. If amenity preferences are negatively correlated, then local amenities are a segregating force. Otherwise, the same amenities draw both Black and White households. Higher prices or preferences for Black neighbors would be the only market forces keeping Black families out of all-White neighborhoods.

3 Data and Definitions

This section describes the census data made available by Ruggles et al. (2020) used to estimate the regression models described in Section 2. It has four parts. First, I describe how I narrow the focus of my analysis to low-skilled Black and White families. In the second, I define neighborhoods. I then construct neighborhood prices. I conclude by describing the neighborhoods where Black and White families live.

[14]Consider random effects in isolation, imposing $\beta_r = \gamma_r = 0$. The result would essentially be a regression of Black neighborhood choices on White neighborhood choices. Such a regression would simply capture segregation—White and Black households choose different neighborhoods—and would not capture amenity effects unless Black and White residents truly did not have racial preferences.

Households i The goal of the paper is to measure differences in preferences across races rather than within class. I focus the analysis on a homogenous population of relatively low-income families: households with both (1) employed male heads between the ages of 18–50; and (2) a cohabiting wife and and at least one cohabiting child. I exclude families living in group housing, where data on housing costs are generally not available. In the 46 tracted metropolitan areas in my sample, the top panel of Appendix Table A.1 reports the number of households captured by these restrictions. Excluding households headed by the elderly, women, or the unemployed, the first restriction applies to 62% of Black households and 64% of White households. Of the remaining, roughly half are cohabiting families. Second, I group families based on occupation groupings. I aim to make groups broad enough to balance homogeneity with parsimoniously summarizing a large number of households' decisions. The bottom panel of Appendix Table A.1 reports the distribution of occupations of household heads. Black household heads are clustered in three broad occupation groups—laborers (46%), service workers (22%), and operators (18%). Men in these relatively low-skilled occupations include longshoremen, cooks, janitors, deliverymen, and valets. In keeping with a focus on racial preferences rather than class differences, much of my analysis focuses on the occupation groups typical of Black men during this period. Whereas these three categories of occupations account for 86% of Black heads of household, only 39% White households are in these three low skilled occupation groups. Instead, White heads of households are broadly distributed in blue collar work (e.g. craftsmen) and white collar work (e.g. managers). Nonetheless, the focus of my analysis is on separate models estimated for low-skilled Blacks and low-skilled Whites, reflecting the decisions of families of almost 14 million residents.

Neighborhoods j Having defined householders i, I turn to alternatives j. The first-differenced, panel data regression models require consistent definitions for each neighborhood j. I define neighborhoods as census tracts as they were defined in 1940. Census tracts are designed to have a few thousand residents. The 1940 census was the first to broadly report standardized census tracts.[15] To construct 1940 census tracts in 1930, I assign households in 1930 using available street addresses. I detail the procedure in Appendix E.1. I restrict the sample to tracts those where a large share of addresses could reliably be attributed to a 1940 census tract definition. I also limit the analysis to tracts with between 1,000 and 20,000

[15] Census tracts were available earlier on a limited basis, but tract definitions change each decade, a practice that continues to this day.

residents in both 1930 and 1940. 6,132 census tracts in 46 metropolitan areas make up my analysis sample. I construct the estimated choice probabilities $\ln \hat{\pi}_{rjt}$ for each race and occupation category that I analyze using neighborhoods where there at least 10 families in the respective race and occupation cell. In doing so, I avoid estimating choice probabilities from a single digit number of families, which may reflect measurement or sampling error.

Neighborhood Price Indices P_{jt} Neighborhoods do not have prices—houses do. I create a neighborhood price index that combines information from neighborhood rents (for renter-occupied dwellings) and prices (for owner-occupied) dwellings. Appendix XX details how I estimate user-cost or rental-equivalent costs of housing to convert log rents into equivalent log house price units. Appendix D shows that the simple neighborhood price index defined in this section can proxy for the price of the "inclusive value" of the distribution of houses in the neighborhood in a multinomial choice model where houses are nested into neighborhoods.

Where did Black and White families live? To give a sense of the characteristics of neighborhoods of the typical Black and White resident, Table 1 reports neighborhood medians in 1940 weighted by the number of people in the populations denoted by the column headers. The neighborhood for a typical family resembles that for a typical White family, the majority in the population. The median White family lived in a neighborhood where the median home price (among home owners) was \$3,500 and the median monthly rent (among renters) was \$27 per month.

Black neighborhoods were generally poorer with lower income, lower employment rates, and lower education levels. Black families lived in neighborhoods where the local cost of housing was about 30% lower than White neighborhoods. Similarly situated low-skilled White families lived in neighborhoods where the local cost of housing was only about 13% lower than White families as a whole. However, where the typical Black family's neighborhood was 73% Black, the typical White family lived in a neighborhood with practically no Black people.

Did segregation arise because poorer White families were willing to pay 20% more to live in White neighborhoods while poorer Black families were not? A cross-sectional regression analysis of the patterns of segregation that does not take into account the role of constraints for Black families would suggest a naive reading of the data. The typical Black family would have to be either very price sensitive or have a strong affinity for Black neighbors. Absent those explanations, White neighborhoods would have needed to be much more expensive for segregation to be explained by White racial preferences alone. The remainder of the paper tries to understand the extent to which the distribution of neighborhood prices and Black shares could support the housing market equilibrium observed in 1940.

4 Identifying how households trade off between price and neighborhood racial composition

Migrant inflows approximate that thought experiment. To illustrate the randomized population shock experiment laid out in Section 2.2, Figure 1 plots Black (in purple) and White (in green) migrant inflows from rural counties in Texas and Oklahoma to Los Angeles between 1935–1940. Rural origin counties with larger outflows to any city are shaded according to their intensity. Destination census tracts are shaded in red according to the Black share of residents in 1930. Black migrant flows concentrate toward Watts and Compton, areas with a relatively high share of Black residents. Nevertheless, the flows are both directed and disperse. For instance, Black migrants from rural counties near Austin flow toward census tracts near Glendale and Pasadena. Black migrants from rural counties outside Oklahoma City are drawn toward Carson and south Compton. Rural White migrants from Oklahoma are similarly directed, but White migrants from Texas are drawn to cities other than Los Angeles.

The section is organized as follows. First, I detail how I proxy for migrant enclaves using surname distributions. Second, I estimate simple reduced form regression models that operationalize the equilibrium predictions in Section 2.2.2, including the first stage models for the demand estimation. Finally, I estimate the demand parameters that govern households' preferences over price and racial composition.

4.1 The past settlement instrument

The identification arguments of the demand model in Section 2.2.1 require granular neighborhood variation. A diverse set of rural origin counties provide that variation. Recall the definition of the instrument, $Z_{rj} = \sum_g \pi_{rgj0} \times q_{rgc0} \times M_{rg}^{-c}$, and denote the "shares" as $\pi q_{rgc0} = \pi_{rgj0} \times q_{rgc0} = Pr\left[j, c|r, g\right]$, the joint probability that past migrants chose neighborhood j in city c. The shares cannot be computed directly because origin county of birth is not available in the 1930 Census.

Clustered surname distributions offer an avenue to predict counties of origin. As an illustration, Figure 2 plots the resident shares of three common last names for Whites and Blacks in Texas: Adams, Carter, and Jones. Whereas Black Adamses are more represented in Navarro County, Black Carters and Joneses are overrepresented in Freestone and Walker Counties. White surnames are similarly predictive of location. Traditionally passed patrillineally, clustered surnames measure genetic drift—i.e. migration—and the shared experiences of similar migrants. Many native born Whites inherited surnames from European migrants from the late 19th and early 20th centuries that themselves clustered in immigrant enclaves (Tabellini 2018). Last names of Blacks were often imposed by slave masters in the antebellum era. Cook, Logan, and Parman (2014) find not only evidence of distinctive Black first names in the beginning of the 20th century but also find that African Americans are more likely to have the last names of famous figures (e.g. George Washington). African Americans also took surnames celebrating emancipation (e.g. Freeman) or reflecting their occupation (e.g. Smith).

In Appendix **??**, I show systematically that surnames are geographically clustered. I detail how I use surname distributions and Bayes' rule to produce a plug-in estimate of past migrants' neighborhood choice probabilities $\widehat{\pi q}_{rgj0}$. I use a series of regression analyses to validate that the surname-generated choice probabilities predict subsequent migrant predictions πq_{rgj1}, directly estimable from the 1940 census. The unit of analysis is an origin (rural county)-destination (urban census tract) flow. I weigh each observation by the total number of outmigrants from county g to any city between 1935–1940, and I cluster standard errors by origin county g.

Table 2 reports the results. For both races, column 1 shows that the surname-generated choice probabilities strongly predict actual migration patterns. The identification arguments in Section 2.2 require that migrants not all be drawn to the same well-connected neighborhoods. Surname predicted probabilities are still highly significant after accounting for neighborhoods that are attractive to all migrants with the inclusion of tract fixed effects in column 2. The remaining columns saturate the regression models with increasing number of fixed effects to unpack the underlying variation. Column 3 adds state of origin by destination city fixed effects. The predicted probabilities are still highly significant predictors, and the modest improvement in the models' overall explanatory power suggests that the granular variation in neighborhood choices is not largely driven by affinities of rural migrants from particular states for particular cities. Even in column 4 with the inclusion of county of origin by destination city fixed effects that absorb proximity to local transportation networks, the 1930 probabilities continue to strongly predict 1935–1940 migrant flows. Finally, column 5 adds state of origin by destination tract fixed effects. The regression analyses are suggest the importance of familial and kinship relationships that underlie the motivation behind the past-settlement instrument.

4.2 Equilibrium effects of Black and White migrant shocks

In this section, I estimate two sets of reduced form relationships using the set of instruments. First, I test the population predictions of the model, summarized by Remarks 1 and 2. Black migrants increase the local Black population and decrease the local White population. The effects may offset and decrease total neighborhood population depending on how intense racial preferences are. The remarks make similar predictions for White migrants. Second, I estimate the neighborhood effects on price and neighborhood Black share, which are the first stage regression specifications in equations 3 and 4 that I use to recover residents' preferences.

4.2.1 Population effects

Black migrants mechanically change the local Black population and change the local White population depending on White racial preferences. White migrants have analogous effects. The theory in Section 2.2.2 argues that population changes (1) are heterogeneous along baseline Black share and (2) trace out corresponding changes in local price if housing supply slopes upward. Correspondingly, I estimate regression models that parallel the first stage equations 3 and 4, except with neighborhood population changes as dependent variables.[16]

Table 3 reports each model's coefficient estimates. Unsurprisingly, Black migrant shocks increase the local Black population and White migrants increase the local White population. Several additional patterns emerge that support the theory. First, own race effects are consistent with sorting. The coefficient on $Z_{Bj} \times s_{j0}$ in column 1 shows that Black migrant shocks increase the local Black population

[16]Migrants' causal effects on neighborhood populations involve complicated social interactions. Migrants' effects reflect their first order effects plus amplified, cascading responses as residents continuously respond to changes in the local population. Instrumenting for changes in Black population as in Boustan (2010) and Shertzer and Walsh (2016) effectively assumes that changes in Black population arise *only* from migrants and not from sorting along racial preferences. The reduced-form specifications emerge from the simple structural model in Lemmas 2 and 3. Accordingly, I interpret the results only qualitatively and do not compare the magnitude of coefficient estimates between Z_{Bj} and Z_{Wj}.

more in less Black neighborhoods as White residents leave. Similarly, the coefficient on $Z_{Wj} \times s_{j0}$ in column 2 shows that White migrant shocks increase the local White population more in more Black neighborhoods. Second, in column 2, Black migrant shocks are associated with a decrease in the local White population across the spectrum of 1930 Black share, consistent with White flight and Remark 1. In column 1, White migrant shocks' effects on the local Black population are less clear. The coefficient estimates suggest that the effect is negative in neighborhoods with a low Black share and positive in neighborhoods with a high Black share. Only the former is statistically significant.[17] The lack of clear association between White migrants and Black population is consistent with Black households having weak or positive preferences toward White neighbors but may also simply reflect statistical imprecision.

The model generates predictions of migrants' effects on total population, which are important for estimating price effects. Remark 2 notes that if preferences on the neighborhood's racial composition are particularly intense, then migrant shocks may generate decreases in the total population of the neighborhood. Column 3 reports results. Black migrant shocks predict decreases in the total neighborhood population in relatively White neighborhoods and increases in the total neighborhood population in relatively Black neighborhoods. These results are consistent with White resident's harboring relatively intense preferences over neighborhood racial composition $\gamma_W \leq -1$. On the other hand, White migrant shocks are associated with population increases across the spectrum of 1930 Black share s_{j0}.

4.2.2 First stage regressions: migrant effects on Black share and price

I turn now to migrants' equilibrium effects on Black share and price, the endogenous variables in the demand relationships of interest in equation 5.

Column 1 of Table 4 reports migrants' effects on price. Migrants' predicted price effects are closely linked to their effects on neighborhood population. Black migrants are associated with price increases in more-Black neighborhoods and price declines in less-Black neighborhoods. Interestingly, while White migrants are associated with price declines in Black neighborhoods, the price increases are not statistically significant in even the most White neighborhoods. Column 2 in

[17] Specifically, the coefficient on $Z_{jW} \times s_{j0}$ is relatively imprecise and the covariance of the estimate with the main effect is only slightly negative. Thus, the implied effects of Z_{jW} on the local Black population are negative and statistically significant for $s_{j0} < 0.128$ at the 5% level and not statistically significant otherwise.

Table 4 reports the first stage results for the neighborhood Black share. Both sets of migration shocks are predictive of changes in the neighborhood's Black share. In neighborhoods that are already predominantly Black, Black migrants will have little effect on the neighborhood racial composition, and similarly for White migrants. Naturally, Black shocks are relatively more predictive in White neighborhoods and White shocks are relatively more predictive in Black neighborhoods. The Black instruments generally have more statistical power. This is consistent with several hypotheses. First, migrant networks may be stronger for Black migrants—past settlement may be more predictive of future decisions. Second, surnames may be more predictive of origin for Blacks than Whites. But even holding those forces constant, Black migrants may elicit stronger behavioral responses and generate larger shifts in the equilibrium.

Nevertheless, both the main and interacted effects of the Black and White migrant shock instruments are statistically predictive of the endogenous variables both individually and jointly. A Wald test for nullity of all eight coefficients across the two regressions yields an F-test statistic of 21.9 and rejects the null hypothesis at a level of 0.001.

4.3 Estimates of Racial Preferences

The equilibrium predictions in Section 2.2.2 come from two structural relationships: the target, parameterized race-specific housing demand in equation 1 and a non-parametric neighborhood-specific housing supply relationship. As noted in section 3, because of constraints, the choice probabilities are constructed using neighborhood counts where there at least 10 families in the respective race and occupation cell.[18] I use identifying variation from the full sample of census tracts so that the first stage relationships are the same as those reported in Table 4 and constant across demand models. I estimate the demand parameters of equation 5 using two-sample 2SLS where the primary outcome of interest is changes in occupation- and race-specific neighborhood choice probabilities. I report heteroskedastic robust standard errors specific to the two-sample procedure according to Pacini and Windmeijer (2016).

Table 5 reports the effects of price and neighborhood Black share for Black families (panel A) and White families (panel B). Column 1 reports my preferred estimates for families with heads of household in low-skilled occupations because

[18]The independence of irrelevant alternatives assumption implicit in the multinomial logit model allows one to ignore censored mean utilities and construct choice probabilities conditional on the subset of available choices.

they encompass most Black families. Demand slopes downward for both Black and White families. The larger magnitude of β_W combined with the larger choice set of neighborhoods from which to substitute together imply that Whites are more price sensitive than Blacks. On the one hand, low-skilled Black families do not seem to exhibit particularly strong preferences for neighborhood racial composition. On the other hand, similarly situated White families have intensely negative preferences for Black neighbors. To quantify the tradeoff, I report a utility-constant, compensated semi-elasticity $\frac{\gamma_r}{\beta_r}$. On the one hand, Black families do not have to be compensated by changes in the local Black share. On the other, White families must be compensated by nearly a 1% decrease in the local price of housing for each 1 p.p. increase in the local Black share. Column 2 reports estimates for families whose head is not occupied in the three low-skilled occupation groups. In panel B, preference estimates for families headed by higher-skilled White workers are largely consistent with those estimates for lower-skilled Whites. Relatively few Black families are not low-skilled, so column 2 in panel A should be viewed with some caution. But, these estimates also do not suggest that segregation is driven by Black families' strong preferences for more Black neighborhoods.

Using migrant shocks addresses potential reflection problems, but nevertheless finds White racial preferences consistent with the findings of other research. However, previous research finds that homophilic racial preferences are universal across different racial groups, a potential symptom of reflection. In contrast with other work, I find that Black residents' responses to migrants are muted, consistent with weak racial preferences quantified by the IV estimates of the structural model. Despite the disparity in homophilic preferences across races, Whites' high willingness-to-pay for White neighborhoods without Black neighbors may still be sufficient to drive segregation (Cutler, Glaeser, and Vigdor 1999). All else equal, White racial preferences will drive up the equilibrium prices of all-White neighborhoods, pricing out Black residents. However, even without neighborhood price differentials and homophilic preferences, low-skilled Black residents may not demand the same neighborhoods as low-skilled White residents if they have different amenity preferences, the subject of the next section.

5 Household valuations of local amenities and correlated random effects

Neighborhoods are not equal. Ignoring racial preferences, higher quality amenities draw more Black and White residents. Better amenities are capitalized into price—ξ_{rjt} is correlated with $\ln P_{jt}$—motivating the instrumental variable strategy. However, Black and White residents may have preferences for different amenities. Even holding overall demand constant so that comparable neighborhoods have similar price, heterogeneous preferences may drive segregation.

BFM show that adjusting choices by price effects provides a revealed-preference measure of amenities' hedonic value. Using this insight, BFM measure the value of observable amenities.[19] I apply the same logic to unobservables. Casting amenities' effects as CREs exploits the available panel data and parallels fixed effects regressions that use dummy variables to capture the effects of both observables and unobservables. I use the CREs to measure amenities' effects on demand and differential preferences for local amenities.

The broad strategy of using demand to infer the values of amenities is an exercise in prediction. As such, the credibility of the strategy relies on the credibility that the "outcome variables"—the residuals—contain information about households' amenity preferences. This in turn relies on the credibility of the estimates of racial preferences. If the research design is subject to reflection and overstates homophily, then equilibrium choices would be rationalized by undervaluing amenities in more racially homogenous neighborhoods.

Estimating the amenity value of neighborhood characteristics I follow the procedure from Section 2.3 to estimate parameters governing the CREs, addressing the overfitting problem that comes with using incidental parameters for prediction.[20] Namely, I first residualize the choice probabilities $\hat{u}_{rjt} = \ln \hat{\pi}_{rjt} - \hat{\beta}_r \ln P_{jt} - \hat{\gamma}_r s_{jt}$ using the consistent estimates of β_r and γ_r. I then project the residuals on the Black and White migrant shocks, the connectedness controls, 1930 neighborhood population, and city by decade fixed effects to absorb the inclusive value.

[19] Specifically, they show that mean utilities in a logit model can be used a control function to selection-correct a scaled hedonic price regression. This is related to approaches that relate structural "second stage" estimates to recover structural "first stage" parameters. See e.g. Abdulkadiroğlu et al. (2020) and French and Taber (2011).

[20] In my setting, each fixed effect would be the average residual from the same neighborhood in two decades.

Denote the residuals of the auxiliary regressions $\widetilde{\xi u}_{rjt}$. These residuals reflect race-specific valuations of static unobservables ψ_{rj}, time-varying unobservables $\tilde{\xi}_{rjt}$, and estimation error $\tilde{u}_{rjt}$. Following Section 2.3, I stipulate that the serial correlation in residual preferences is driven by permanent characteristics of the neighborhood. I obtain estimates for the variance components of ψ_{rj} by relating the residuals across decades in the neighborhoods where both White and Black families live. Estimates of the parameters come from sample covariances, $\hat{\sigma}_r^2 = \frac{1}{J-K}\sum_j \widetilde{\xi u}_{rj0} \cdot \widetilde{\xi u}_{rj1}$ and $\hat{\sigma}_{BW} = \frac{1}{2J-K}\sum_j \left(\widetilde{\xi u}_{Wj0} \cdot \widetilde{\xi u}_{Bj1} + \widetilde{\xi u}_{Wj1} \cdot \widetilde{\xi u}_{rj0}\right)$, respectively, where J are the number of neighborhoods where both White and Black families live in both decades and the degrees of freedom adjustment $K = 6$ is the number of covariates in the regression model plus one. The top panel of Appendix Table A.2 summarizes the estimates of the variance components of the unobservable effects.

Using the parameter estimates, I generate in-sample predictions of race-specific preferences for neighborhood characteristics $\hat{\xi}_{rj}$.[21] The result are essentially shrunken fixed effects, whose distributions I discuss below.

Amenities in White neighborhoods First, I visualize the distribution of low-skilled White amenity preferences $\hat{\xi}_{Wj}$ alone in Figure 3 to assess whether neighborhood unobservables have systematically different effects on demand between all-White and mixed neighborhoods. Panel A plots amenities' predicted effects, and panels B and C separate out contributions due to observable characteristics and unobservable characteristics, respectively. The analysis shows that after adjusting for neighborhood price and racial composition, the distributions of White amenity valuations are similar between all-White and mixed neighborhoods. Put differently, the analysis shows that White families lived in all-White neighborhoods that are more expensive because they had no Black neighbors rather than because of their improved amenities. The analysis also shows that White amenity valuations share common support between all-White and mixed neighborhoods. Common support along with the covariance between White CREs and Black CREs will allow me to use White amenity valuations of all-White neighborhoods to predict Black amenity valuations where there were no Black residents.

[21]Namely, $\hat{\xi}_{rj} = \hat{F}_r' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j'\right]' + \hat{\psi}_{rj}$, where $\hat{\psi}_{rj} = \boldsymbol{E}\left[\psi_{rj} | \widetilde{\xi u}_{rj0}, \widetilde{\xi u}_{rj1}\right] = \frac{\hat{\sigma}_r^2}{\hat{\tau}_r^2}\left(\frac{\widetilde{\xi u}_{rj0}+\widetilde{\xi u}_{rj1}}{2}\right)$ and $\hat{\tau}_r^2 = \frac{1}{2J-K}\sum_j \widetilde{\xi u}_{rjt}^2$.

Do amenities drive segregation? Second, I visualize the joint distribution of White amenity preferences $\hat{\xi}_{Wj}$ with Black amenity preferences $\hat{\xi}_{Bj}$ in mixed neighborhoods in Figure 4. Paralleling Figure 3, Panel A plots the joint distribution of neighborhood valuations, and panels B and C separate out contributions due to observable and unobservable characteristics, respectively. The relationship in each graph is upward sloping. This suggests that neighborhood amenities that White families value are the same as those that Black families value. Consequently, amenities were not systematically a major driver of segregation.

6 Decomposing Segregation

Sections 2 through 5 in the first part of the paper lay out and estimate a model of neighborhood choices. Notably, the analysis suggests that Black homophily and differential amenity preferences are not major drivers of segregation. However, de facto and de jure neighborhood constraints restricted Black residents from moving in, generating all-White neighborhoods. This section measures the extent to which neighborhood constraints were binding. I use the model to predict Black demand for all-White neighborhoods and decompose observed segregation. If Black demand for all-White neighborhoods is low either because of homophily or different amenity preferences, then the constraints have little effect. If Black demand for all-White neighborhoods is high, then the constraints bind.

It is worth emphasizing that quantifying the role of constraints is inherently extrapolative—the objective is to predict Black demand where there were no Black residents. Paradoxically, the greater the role of constraints in enforcing segregation, the more extrapolative the predictions will be. The tension is not resolved by locating and measuring specific constraints. Measuring the effect of neighborhood constraints requires both the research design and panel data. First, program evaluation of the demand effects of specific constraints does not measure homophily, even if constraints were randomly assigned to neighborhoods. If Black residents had strong homophilic preferences, there would be little demand for those neighborhoods. Second, consider a neighborhood demand analysis that fails to address reflection and subsequently overstates Black homophily. Such an analysis will consequently predict low demand for all-White neighborhoods and conclude that the constraints do not bind. Third, models fit to cross-sectional data rationalize equilibrium choices. Because they fit the data, they cannot predict high Black demand in all-White neighborhoods. Such an analysis will similarly conclude that constraints do not bind. The research design in this paper permits homophily to suppress Black demand for all-White neighborhoods but does not assume or impose it.

6.1 Setup

The segregation analysis has two parts. The first generates counterfactual predictions of Black demand absent constraints, including all-White neighborhoods. The second uses the counterfactual predictions to decompose segregation.

Predicting Black demand in all-White neighborhoods To compare how Black and White households value amenities in mixed neighborhoods in the last section, I made in-sample predictions using the CREs. To produce counterfactual Black demand, I make out-of-sample predictions exploiting (1) the measured covariance of Black and White random effects and (2) White random effects are measured in every neighborhood.[22] This generates predictions of how Black residents value amenities $\hat{\xi}_{Bj}$, including in all-White neighborhoods.

In the spirit of McFadden (1974) and Petrin (2002) that predict the demand of new products, I use $\hat{\xi}_{Bj}$ to predict unnormalized Black mean utilities, $\hat{\delta}_{Bjt} = \hat{\beta}_B \ln P_{jt} + \hat{\gamma}_B s_{jt} + \hat{\xi}_{Bjt}$. I obtain predictions of counterfactual choices by subtracting from the mean utilities the counterfactual inclusive value $\hat{\theta}^{CF}_{Bc} = \ln \sum_{j \in \mathcal{J}^*_c} \left(\exp \hat{\delta}_{Bj} \right)$, which forces the choice probabilities in each city to sum to 1, $\widehat{\ln \pi^{CF}_{Bjt}} = -\hat{\theta}^{CF}_{Bc} + \hat{\delta}_{Bjt}$.

Decomposing the KL Divergence Denote the Kullback-Leibler (KL) divergence of city c, $KL_c \left(\boldsymbol{\pi}_{Bct} || \boldsymbol{\pi}_{Wct} \right) \equiv \sum_{j \in \mathcal{J}^*_c} \pi_{Bjt} \ln \frac{\pi_{Bjt}}{\pi_{Wjt}}$, measuring how different the multinomial distributions of White choices $\boldsymbol{\pi}_{Wct}$ are relative to Black choices $\boldsymbol{\pi}_{Bct}$ in city c. More literally, the KL divergence is an average for Black families. Treating the neighborhood choice probabilities as a characteristic, it measures how much more often Black families choose their neighborhoods than White families on average. Black families on average live in neighborhoods that are roughly $100 \times KL_c$ percent more likely to be chosen by Black families than White families. Intuitively, the larger this number, the more segregated a city is.

Adding and subtracting $\widehat{\ln \pi^{CF}_{Bjt}}$ from the π_{Bjt}-scaled quantity yields the decom-

[22]Namely, $\hat{\psi}_{Bj} = \boldsymbol{E} \left[\psi_{Bj} | \widetilde{\xi u}_{Wj0}, \widetilde{\xi u}_{Wj1} \right] = \frac{\hat{\sigma}_{BW}}{\hat{\tau}^2_W} \left(\frac{\widetilde{\xi u}_{Wj0} + \widetilde{\xi u}_{Wj1}}{2} \right)$, the expected *Black* random effect, conditional on the *White* residuals. The observable component of Black CREs remains the same.

position,

$$KL_c = \underbrace{\sum_{j \in \mathcal{J}_c^*} \pi_{Bjt} \left(\ln \pi_{Bjt} - \widehat{\ln \pi_{Bjt}^{CF}} \right)}_{\text{non-market constraints}} + \underbrace{\sum_{j \in \mathcal{J}_c^*} \pi_{Bjt} \left(\widehat{\ln \pi_{Bjt}^{CF}} - \ln \pi_{Wjt} \right)}_{\text{sorting}}. \tag{7}$$

The decomposition of the KL divergence yields two comparisons. The first expression compares actual Black choices to Black choices in an unrestricted counterfactual.[23] Note that counterfactual choices $\widehat{\ln \pi_{Bjt}^{CF}}$ are weighted by π_{Bjt}. The first term captures the reduction in demand for existing Black neighborhoods in an unrestricted counterfactual, quantifying the degree to which non-market forces constrain Black families to specific neighborhoods. The second expression compares unrestricted Black choices to White choices, measuring the extent to which divergent choices actually reflect divergent preferences.

6.2 Results

Table 6 reports the decomposition results. The top panel reports results separately for the 21 cities in my sample with a Black population of at least 50,000, and the bottom panel reports averages and averages weighting by the local Black population. Columns 1, 2, and 3 report the overall KL divergence, the contribution of constraints, and the contribution of preferences based explanations, respectively. Column 4 reports the fraction of the overall divergence explained by constraints.

Cities were segregated. Across the cities, the first column in the bottom panel of Table 6 shows that an average Black family lived in a neighborhood that was roughly 200 log points more likely to be chosen by a Black resident than a White resident. Even the least segregated cities in the table were still substantially segregated. For example, in Richmond, VA, average Black families lived in neighborhoods that were chosen by Black families at almost double the rate of White families. However, quantifying constraints in column 2, Black families' neighborhoods were also on average roughly 100 log points more likely to be chosen by an actual (constrained) Black residents than counterfactual (unconstrained) Black residents. The model predicts that absent constraints, Black families would begin to move into all-White neighborhoods at the prevailing prices, but not enough to achieve complete integration. In column 3, the decomposition suggests that

[23] Substituting, this simplifies to an average difference in the estimated inclusive values $\sum_{j \in \mathcal{J}_c^*} \pi_{Bjt} \left(\ln \pi_{Bjt} - \ln \hat{\pi}_{Bjt}^{CF} \right) = \sum_{j \in \mathcal{J}_c^*} \pi_{Bjt} \left(\theta_{Bc(j)} - \hat{\theta}_{Bc(j)}^{CF} \right)$, weighted by the Black choice probabilities. Because the inclusive value is the expected value of the indirect utility, this is a simple quantitative measure of the welfare effects of constraints.

preferences mediate the remaining 100 log points—roughly half—of observed segregation through prices.

Both segregation and constraints vary across city and region. Low-skilled Black and White residents in cities in the Midwest—Chicago, Cincinnati, Cleveland, and Detroit—were quite segregated, reflected in the high overall divergence in column 1 of the top panel. Nonetheless, there constraints explain only a modest share of overall segregation. In contrast, constraints explain a large share of segregation for cities in the Northeast—New York and Philadelphia. Cities in the South were generally less segregated, consistent with the findings of Cutler, Glaeser, and Vigdor (1999). Correspondingly, equilibria in cities like Birmingham, Nashville, and Savannah were characterized by somewhat fewer constraints, perhaps reflecting greater segregation driven by income differences or less "necessity" for residential segregation where explicitly racist policies ensured separation in schools and public life.

One conspicuous exception in the South is Atlanta. In their case study, Cutler, Glaeser, and Vigdor (1999) recall Atlanta's repeated attempts to encode segregation into legal statute in a series of racial zoning laws. A law passed in 1913 was struck down by the Georgia Supreme Court in *Carey v. City of Atlanta (1915)*. A law passed in 1916 was among those struck down by the US Supreme Court in *Buchanan v. Warley* (1917). Atlanta passed another law in 1922,[24] another in 1929, and another in 1931 (Bayor 1988; Bayor 1996; Rothstein 2017). While the legislative efforts failed in the courts, the analysis reported in table 6 suggests that non-market constraints played an important role in explaining the high amount of segregation seen in Atlanta in 1940. The results raise the question of whether the courts really deterred the city and the citizenry from enforcing segregation in less formal ways.[25]

New Perspectives on Post-War Segregation Part of the civil rights movement of the second half of the twentieth century was meant to chip away at the explicit constraints that prevailed in the first half. *Shelly v. Kraemer* (1948) struck down racially restrictive covenants. The Fair Housing Act portion of the landmark 1968 Civil Rights Act made it illegal to discriminate on the basis of race in housing markets. The Equal Credit Opportunity Act (1974) made it illegal to discriminate on the basis of race in lending. Civil rights advanced, and racist

[24]The Whitten plan was struck down by the Georgia Supreme Court in *Bowen v. City of Atlanta (1924)*.

[25]In 1922, Atlanta elected Walter A. Sims, a well-known member of the Ku Klux Klan, as mayor (Amsterdam 2016).

collective action, institutional and otherwise, declined. Researchers have argued that the slow pace of segregation's declines since the civil rights movement owes to the persistence of decentralized White preferences for White neighborhoods.

But, racial preferences in neighborhood demand models are endogenous social interactions—the models permit multiple equilibria (Brock and Durlauf 2001). The multiplicity of equilibria raise the question: even absent constraints, does segregation reflect just preferences? The century's worth of both legal and extralegal housing choice restrictions following the Civil War can be interpreted as a mechanism for a White majority collectively selecting the more segregated equilibria among many potential outcomes. One possibility is that segregated equilibria persist even as preferences and attitudes change. To assess this possibility, I compare segregation across cities and relate segregation measured in each decade between 1960–2010 to segregation measured in 1940.[26] I estimate two sets of regression models:

$$KL_{ct} = a_t + b_t KL_{c,1940} + e_{ct} \tag{8}$$

$$KL_{ct} = c_t + d_{1t} Constraints_{c,1940} + d_{2t} Preferences_{c,1940} + u_{ct}, \tag{9}$$

where constraints and preferences are measured via the decomposition and reported in appendix table A.3.[27]

Figure 5 plots the coefficients. The solid Black series plots $\hat{b}_t$. Despite cities undergoing dramatic changes from subsequent waves of Black migration and broader trends in suburbanization, segregation is correlated over time. Each unit increase in the KL divergence in 1940 predicts a roughly 0.4 unit increase in the KL divergence during the 1960's. The effect decays to roughly half by the early aughts. However, the persistence of segregation is not driven in equal parts by constraints and preferences. The dashed green series plotting the coefficients on preferences $\hat{d}_{2t}$ has the shape resembling a typical impulse response. It starts with a similar magnitude to the coefficient on constraints, but it decays. 40 years later in 1980, $\hat{d}_{2t}$ is no longer significant, and it is very close to zero between 1990–2010. In contrast, the dashed purple series plotting the coefficients on constraints $\hat{d}_{1t}$ is larger throughout the period, and it persists. By 2010, the coefficient decays by only half, explaining the entirety of the serial correlation in segregation 70 years

[26] See appendix section E.2 for details on measuring segregation.

[27] Recall that by construction, $KL_{c,1940} = Constraints_{c,1940} + Preferences_{c,1940}$. Thus, the regression model estimated using the 1940 KL divergence as the dependent variable yields unit coefficients $\hat{b}_{1940} = \hat{d}_{1,1940} = \hat{d}_{2,1940} = 1$. In other decades, the first regression model is equivalent to the second regression model where the coefficients are constrained to be equal $d_{1t} = d_{2t}$.

later.

The result suggests that when historical segregation was reflected in the city's distribution of prices, it had less staying power. Attitudes and preferences changed, and decentralized decisions affected both prices and segregation. At the same time, constraints were cities' "big push" to more segregated equilibria. The civil rights movement and legal protections dismantled preexisting restrictions but did nothing to directly address the level of residential segregation. So as attitudes and preferences have changed, decentralized decisions were not able to by themselves provide an equal and opposite big push back to a more racially integrated equilibrium.

7 Conclusion

This paper estimates a neighborhood demand model with a research design that addresses reflection problems in estimating homophilic preferences. Analyzing sorting, the estimates suggest an important role of White homophily, but little evidence of Black homophily or differential amenity preferences. Simply, low-skilled White households were willing to pay more for neighborhoods that were more White, and all-White neighborhoods were generally more expensive as a result. However, an equilibrium decomposition of segregation suggests that the price premium of all-White neighborhoods was not enough to rationalize observed segregation, suggesting that prevalent formal and informal constraints that restricted Black residents were strongly binding.

Segregation is path dependent. Using the model decomposition as a cross-city measure of constraints, I find that cities whose segregation was driven more by constraints in 1940 are more segregated today. The results push against a simplistic view that observed segregation is an inevitable result of White preferences for White neighborhoods. But by the other side of the same token, integrated neighborhoods are not an inevitable result of improving White attitudes. Convergence from a segregated to an integrated equilibrium is not straightforward.

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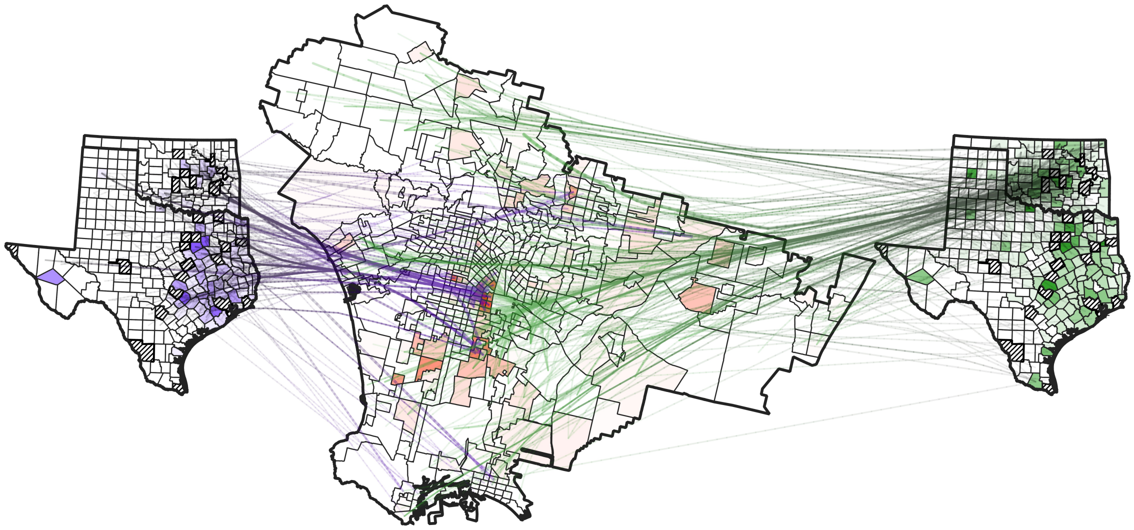
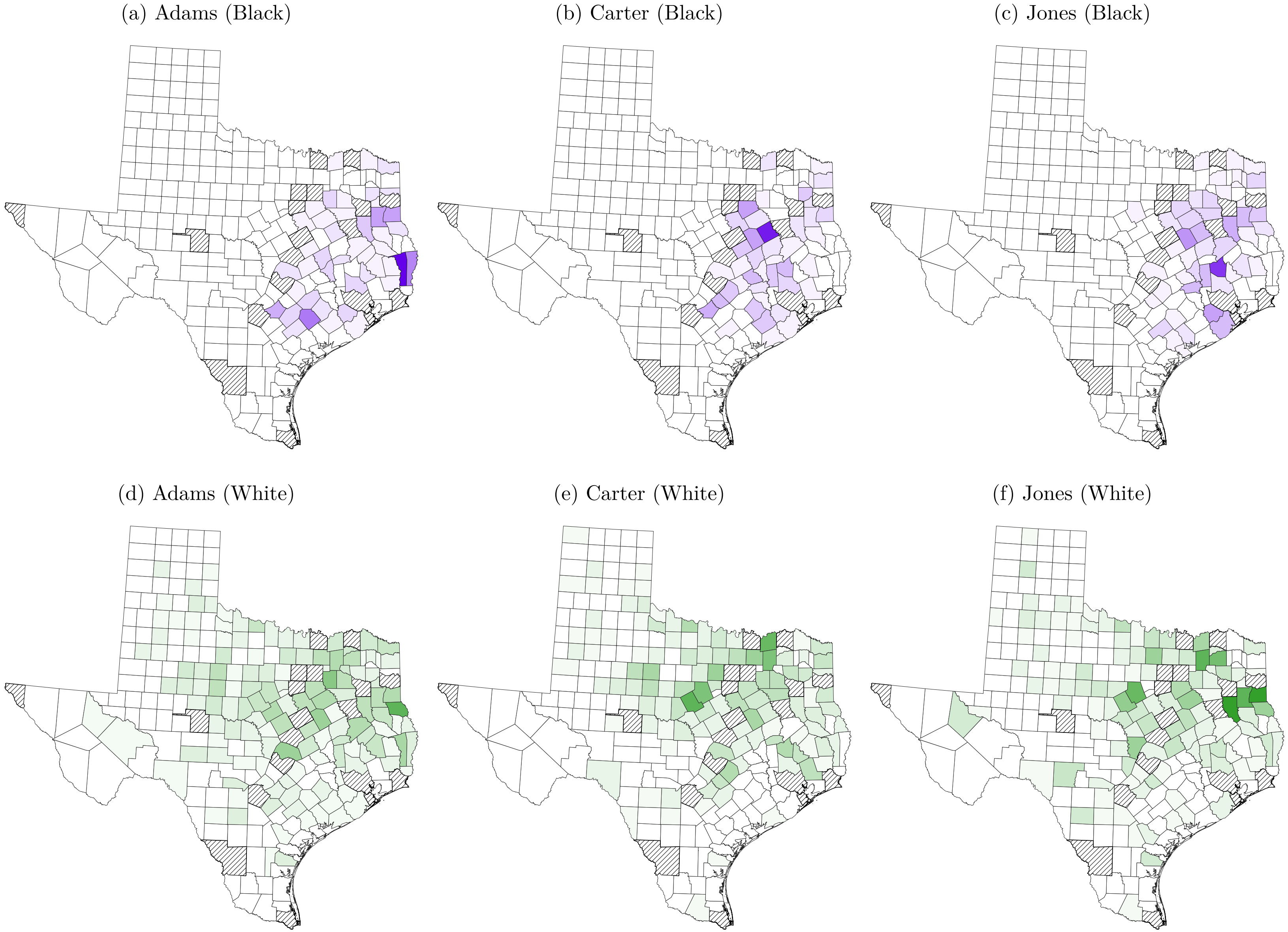
8 Figures and Tables

Figure 1: Rural-to-Urban Migrant Flows from Texas and Oklahoma to Los Angeles, 1935–1940



This figure plots the flows of Black and White migrants between 1935–1940 from Texas and Oklahoma to Los Angeles in purple and green, respectively. The flows are bundled via algorithm documented in Graser et al. (2017) using software from https://github.com/dts-ait/qgis-edge-bundling. Origin counties on the left are shaded in purple with intensity corresponding to the total outflow of Black migrants to major cities with census tracts. Origin counties on the right are shaded in green corresponding to the total outflow of White migrants to major cities with census tracts. Cross-hatched counties on the left and the right are urban counties in Texas and Oklahoma. Census tracts in Los Angeles (center) are shaded in red according to the tract share of Black residents in 1930.

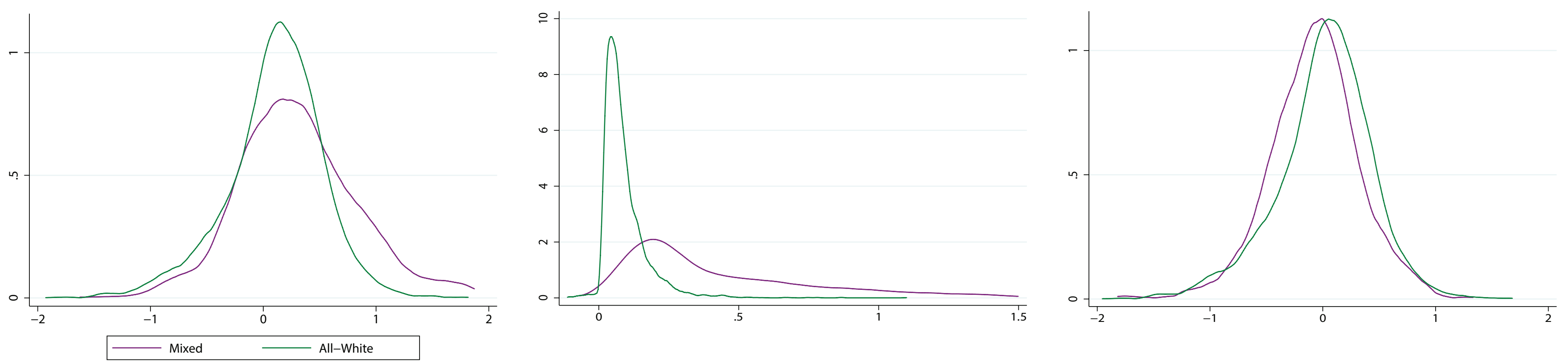
Figure 2: Geographic Distribution of Three Common Last Names in Texas



This figure plots the geographic distribution of Black (top row in purple) and White (bottom row in green) non-migrants in 1930 according to three example surnames. Cross-hatched counties are urban counties.

Figure 3: Marginal Distributions of White Amenity Preferences in Mixed and All-White Neighborhoods, Low-skilled Workers

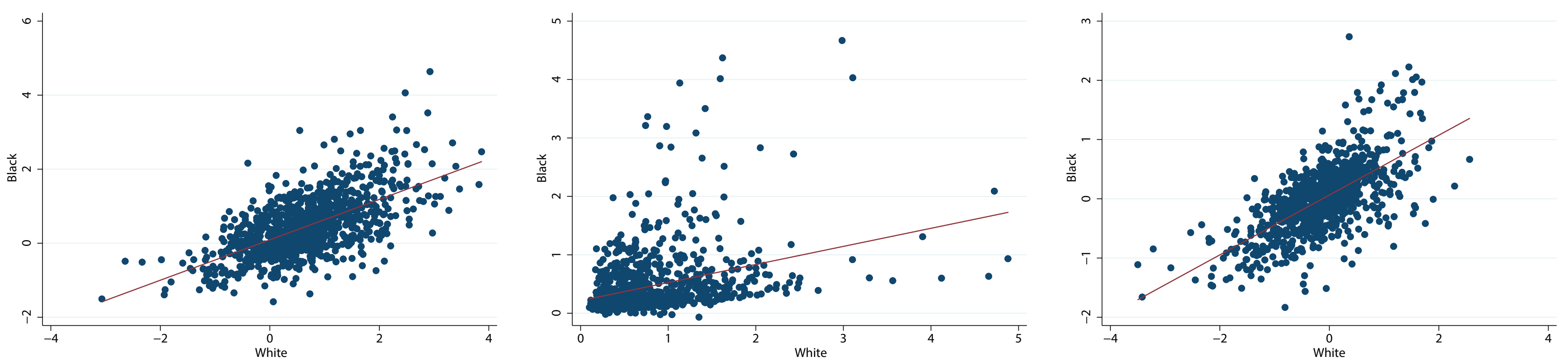
(a) Composite $\hat{\xi}_{Wj}$ (b) Observables $\hat{F}_W' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j'\right]'$ (c) Unobservables $\hat{\psi}_{Wj}$



This figure plots the marginal distributions of components of White amenity preferences $\hat{\xi}_{Wj}$ estimated in section 5. Purple and green denote the marginal distributions of $\hat{\xi}_{Wj}$ in mixed and all-White neighborhoods, respectively. Panels a, b, and c plot the composite $\hat{\xi}_{Wj}$, the portion of the random effects attributed to observables, and the portion of the random effects attributed to unobservables $\hat{\psi}_{Wj}$, respectively.

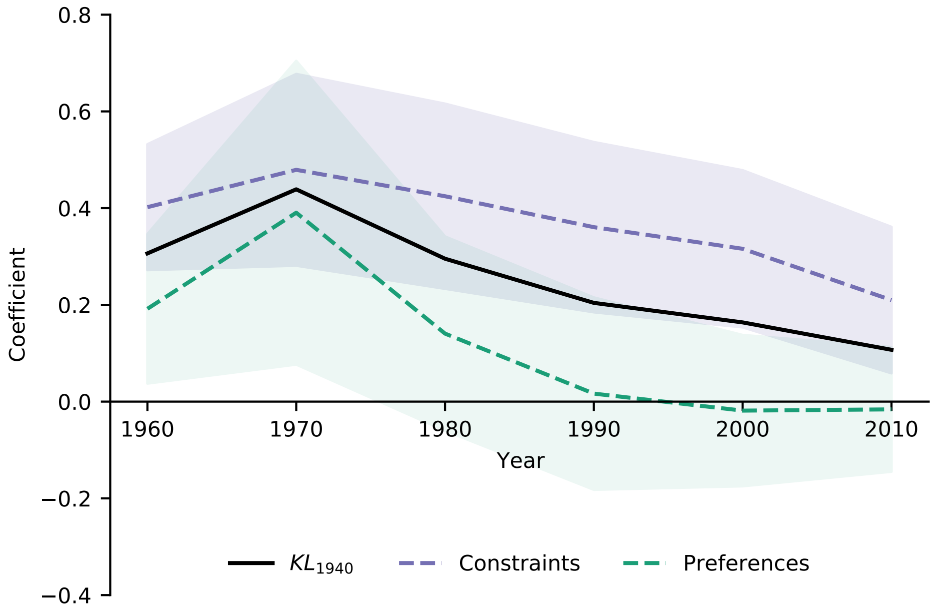
Figure 4: Joint Distribution of Black and White Amenity Preferences, Low-skilled Workers

(a) Composite $\hat{\xi}_{Wj}$ (b) Observables $\hat{F}_W' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j'\right]'$ (c) Unobservables $\hat{\psi}_{Wj}$



This figure plots the joint distributions of White amenity preferences $\hat{\xi}_{Wj}$ and Black amenity preferences $\hat{\xi}_{Bj}$ in mixed neighborhoods, estimated in section 5. Purple and green denote the marginal distributions of $\hat{\xi}_{Wj}$ in mixed and all-White neighborhoods, respectively. Panels a, b, and c plot the composite $\hat{\xi}_{Wj}$, the portion of the random effects attributed to observables, and the portion of the random effects attributed to unobservables $\hat{\psi}_{Wj}$, respectively.

Figure 5: The Origins of Modern Segregation



This figure plots the coefficients of equations 8 and 9 from section 7. Each data point in the Black line is the coefficient estimate from a bivariate regression of the KL divergence measured in the respective year and the KL divergence measured in 1940. The data points in the purple and green lines are coefficient estimates from analogous regression models where the independent variables are the decomposed constraints and preferences explanations for segregation, respectively. These measures are reported in appendix table A.3. 95% confidence intervals are shaded in purple and green, respectively. See appendix E.2 for details on measurement of the KL divergence in each decade.

Table 1: Neighborhood Characteristics of Median Black and White Families, 1940

	(1) All	(2) White	(3) Low-skilled White	(4) Black
Characteristics of Neighborhood Housing				
Median Price	3,402.3	3,500	3,037.8	2,430.2
Median Home Values (Owners)	3,500	3,500	3,000	2,700
Median Rent (Renters)	27	28	25	20
Home Ownership Rate	0.283	0.304	0.286	0.141
Characteristics of Neighbors				
Median Household Income	1,500	1,551	1,500	979
Share Employed (Head)	0.704	0.711	0.690	0.636
Share of HH Heads Employed in Low-skilled Occs	0.280	0.269	0.305	0.401
Average Years of Education of HH Head	8.357	8.506	7.949	7.050
Mean Household Size	3.607	3.590	3.677	3.763
Black Share	0.00289	0.00195	0.00180	0.730
Number of Residents	33,283,800	29,920,195	9,771,394	3,237,710

This table reports tract characteristics for the median household in the 46 major cities with census tracts in my sample. Each cell is a weighted median where the weights are the number of people in families described by the column labels. Column 1 weighs by the median household, column 2 the median White household, column 3 the median White household with a head in a low-skilled occupation, and column 4 the median Black household. The low skilled occupations are laborers, service workers, and operators. See text in section 3 for details. Median neighborhood price combines both home values and rents into a single measure. See section 3 for details.

Table 2: Regressions of 1935–1940 Flow Probabilities on Surname-Constructed Probabilities

(a) Black

	(1)	(2)	(3)	(4)	(5)
Surname-Constructed Prob.	1.979	2.001	2.035	1.952	1.999
	(0.145)	(0.144)	(0.173)	(0.176)	(0.422)
Tract(Dest) FE		✓	✓	✓	
State(Origin) × Metro(Dest) FE			✓		
County(Origin) × Metro(Dest) FE				✓	✓
State(Origin) × Tract(Dest) FE					✓
R^2	0.0996	0.121	0.126	0.166	0.271
Obs	19,185,552	19,185,552	19,185,552	19,185,552	19,166,328

(b) White

	(1)	(2)	(3)	(4)	(5)
Surname-Constructed Prob.	1.601	1.581	1.680	1.625	6.030
	(0.133)	(0.137)	(0.184)	(0.185)	(0.809)
Tract(Dest) FE		✓	✓	✓	
State(Origin) × Metro(Dest) FE			✓		
County(Origin) × Metro(Dest) FE				✓	✓
State(Origin) × Tract(Dest) FE					✓
R^2	0.187	0.200	0.211	0.270	0.444
Obs	23,126,472	23,126,472	23,126,472	23,126,472	23,116,860

This table reports coefficient estimates from regressions where the dependent variables are city-tract choice probabilities of migrants from between 1935–1940 and the independent variables are the corresponding measures constructed from city residents in 1930 and the surname distributions. See the text in section **??** for details. The top panel reports regression results for Black choice probabilities, and the bottom panel reports regression results for White choice probabilities. The unit of observation is an origin county-destination census tract pair. In both panels, each successive column reports the inclusion of additional fixed effects. Column 1 is a bivariate regression. Column 2 includes destination tract fixed effects. Column 3 adds state of origin by destination city fixed effects. Column 4 replaces those fixed effects with county of origin by destination city fixed effects. Finally, Column 5 replaces tract fixed effects with state of origin by destination tract fixed effects. The regressions are weighted by total rural-to-urban origin county migrant outflows between 1935--1940. Robust standard errors clustered by origin county are reported in parenthesis.

Table 3: Reduced Form Population Effects of Migrants

	(1) Black	(2) White	(3) Total
Coefficient Estimates			
Z_B	21.06	-31.24	-10.46
	(5.934)	(5.080)	(5.395)
Z_W	-1.866	3.461	1.218
	(0.452)	(1.785)	(1.845)
$Z_B \times s$	-18.06	36.92	19.03
	(6.453)	(5.097)	(5.796)
$Z_W \times s$	5.897	9.690	15.87
	(3.092)	(3.264)	(4.032)
Implied Effects @ $s = 0.2$			
Z_B	17.45	-23.85	-6.655
	(4.783)	(4.164)	(4.343)
Z_W	-0.687	5.399	4.391
	(0.725)	(2.035)	(2.180)
Implied Effects @ $s = 0.8$			
Z_B	6.608	-1.698	4.762
	(2.423)	(2.096)	(2.061)
Z_W	2.851	11.21	13.91
	(2.466)	(3.482)	(4.074)
Tracts	6132	6132	6132
Wald F-statistics and p-values			
All Instruments	24.73	15.33	7.683
	⟨0.000⟩	⟨0.000⟩	⟨0.000⟩
Black Effects	6.895	27.05	9.693
	⟨0.001⟩	⟨0.000⟩	⟨0.000⟩
White Effects	9.602	5.250	7.780
	⟨0.000⟩	⟨0.005⟩	⟨0.000⟩

This table reports results coefficients of regression models analogous to equations 3 and 4, except replacing the dependent variable with the neighborhood's change in Black, White, and total population between 1930–1940. The primary coefficients of interest are the main effects of Black and White demand shocks Z_B and Z_W, and the effects interacted with the 1930 Black share s_{j0}. See the text in section 4.2 for details. All equations include metropolitan area fixed effects and controls for the 1930 population, Black share, the Black and White sum of shares, and median log housing cost. The Wald test for "All Instruments" tests the joint significance of the coefficients reported in the top panel. "Black Effects" and "White Effects" test the main and interacted effects of Z_B and Z_W, respectively. Robust standard errors reported in parentheses, p-values reported in angular brackets.

Table 4: First Stage Regressions

	(1) Log Price	(2) Black Share
Coefficient Estimates		
$Z_B/1,000$	-1.486	2.899
	(0.437)	(0.365)
$Z_W/1,000$	0.0518	-0.0679
	(0.170)	(0.0370)
$Z_B/1,000 \times s$	2.557	-3.598
	(0.473)	(0.388)
$Z_W/1,000 \times s$	-1.047	-0.276
	(0.344)	(0.186)
Implied Effects @ $s = 0.2$		
$Z_B/1000$	-0.974	2.179
	(0.368)	(0.294)
$Z_W/1000$	-0.158	-0.123
	(0.168)	(0.0475)
Implied Effects @ $s = 0.8$		
$Z_B/1000$	0.560	0.0201
	(0.275)	(0.140)
$Z_W/1000$	-0.786	-0.288
	(0.288)	(0.147)
Tracts	6132	6132
Wald F-statistics and p-values		
All Instruments	19.76	35.51
	$\langle 0.000 \rangle$	$\langle 0.000 \rangle$
Black Effects	15.51	44.60
	$\langle 0.000 \rangle$	$\langle 0.000 \rangle$
White Effects	4.698	3.392
	$\langle 0.009 \rangle$	$\langle 0.034 \rangle$

This table reports results coefficients of the first stage regression models in equations 3 and 4. See the table notes from table 3 for additional information.

Table 5: The Tradeoff Between Price and Racial Composition by Broad Occupation Groups

(a) Black

	(1) Low-skilled	(2) Higher-skilled
Log Price	-1.906	-0.284
	(0.553)	(0.452)
Black Share	-0.0113	0.350
	(0.704)	(0.639)
Tracts	1087	490
Semi-Elasticity	-0.00593	1.230
	(0.368)	(4.092)

(b) White

	(1) Low-skilled	(2) Higher-skilled
Log Price	-4.109	-2.743
	(1.026)	(0.828)
Black Share	-3.982	-2.134
	(1.109)	(0.928)
Tracts	5750	6015
Semi-Elasticity	-0.969	-0.778
	(0.143)	(0.187)

This table reports the two-sample 2SLS structural estimates of the demand parameters in equation 5. The top panel reports estimates for Black families, and the bottom panel reports estimates for White families. In each panel, the first column reports estimates separately for low-skilled families and higher-skilled families. Low-skilled families are those whose head is a laborer, service worker, or operator; higher-skilled families are all other families. See text in section 3 for details. The first stage regressions are reported in table 4. Robust standard errors adjusted for the two-step procedure according to Pacini and Windmeijer (2016) are reported in parentheses. The compensated semi-elasticities are computed as the ratio of the coefficient on neighborhood Black share and the coefficient on neighborhood log price, interpreted as the percentage change in housing costs needed to offset a 1 p.p. increase in the Black share and keep an average household indifferent. Standard errors are computed using the delta method.

Table 6: Decomposition of Segregation of Low-skilled Families, Cities with Large Black Population

	(1)	(2)	(3)	(4)	(5)
	Overall	Constraints	Preferences	Constraints	Black Population
	(KL Divergence Components)			(Percent of Overall KL)	(Thousands)
Atlanta, GA	2.69	1.53	1.17	56.7%	136
Baltimore, MD	2.08	0.65	1.43	31.2%	174
Birmingham, AL	0.99	0.13	0.86	13.1%	178
Chicago, IL	5.26	1.46	3.80	27.8%	322
Cincinnati, OH	2.78	0.74	2.04	26.5%	68
Cleveland, OH	3.53	0.96	2.57	27.3%	87
Dallas, TX	1.53	0.42	1.11	27.7%	90
Detroit, MI	2.79	1.15	1.65	41.1%	165
Houston, TX	1.97	0.31	1.66	15.6%	104
Los Angeles, CA	3.12	1.21	1.91	38.9%	75
Louisville, KY	1.96	0.81	1.15	41.4%	53
Memphis, TN	0.89	0.12	0.76	14.0%	155
Nashville, TN	1.19	0.29	0.90	24.5%	57
New Orleans, LA	1.29	0.31	0.98	24.3%	155
New York, NY	2.39	1.88	0.51	78.5%	634
Philadelphia, PA	1.41	0.91	0.50	64.6%	310
Pittsburgh, PA	1.86	1.01	0.85	54.4%	96
Richmond, VA	0.69	0.20	0.49	29.3%	74
Savannah, GA	1.46	0.32	1.15	21.6%	52
St. Louis, MO	2.20	1.01	1.19	45.9%	145
Washington, DC	0.96	0.29	0.68	29.8%	225
Avg., All Cities	2.24	1.10	1.14	49.1%	
Wgt. Avg., All Cities	2.19	0.98	1.21	44.5%	
Wgt. Avg., Cities w/ Black Pop > 50k	2.05	0.97	1.25	43.6%	

This table reports the decomposition of the KL divergence. Column 1 reports the KL divergence between low-skilled Black and White families. Columns 2 and 3 decompose the KL divergence into constraints and preferences explanations from equation 7, respectively. Column 4 reports the percentage of the KL divergence explained by constraints divided by the overall KL divergence. Column 5 reports the city's Black population. The top panel reports measures separately for cities with at least 50,000 Black residents in 1940. The first three columns of the bottom panel report averages. The first row averages over all 46 cities in the analysis sample. The second row weights those averages by the city's Black population. The third row limits the weighted average to the 21 cities reported in panel A with at least 50,000 Black residents. The percentage of segregation explained by segregation in the fourth column in the bottom panel is not an average. It is recomputed using the averages in the first three columns. See appendix table A.3 for decompositions of all 46 cities.

Appendix for Online Publication

A Appendix Tables

Table A.1: Occupation Distribution by Race, 1940

	(1) Black	(2) White
All Households (thousands)	789	8,358
...with employed male head of household, age 18–55,	488	5,350
... with wife and at least one child	213	3,343
... in tracts with at least 10 with same occ. × race	208	3,341
Broad Occupation Shares		
Low-skilled Occupations		
Laborers	46.4	9.4
Services	21.6	6.7
Operators	18.4	22.6
Other Occupations		
Craftsmen	7.8	23.0
Clerical	2.6	7.9
Professional	1.5	6.1
Sales	1.1	12.2
Managers	0.7	12.2

The top panel reports counts of households (in thousands) living in one of 46 tracted metropolitan areas in 1940. The bottom panel reports the shares of families (a cohabiting husband, wife, and child) living in tracts with at least 10 other families of the same broad occupation and race in both 1930 and 1940.

Table A.2: Scaled Covariances of Correlated Random Effects

	(1) Low-skilled	(2) Higher-skilled
Estimated Covariances and {Correlations}		
σ_B^2	0.494	0.235
	{0.776}	{0.703}
σ_W^2	0.855	0.855
	{0.775}	{0.820}
σ_{BW}	0.449	0.153
	{0.538}	{0.262}
Covariances with $\bar{\xi}_{Wj}$, Raw and [Scaled]		
Composite $\bar{\xi}_{Bj}$	0.650	0.145
	[0.531]	[0.128]
Observables $F_B' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j'\right]'$	0.201	-0.00774
	[0.164]	[-0.00683]
Unobservables ψ_{Bj}	0.449	0.153
	[0.367]	[0.135]
Tracts	915	396

This table summarizes parameters of the correlated random effects. In each panel, the first column reports estimates for low-skilled families, and the second column reports estimates for higher skilled families. See the notes to table 5 for details. The top panel reports estimates of the variance terms of ψ_{rj} from equation. The first line in each cell is the point estimate of the variance, and the second line in each row is the correlation coefficient between the two residuals from which the variance is estimated. The first row is the covariance for Black families, and the second row is the covariance for White families. Each term is identified from cross-decadal correlation in the residuals. The third row reports the covariance estimate between ψ_{Bj} and ψ_{Wj}, the average of the the covariance between the 1930 Black residual and 1940 White residual and the 1940 Black residual and the 1930 White residual and the 1940 Black residual. See section 5 for details and the formulas. The bottom panel reports the covariances of the Black composite correlated random effect $\bar{\xi}_{Bj}$, its observable component $F_B' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j'\right]'$, and its unobservable component ψ_{Bj} with the composite correlated random effect for White families $\bar{\xi}_{Wj}$. The top number is the raw covariance, and the bottom number scales the raw covariance by the estimate of $\boldsymbol{Var}\left[\bar{\xi}_{Wj}\right]$, reflecting an implied regression coefficient. The parameters are estimated on the subset of tracts for which there are both Black and White residuals.

Table A.3: Decomposition of Segregation of Low-skilled Families, All Cities

	KL Divergence		
	Overall	Constraints	Preferences
Akron, OH	1.49	1.03	0.46
Atlanta, GA	2.69	1.53	1.17
Atlantic City, NJ	2.02	1.25	0.77
August, GA/SC	1.52	0.22	1.30
Austin, TX	1.35	0.19	1.16
Baltimore, MD	2.08	0.65	1.43
Beaumont, TX	0.00	0.09	-0.09
Birmingham, AL	0.99	0.13	0.86
Boston, MA	3.25	2.07	1.17
Buffalo, NY	2.74	1.66	1.08
Chicago, IL	5.26	1.46	3.80
Cincinnati, OH	2.78	0.74	2.04
Cleveland, OH	3.53	0.96	2.57
Columbus, OH	1.80	0.67	1.13
Dallas, TX	1.53	0.42	1.11
Dayton, OH	2.19	1.17	1.02
Denver, CO	2.89	0.23	2.65
Des Moines, IA	2.32	1.42	0.91
Detroit, MI	2.79	1.15	1.65
Flint, MI	2.33	1.95	0.38
Hartford, CT	2.71	1.60	1.11
Houston, TX	1.97	0.31	1.66
Los Angeles, CA	3.12	1.21	1.91
Louisville, KY	1.96	0.81	1.15
Macon, GA	0.28	0.11	0.17
Memphis, TN	0.89	0.12	0.76
Milwaukee, WI	3.69	2.00	1.69
Minneapolis-St. Paul, MN	3.61	1.89	1.72
Nashville, TN	1.19	0.29	0.90
New Haven, CT	3.31	1.98	1.33
New Orleans, LA	1.29	0.31	0.98
New York, NY	2.39	1.88	0.51
Oklahoma City, OK	2.08	0.74	1.34
Philadelphia, PA	1.41	0.91	0.50
Pittsburgh, PA	1.86	1.01	0.85
Providence, RI	2.17	1.94	0.23
Richmond, VA	0.69	0.20	0.49
Rochester, NY	3.60	3.08	0.52
San Francisco, CA	3.01	2.18	0.83
Savannah, GA	1.46	0.32	1.15
Seattle, WA	4.44	2.58	1.86
St. Louis, MO	2.20	1.01	1.19
Syracuse, NY	2.92	2.71	0.21
Toledo, OH	2.94	1.28	1.66
Trenton, NJ	1.33	0.83	0.50
Washington, DC	0.96	0.29	0.68

This table reports decomposition results for all 46 cities. Column 1 reports the overall KL divergence between low-skilled Black and White families.

B Controlling for the sum of shares

Proposition 1 (Conditional independence)**.** *Under assumption 3, if $\boldsymbol{X}_j$ includes the sum of shares then $Z_{rj} \perp \Delta\xi_{r'j}|\boldsymbol{X}_j \quad \forall r, r'$.*

Proof. Consider $\hat{\pi}_{rgj0} = \frac{Q_{rgj0}}{M_{rg}}$, where Q_{rgj0} is the number of migrants of race r from origin g that choose neighborhood j in the base period, and the denominator is the total number of outmigrants of race r from origin g. The numerator is a binomially distributed random variable $Q_{rgj0} \sim Binom\left(M_{rg}, \pi_{rgj0}\right)$. By iterated expectations, $\boldsymbol{E}\left[Q_{rgj0}|\pi_{rj0}\right] = M_{rg}\pi_{rj0}\boldsymbol{E}\left[\exp \eta_{rgj0}\right]$.

For large numbers of *migrants* M_{rg}, $\hat{\pi}_{rgj0} \xrightarrow{d} \mathcal{N}\left[\pi_{rgj0}, \pi_{rgj0}\left(1-\pi_{rgj0}\right)\right]$ by the central limit theorem. Thus, one can view, $\left\{\hat{\pi}_{rgj0}\right\}|\pi_{rj0} \overset{iid}{\sim} \mathcal{N}\left[\pi_{rj0}\boldsymbol{E}\left[\exp \eta_{rgj0}\right], \pi_{rj0}\boldsymbol{E}\left[\exp \eta_{rgj0}\right]\left(1 - \pi_{rj0}\boldsymbol{E}\left[\exp\right.\right.\right.$ Correspondingly, it follows immediately that $SOS_{rj} \equiv \sum_g \hat{\pi}_{rgj0}$ is a sufficient statistic for π_{rj0} from the well-known result that the sample average (*over origins* g) is sufficient for the population mean of a normally distributed random variable, $\pi_{rj0} \perp \pi_{rgj0}|SOS_{rj}$.

Fix r'. Since $Z_{rj} = \sum_g M_{rg}^{-c}\hat{\pi}_{rgj0}$, it is sufficient to show that $\Delta\xi_{r'j} \perp \hat{\pi}_{rgj0}|SOS_{rj}$ for some arbitrary g. Thus, abusively denoting densities as $\Pr\left[\cdot\right]$,

$$\begin{aligned}
\Pr\left[\Delta\xi_{r'j}, \pi_{rgj0}|SOS_{rj}\right] &= \Pr\left[\Delta\xi_{r'j}|\hat{\pi}_{rgj0}, SOS_{rj}\right]\Pr\left[\pi_{rgj0}|SOS_{rj}\right] \\
&= \left(\int \Pr\left[\Delta\xi_{r'j}|\pi_{rgj}, \cancel{\hat{\pi}_{rgj0}}, SOS_{rj}\right]\Pr\left[\pi_{rgj}|\cancel{\hat{\pi}_{rgj0}}, SOS_{rj}\right]d\pi_{rgj}\right)\Pr\left[\pi_{rgj0}|SOS_{rj}\right] \\
&= \Pr\left[\Delta\xi_{r'j}|SOS_{rj}\right]\Pr\left[\pi_{rgj0}|SOS_{rj}\right]
\end{aligned}$$

where the last line follows from $\hat{\pi}_{rgj0}|\pi_{rj0}$ independent $\forall g$ and ς_{rj} being sufficient for π_{rj0}. □

See Li (2021) for additional examples and discussion.

C Theoretical effects of migrants on neighborhood equilibria

The comparative statics in this section analyze migrants' equilibrium effects on population and price. The analysis does not preclude the existence of multiple equilibria (Brock and Durlauf 2002). It studies how existing equilibria may change under small perturbations.

C.1 Setup

Recall from the text that i indexes households, $r(i)$ indexes the household's race, $g(i)$ indexes their county of origin, j indexes neighborhoods in city c, and t indexes time. For notational simplicity, I omit city and time indices, but all expressions can be viewed as comparisons of the same neighborhood over time.

Let total population be the sum of the Black and White population $Q_j = Q_{Bj} + Q_{Wj}$. Whereas *neighborhood* populations are denoted using Q, the *city* populations are given by N. Neighborhood populations are given by the product of the city population and neighborhood choice probabilities: $Q_{rj} = N_r \pi_{rj}$. Continuing to abuse notation, the Black and White populations themselves are the sum of group-specific populations $Q_{Bj} = \sum_g Q_{Bgj}$ and $Q_{Wj} = \sum_g Q_{Wgj}$. Further, define the neighborhood-specific elasticity as $\lambda_j(Q_j) \equiv \frac{\partial \ln P_j}{\partial \ln Q_j}$.

For convenience, I repeat the assumptions made in the text:

Assumption 1 (Multinomial logit). *ε_{ijt} is an i.i.d. draw from a standard extreme-value type I distribution*

Assumption 2 (Linearity in parameters). *Race-specific mean utilities can be written linearly as*

$$\delta_{rjt} = \beta_r \ln P_{jt} + \gamma_r s_{jt} + \xi_{rjt}$$

where P_{jt} is the local price of housing in neighborhood j, s_{jt} is the Black share of the neighborhood, and ξ_{rjt} is a residual that summarizes preferences over local amenities (e.g. parks or good schools) and disamenities (e.g. pollution).

Assumption 3 (Decomposition of multinomial logit variance components). *The i.i.d. extreme value error ε_{ijt} can be decomposed into $\varepsilon_{ijt} = \eta_{r(i),g(i),jt} + \tilde{\varepsilon}_{ijt}$, where $\tilde{\varepsilon}_{ijt}$ is distributed extreme value type I and η_{rgjt} is distributed according to the appropriately scaled and parameterized distribution formalized in Cardell (1997).*

Assumption 3 implies that migrants from origins g have affinities for particular neighborhoods, $\ln \pi_{rgj} = \ln \pi_{rj} + \eta_{rgj}$. These affinities form an important part of the identifying variation. Correspondingly, neighborhood populations are given by $Q_{rj} = \sum_g Q_{rgj} = \sum_g N_{rg} \pi_{rgj}$. Applying the notation, the choice probabilities are given by $\pi_{rgj} = \frac{Q_{rgj}}{N_{rg}}$, and the neighborhood Black share is given by $s_j = \frac{Q_{Bj}}{Q_j}$.

For the theoretical analysis, I define "exogenous" migrant flows as a unit increase in the stock of group-specific population dN_{rg} of the city. The effect of an exogenous migrant on a neighborhood's log prices is given by

$$\begin{aligned} \frac{\partial \ln P_j}{\partial N_{rg}} &= \lambda_j(Q_j) \frac{\partial \ln Q_j}{\partial N_{rg}} \\ &= \frac{\lambda_j(Q_j)}{Q_j} \frac{\partial Q_j}{\partial N_{rg}} \end{aligned}$$

The simple supply specification suggests that price effects roughly trace out population effects, which I develop in the remainder of this appendix. The effect of an exogenous migrant on the neighborhood Black share is given by

$$\frac{\partial s_j}{\partial N_{rg}} = \frac{1}{Q_j}\left(\frac{\partial Q_{Bj}}{\partial N_{rg}} - s_j \frac{\partial Q_j}{\partial N_{rg}}\right)$$

Hereafter, I focus on a single neighborhood and hold constant local amenities ξ and the inclusive value θ. Throughout the theoretical analysis, I use the following shorthand for notational convenience. First, I suppress the neighborhood index j. Second, I suppress the supply elasticity's dependence on population $\lambda \equiv \lambda(Q)$.

One useful result is simply examining the effect of an exogenous migrant on the race-specific choice probabilities.

Lemma 1. *The effect of an exogenous migrant of race r' from origin g on the neighborhood choice probabilities of race r is given by*

$$\frac{\partial \ln \pi_r}{\partial N_{r'g}} = \frac{1}{Q}\left[\left(\beta_r\lambda - \gamma_r s\right)\frac{\partial Q_W}{\partial N_{r'g}} + \left(\beta_r\lambda + \gamma_r\left(1-s\right)\right)\frac{\partial Q_B}{\partial N_{r'g}}\right]$$

Proof.

$$\begin{aligned}
\frac{\partial \ln \pi_r}{\partial N_{r'g}} &= \frac{\partial\left(\beta_r \ln P + \gamma_r s\right)}{\partial N_{r'g}} \\
&= \beta_r \frac{Q}{Q}\frac{\partial \ln P}{\partial Q}\frac{\partial Q}{\partial N_{r'g}} + \gamma_r \frac{\partial\left(\frac{Q_B}{Q}\right)}{\partial N_{r'g}} \\
&= \beta_r \frac{1}{Q}\frac{\partial \ln P}{\partial \ln Q}\frac{\partial Q}{\partial N_{r'g}} + \gamma_r \frac{Q\frac{\partial Q_B}{\partial N_{Bg}}}{Q^2} - \gamma_r \frac{Q_B \frac{\partial Q}{\partial N_{r'g}}}{Q^2} \\
&= \beta_r \frac{1}{Q}\lambda \frac{\partial Q}{\partial N_{r'g}} + \gamma_r \frac{\frac{\partial Q_B}{\partial N_{r'g}}}{Q} - \gamma_r s \frac{\frac{\partial Q}{\partial N_{r'g}}}{Q} \\
&= \left(\beta_r \frac{1}{Q}\lambda - \frac{\gamma_r s}{Q}\right)\frac{\partial Q}{\partial N_{r'g}} + \frac{\gamma_r}{Q}\frac{\partial Q_B}{\partial N_{r'g}} \\
&= \left(\beta_r \frac{1}{Q}\lambda - \frac{\gamma_r s}{Q}\right)\left(\frac{\partial Q_W}{\partial N_{r'g}} + \frac{\partial Q_B}{\partial N_{r'g}}\right) + \frac{\gamma_r}{Q}\frac{\partial Q_B}{\partial N_{r'g}} \\
&= \frac{1}{Q}\left\{\left(\beta_r\lambda - \gamma_r s\right)\frac{\partial Q_W}{\partial N_{r'g}} + \left[\beta_r\lambda + \gamma_r\left(1-s\right)\right]\frac{\partial Q_B}{\partial N_{r'g}}\right\}
\end{aligned}$$

□

C.2 Population effects of migrants

Because price effects of migrants trace out population effects of migrants, this section derives expressions for the population effects of migrants.

C.2.1 The effect of a Black migrant

Here, I derive the effect of a Black migrant on the White and Black populations, respectively. Prior to applying lemma 1, one can write

$$\begin{aligned}\frac{\partial Q_W}{\partial N_{Bg}} &= \frac{\partial \left(N_W \pi_W\right)}{\partial N_{Bg}} \\ &= N_W \frac{\partial \pi_W}{\partial N_{Bg}} \\ &= N_W \pi_W \frac{\partial \ln \pi_W}{\partial N_{Bg}} \\ &= Q_W \frac{\partial \ln \pi_W}{\partial N_{Bg}}\end{aligned}$$

and

$$\begin{aligned}\frac{\partial Q_B}{\partial N_{Bg}} &= \frac{\partial \left(\sum_{g'} N_{Bg'} \pi_{Bg}\right)}{\partial N_{Bg}} \\ &= \pi_{Bg} + N_B \frac{\partial \pi_{Bg}}{\partial N_{Bg}} + \sum_{g' \neq g} N_{Bg'} \frac{\partial \pi_{Bg'}}{\partial N_{Bg}} \\ &= \pi_{Bg} + N_{Bg} \pi_{Bg} \frac{\partial \ln \pi_{Bg}}{\partial N_{Bg}} + \sum_{g' \neq g} N_{Bg'} \pi_{Bg'} \frac{\partial \ln \pi_{Bg'}}{\partial N_{Bg}} \\ &= \pi_{Bg} + Q_{Bg} \frac{\partial \left(\ln \pi_B + \eta_{Bg}\right)}{\partial N_{Bg}} + \sum_{g' \neq g} Q_{Bg'} \frac{\partial \ln \pi_{Bg'}}{\partial N_{Bg}} \\ &= \pi_{Bg} + Q_B \frac{\partial \ln \pi_B}{\partial N_{Bg}}.\end{aligned}$$

The migrant enclave instrument emerges naturally from the model. Group-specific affinities for particular neighborhoods η_{Bg} are embedded in π_{Bg} in the fourth and fifth lines, forming an important source of identifying information (see appendix B).

Inserting lemma 1 yields:

$$\begin{aligned}\frac{\partial Q_W}{\partial N_{Bg}} &= Q_W \frac{\partial \ln \pi_W}{\partial N_{Bg}} \\ &= (1-s)\left\{\left(\beta_W \lambda - \gamma_W s\right) \frac{\partial Q_W}{\partial N_{Bg}} + \left[\beta_W \lambda + \gamma_W (1-s)\right] \frac{\partial Q_B}{\partial N_{Bg}}\right\}\end{aligned}$$

$$\left[1 - \beta_W \lambda (1-s) + \gamma_W s (1-s)\right] \frac{\partial Q_W}{\partial N_{Bg}} = \left[\beta_W \lambda + \gamma_W (1-s)\right] (1-s) \frac{\partial Q_B}{\partial N_{Bg}} \tag{10}$$

and

$$\begin{aligned}
\frac{\partial Q_B}{\partial N_{Bg}} &= \pi_{Bg} + Q_B \frac{\partial \ln \pi_B}{\partial N_{Bg}} \\
&= \pi_{Bg} + s \left\{ \left(\beta_B \lambda - \gamma_B s\right) \frac{\partial Q_W}{\partial N_{Bg}} + \left[\beta_B \lambda + \left(1 - s\right) \gamma_B\right] \frac{\partial Q_B}{\partial N_{Bg}} \right\} \\
\left[1 - \beta_B \lambda s - \gamma_B s \left(1 - s\right)\right] \frac{\partial Q_B}{\partial N_{Bg}} &= \pi_{Bg} + \left(\beta_B \lambda - \gamma_B s\right) s \frac{\partial Q_W}{\partial N_{Bg}}. \qquad (11)
\end{aligned}$$

Black migrants' first order effect π_{Bg} has a first order effect on the White population. The first order effect on the White population is amplified by a multiplier. The adjustment of the White population has a corresponding effect on the Black population, which is also amplified by a multiplier. Equilibrium is determined as the solution of the system of differential equations in equations 10 and 11.

However, if $1 - \beta_W \lambda (1 - s) + \gamma_W s (1 - s) < 0$ (or $1 - \beta_B \lambda s - \gamma_B s (1 - s) < 0$ for White migrant shocks), the initial conditions are necessarily not stable. In the second line of each expression, one can see growing cascading effects. For instance, suppose $\gamma_B = \beta_B = 0$. The initial change in the neighborhood's Black population from the migrant increases the neighborhood's Black share. If $\gamma_W \leq 0$ and $\beta_W \leq 0$, White residents leave, further increasing the neighborhood's Black share. More White residents leave with each subsequent round larger than the previous.

The "initial" equilibria I observe in 1930 are unlikely to be unstable since any perturbation would result cascading effects toward a stable equilibrium. I generate predictions for stable equilibria, defined as follows:

Definition 1. Let

$$\mu(s) = \frac{1}{1 - \lambda\left[\beta_B s + \beta_W (1 - s)\right] - \left(\gamma_B - \gamma_W + \lambda \beta_B \gamma_W - \lambda \beta_W \gamma_B\right) s (1 - s)}.$$

A neighborhood equilibrium is *stable* if

1. $\mu(s) \geq 0$
2. $1 - \beta_W \lambda (1 - s) + \gamma_W s (1 - s) \geq 0$
3. $1 - \beta_B \lambda s - \gamma_B s (1 - s) \geq 0$.

The analysis considers small migrant shocks dN_{rg}, and I define stability so that neighborhoods are robust to such small shocks. However, large migrant shocks may perturb "near"-unstable neighborhoods beyond the domain of stability (Card, Mas, and Rothstein 2008; Schelling 1971).

Some algebra yields the solution to the simple linear differential equation system.

Lemma 2. *The effect of an exogenous Black migrant from origin g on the populations of stable neighborhood equilibria is given by*

1. $\frac{\partial Q_W}{\partial N_{Bg}} = \mu(s)(1-s)[\lambda\beta_W + \gamma_W(1-s)]\pi_{Bg}$
2. $\frac{\partial Q_B}{\partial N_{Bg}} = \mu(s)[1-\lambda\beta_W(1-s)+\gamma_W s(1-s)]\pi_{Bg}$
3. $\frac{\partial Q}{\partial N_{Bg}} = \mu(s)[1+\gamma_W(1-s)]\pi_{Bg}$

Proof. For simplicity, define:

$$
\begin{aligned}
a_W &= 1-\beta_W\lambda(1-s)+\gamma_W s(1-s) \\
b_W &= [\beta_W\lambda+\gamma_W(1-s)](1-s) \\
a_B &= 1-\beta_B\lambda s-\gamma_B s(1-s) \\
b_B &= (\beta_B\lambda-\gamma_B s)s
\end{aligned}
$$

such that the linear system of differential equations can be expressed as

$$
\begin{aligned}
a_W\frac{\partial Q_W}{\partial N_{Bg}} &= b_W\frac{\partial Q_B}{\partial N_{Bg}} \\
a_B\frac{\partial Q_B}{\partial N_{Bg}} &= \pi_{Bg}+b_B\frac{\partial Q_W}{\partial N_{Bg}}.
\end{aligned}
$$

Substituting and solving yields

$$
\begin{aligned}
\frac{\partial Q_W}{\partial N_{Bg}} &= \frac{b_W}{a_B a_W-b_B b_W}\pi_{Bg} \\
\frac{\partial Q_B}{\partial N_{Bg}} &= \frac{a_W}{a_B a_W-b_B b_W}\pi_{Bg},
\end{aligned}
$$

and the desired expressions can be obtained by substituting and simplifying.

For interested readers, I reproduce the algebra below. Further define:

$$
\begin{aligned}
c_W &= \beta_W\lambda(1-s) \\
d_W &= \gamma_W(1-s) \\
c_B &= \beta_B\lambda s \\
d_B &= \gamma_B s
\end{aligned}
$$

to obtain simplified expressions

$$
\begin{aligned}
a_W &= 1 - c_W + d_W s \\
b_W &= c_W + d_W (1-s) \\
a_B &= 1 - c_B - d_B (1-s) \\
b_B &= c_B - d_B s.
\end{aligned}
$$

Thus,

$$
\begin{aligned}
a_B a_W - b_B b_W =& (1 - c_W + s d_W) [1 - c_B - d_B (1-s)] \\
& - [c_W + (1-s) d_W] (c_B - d_B s) \\
=& 1 - c_B - d_B (1-s) - c_W + \cancel{c_W c_B} + c_W d_B (1 - \cancel{s}) + s d_W - \cancel{s c_B d_W} \\
& - \cancel{d_W d_B s (1-s)} - \cancel{c_W c_B} + \cancel{c_W d_B s} - c_B d_W (1 - \cancel{s}) + \cancel{d_B d_W s (1-s)} \\
=& 1 - c_B - c_W - d_B (1-s) + s d_W - c_B d_W + c_W d_B \\
=& 1 - \lambda \beta_B s - \lambda \beta_W (1-s) - \gamma_B s (1-s) + \gamma_W s (1-s) \\
& - \lambda \beta_B \gamma_W s (1-s) + \lambda \beta_W \gamma_B s (1-s) \\
=& 1 - \lambda \beta_B s - \lambda \beta_W (1-s) - s (1-s) (\gamma_B - \gamma_W + \lambda \beta_B \gamma_W - \lambda \beta_W \gamma_B) .
\end{aligned}
$$

□

Each effect has a different social multiplier (Glaeser, Sacerdote, and Scheinkman 2003). The effect on the White population is the product of the first order response ($(1-s)[\beta_W \lambda + \gamma_W (1-s)]$) to a Black migrant ($\pi_{Bg} dN_{Bg}$) amplified as the neighborhood's local prices and racial composition shift toward equilibrium ($\mu(s)$). The first order effect on the local Black population is the migrant themself ($\pi_{Bg} dN_{Bg}$). Note that the corresponding social multiplier ($\mu(s)\{1 - \beta_W \lambda (1-s) + \gamma_W s (1-s)\}$) naturally equals 1 if Black residents' preferences are not governed by prices or racial composition, $\beta_B = \gamma_B = 0$. The effect on the neighborhood's total population is the sum of the effects.

C.2.2 The effect of a White migrant

The derived effects of White migrants mirror the effects of Black migrants.

Lemma 3. *The effect of an exogenous White migrant from origin g on the populations of stable neighborhood equilibria is given by*

1. $\frac{\partial Q_W}{\partial N_{Wg}} = \mu(s) [1 - \beta_B \lambda s - \gamma_B s (1-s)] \pi_{Wg}$
2. $\frac{\partial Q_B}{\partial N_{Wg}} = \mu(s) [s (\beta_B \lambda - \gamma_B s)] \pi_{Wg}$
3. $\frac{\partial Q}{\partial N_{Wg}} = \mu(s) (1 - \gamma_B s) \pi_{Wg}$

C.3 Heterogeneity of migrant effects on neighborhood prices

To apply the lemmas, I make several mild equilibrium assumptions.

Assumption 4 (Equilibrium assumptions)**.**

1. *All else constant, an (inverse) neighborhood housing supply relationship slopes upward with respect to the local population,* $\lambda_j > 0$.

2. *Demand slopes downward:* $\beta_W, \beta_B \leq 0$.

3. *White residents weakly prefer White neighborhoods* $\gamma_W \leq 0$*, and Black residents weakly prefer Black neighborhoods* $\gamma_B \geq 0$.

Here, I lay out the arguments for the remarks in the main text, straightforward implications from inspection of lemmas 2 and 3 under assumption 4.

Remark 1. Under assumptions 1–4, migrants' population effects are always offsetting.

1. A Black migrant increases the local Black population $\frac{\partial Q_B}{\partial N_{Bg}} > 0$ and decreases the local White population $\frac{\partial Q_W}{\partial N_{Bg}} < 0$.

2. A White migrant increases the local White population $\frac{\partial Q_W}{\partial N_{Wg}} > 0$ and decreases the local Black population $\frac{\partial Q_B}{\partial N_{Wg}} > 0$.

Remark 2. Under assumptions 1–4, if White preferences for White neighborhoods are particularly strong $\gamma_W \leq -1$, the total population and price declines in response to a Black migrant in stable, White neighborhoods. Similarly, if Black preferences for Black neighborhoods is particularly strong $\gamma_B \geq 1$, the total population and price declines in response to a White migrant in stable, Black neighborhoods. However, effect heterogeneity with respect to the neighborhood Black share crosses from positive to negative at most once. That crossing point is given by $s_B^* = \frac{1+\gamma_W}{\gamma_W}$ for Black migrants' effects and $s_W^* = \frac{1}{\gamma_B}$ for White migrants' effects.

Proof. Remark 2 is an immediate implication of the focus on stable neighborhoods where $\mu(s) > 0$ by definition. Applying lemmas 2 and 3, note that

1.

   (a) If $\gamma_W \in [-1, 0]$ then $\frac{\partial Q}{\partial N_{Bg}} > 0 \ \forall s$.

   (b) If $\gamma_W < -1$ then $\frac{\partial Q}{\partial N_{Bg}} \leq 0$ for $s \leq \frac{1+\gamma_W}{\gamma_W}$ and $\frac{\partial Q}{\partial N_{Bg}} > 0$ for $s > \frac{1+\gamma_W}{\gamma_W}$

2.

   (a) If $\gamma_B \in [0, 1]$ then $\frac{\partial Q}{\partial N_{Wg}} > 0 \ \forall s$.

   (b) If $\gamma_B > 1$ then $\frac{\partial Q}{\partial N_{Wg}} \geq 0$ for $s \leq \frac{1}{\gamma_B}$ and $\frac{\partial Q}{\partial N_{Wg}} < 0$ for $s > \frac{1}{\gamma_B}$

□

As γ_W decreases to $\gamma_W < -1$, neighborhoods with increasing Black shares would suffer population and price declines as result of migration. However, under such preferences, there would be fewer of these neighborhoods since the equilibria would likely not be stable. Similar implications follow for neighborhoods with decreasing Black shares as γ_B grows to $\gamma_B > 1$.

Ambiguity in the direction migrants' average effects comes from migrants in some neighborhoods pushing up prices and migrants in others pushing down prices. The single-crossing property in migrants' heterogeneous effects suggests a natural partition at the threshold. Differentiating the population effects with respect to s yields:

$$\frac{\partial^2 Q}{\partial N_{Bg} \partial s} = \mu'(s)\left[1 + \gamma_W (1-s)\right] \pi_{Bg} - \gamma_W \mu(s)\, \pi_{Bg}$$
$$\frac{\partial^2 Q}{\partial N_{Wg} \partial s} = \mu'(s)\left(1 - \gamma_B s\right) \pi_{Wg} - \gamma_B \mu(s)\, \pi_{Wg},$$

where if $\gamma_W \leq -1$ and $\gamma_B \geq 1$, the first term in each expression containing $\mu'(s)$ vanishes at the thresholds $s_B^* = \frac{1+\gamma_W}{\gamma_W}$ and $s_W^* = \frac{1}{\gamma_B}$. A simple approximation, a Taylor expansion about the threshold yields

$$\frac{\partial Q}{\partial N_{Bg}} \frac{1}{\pi_{Bg}} = -\gamma_W \mu\left(\frac{1+\gamma_W}{\gamma_W}\right)\left(s - \frac{1+\gamma_W}{\gamma_W}\right) + \mathcal{O}\left(\left(s - \frac{1+\gamma_W}{\gamma_W}\right)^2\right)$$
$$\frac{\partial Q}{\partial N_{Wg}} \frac{1}{\pi_{Wg}} = -\gamma_B \mu\left(\frac{1}{\gamma_B}\right)\left(s - \frac{1}{\gamma_B}\right) + \mathcal{O}\left(\left(s - \frac{1}{\gamma_B}\right)^2\right).$$

C.4 Aggregating over origins

Proposition 2 (Reduced form first stage relationships)**.** *Assumptions 1–4 imply the following linear approximations for migrants' effects in stable neighborhoods:*

1. $\frac{\partial \ln P}{\partial Z_B} = b_{1B} + c_{1B} \times s + \tilde{e}_{1B}$, *with* $b_{1B} < 0$, $c_{1B} > 0$, $\tilde{e}_{1B} = O\left(\left(s - \frac{1-\gamma_W}{\gamma_W}\right)^2\right)$, *and* $\tilde{e}_{1B}\left(s - \frac{1-\gamma_W}{\gamma_W}\right) \geq 0$
2. $\frac{\partial \ln P}{\partial Z_W} = b_{1W} + c_{1W} \times s + \tilde{e}_{1W}$, *with* $b_{1W} > 0$, $c_{1W} < 0$, $\tilde{e}_{1W} = O\left(\left(s - \frac{1}{\gamma_B}\right)^2\right)$, *and* $\tilde{e}_{1W}\left(s - \frac{1}{\gamma_B}\right) \leq 0$
3. $\frac{\partial s}{\partial Z_B} = b_{2B} + c_{2B} \times s + \tilde{e}_{2B}$, *with* $b_{2B} = c_{2B} > 0$, *and* $\tilde{e}_{2B} = O\left((1-s)^2\right)$
4. $\frac{\partial s}{\partial Z_W} = c_{2W} \times s + \tilde{e}_{2W}$, *with* $c_{2W} > 0$, *and* $\tilde{e}_{2W} = O\left(s^2\right)$

Proof. Appendix section C.3 approximates the effects of migrants from a single origin. The effect of migrants from all origins comes from summing the individual price effects. Correspondingly, the total differential is represented by

$$
\begin{aligned}
d\ln P =& \sum_{r,g} \frac{\partial \ln P}{\partial N_{rg}} dN_{rg} \\
=& \frac{\lambda}{Q} \sum_{r,g} \frac{\partial Q}{\partial N_{rg}} dN_{rg} \\
=& \frac{\lambda}{Q} \left[-\gamma_W \mu \left(\frac{1+\gamma_W}{\gamma_W} \right) \left(s - \frac{1+\gamma_W}{\gamma_W} \right) + \underbrace{\mathcal{O}\left(\left(s - \frac{1+\gamma_W}{\gamma_W} \right)^2 \right)}_{\tilde{e}_{1B}} \right] \underbrace{\sum_g \pi_{Bg} dN_{Bg}}_{dZ_B} \\
&+ \frac{\lambda}{Q} \left[-\gamma_B \mu \left(\frac{1}{\gamma_B} \right) \left(s - \frac{1}{\gamma_B} \right) + \underbrace{\mathcal{O}\left(\left(s - \frac{1}{\gamma_B} \right)^2 \right)}_{\tilde{e}_{1W}} \right] \underbrace{\sum_g \pi_{Wg} dN_{Wg}}_{dZ_W}.
\end{aligned}
$$

Thus, the partial derivatives are given by

$$
\begin{aligned}
\frac{\partial \ln P}{\partial Z_B} &= \underbrace{\frac{\lambda}{Q} \left(1+\gamma_W\right) \mu \left(\frac{1+\gamma_W}{\gamma_W} \right)}_{b_{1B}} \underbrace{- \frac{\lambda}{Q} \gamma_W \mu \left(\frac{1+\gamma_W}{\gamma_W} \right)}_{-c_{1B}} s + \tilde{e}_{1B} \\
\frac{\partial \ln P}{\partial Z_W} &= \underbrace{\frac{\lambda}{Q} \mu \left(\frac{1}{\gamma_B} \right)}_{b_{1W}} \underbrace{- \frac{\lambda}{Q} \gamma_B \mu \left(\frac{1}{\gamma_B} \right)}_{-c_{1W}} s + \tilde{e}_{1W}
\end{aligned}
$$

yielding a reduced form price relationship. The equilibrium assumptions immediately yield the coefficient inequalities.

Similarly,

$$
\begin{aligned}
ds =& \sum_{r,g} \frac{\partial s}{\partial N_{rg}} dN_{rg} \\
=& \frac{1}{Q} \left\{ \mu(s) \left[1 - \lambda \beta_W (1-s) + \gamma_W s (1-s)\right] \underbrace{\sum_g \pi_{Bg} dN_{Bg}}_{dZ_B} \right. \\
& \left. + \mu(s) \left[s \left(\beta_B \lambda - \gamma_B s\right)\right] \underbrace{\sum_g \pi_{Wg} dN_{Wg}}_{dZ_W} \right\} \\
& - \frac{s}{Q} \left\{ \mu(s) \left[1 + \gamma_W (1-s)\right] \underbrace{\sum_g \pi_{Bg} dN_{Bg}}_{dZ_B} \right. \\
& \left. + \mu(s) \left(1 - \gamma_B s\right) \underbrace{\sum_g \pi_{Wg} dN_{Wg}}_{dZ_W} \right\} \\
=& \frac{1}{Q} \mu(s) (1-s) \left[1 - \lambda \beta_W\right] dZ_B + \frac{1}{Q} \mu(s)\, s \left[\beta_B \lambda - 1\right] dZ_W
\end{aligned}
$$

In line with Remark 2, the Z_B corresponds to an increase in the Black share of the neighborhood, and Z_W corresponds to a decrease. Applying a Taylor expansion about $s = 1$ and $s = 0$ for the terms multiplying Z_B and Z_W yields

$$
\begin{aligned}
ds = & \left[\frac{1}{Q} \mu(1) \left(1 - \lambda \beta_W\right) (1-s) + \underbrace{O\left((1-s)^2\right)}_{\tilde{e}_{2B}} \right] Z_B \\
& + \left[\frac{1}{Q} \mu(0) \left(\beta_B \lambda - 1\right) s + \underbrace{O\left(s^2\right)}_{\tilde{e}_{2W}} \right] Z_W .
\end{aligned}
$$

Corrrespondingly,

$$
\begin{aligned}
\frac{\partial s}{\partial Z_B} &= \underbrace{\frac{1}{Q} \mu(1) \left(1 - \lambda \beta_W\right)}_{b_{2B}} - \underbrace{\frac{1}{Q} \mu(1) \left(1 - \lambda \beta_W\right) s}_{-c_{2B}} + \tilde{e}_{2B} \\
\frac{\partial s}{\partial Z_W} &= \underbrace{\frac{1}{Q} \mu(0) \left(\beta_B \lambda - 1\right) s}_{c_{2W}} + \tilde{e}_{1W}
\end{aligned}
$$

yielding a reduced form Black share relationship. The equilibrium assumptions immediately yield the coefficient inequalities. □

D Choices of houses, the neighborhood inclusive value, and price indices

The goal of the conceptual framework in section 2 is to understand how households choose neighborhoods. The "price" of the neighborhood is defined in section 3. However, the same regression specification can be viewed through the lens of a nested multinomial logit choice framework where individuals choose houses with prices within neighborhoods as in BFM. In this case, the price index defined in section 3 proxies for the neighborhood's inclusive value.

To see this, let h index houses in neighborhood $j(h)$. Within a neighborhood, there is a distribution of house prices $\ln P_{ht} \sim G_{jt}$. Correspondingly, I define a nested logit choice framework as

$$v_{iht} = \gamma_{r(i)} s_{j(h)t} + \xi_{r(i)j(h)t} + \varepsilon_{ij(h)t} + \beta_{r(i)} \ln P_{ht} + \varsigma_{r(i)ht} + \rho \tilde{\varepsilon}_{iht}$$

where P_{ht} is the price of a house, ς_{rht} are house unobservables, and $\rho \tilde{\varepsilon}_{iht}$ is parameterized and distributed according to Cardell (1997).[28]

Continuing to focus on segregation and the demand for neighborhoods rather than houses, equation 1 becomes

$$\ln \pi_{rjt} = -\theta_{rct} + \gamma_r s_{jt} + \xi_{rjt} + \rho \vartheta_{rjt},$$

where the neighborhood inclusive value

$$\vartheta_{rjt} = \ln \left\{ \sum_{j(h)=j} \exp \left[\left(\beta_r \ln P_{ht} + \varsigma_{rht} \right) / \rho \right] \right\}.$$

ϑ_{rjt} is the logarithm of a power sum of i.i.d. random draws of $\left(\beta_r \ln P_{ht} + \varsigma_{rht} \right) / \rho$.

Marlow (1967) shows that logarithms of power sums follow a central limit theorem. With a large neighborhood supply of houses $Q_{jt} \to \infty$, one can approximate

$$\vartheta_{rjt} \xrightarrow{d} \mathcal{N} \left(\ln Q_{jt} + \ln a_{rjt}, \frac{b_{rjt}}{Q_{jt} a_{rjt}^2} \right)$$

where $a_{rjt} = \boldsymbol{E}_{rjt} \left\{ \exp \left[\left(\beta_r \ln P_{ht} + \varsigma_{rht} \right) / \rho \right] \right\}$ and $b_{rjt} = \boldsymbol{Var}_{rjt} \left\{ \exp \left[\left(\beta_r \ln P_{ht} + \varsigma_{rht} \right) / \rho \right] \right\}$.

[28] In BFM, each house h is inelastically supplied to one household i—hence the separate indices. However, all N households have well-defined preferences over all N houses, yielding a conditional logit regression model with N^2 house-household pairs.

The subscripts are a reminder that each neighborhood can have its own joint distribution of $(\ln P_{ht}, \varsigma_{rht})$. Thus, the inclusive value can be substituted as a mean $\boldsymbol{E}_{rjt}[\vartheta_{rjt}]$ plus classical, normally distributed sampling error $\tilde{\vartheta}_{rjt}$. Substituting, the choice probabilities are given by:

$$\ln \pi_{rjt} = -\theta_{rct} + \gamma_r s_{jt} + \xi_{rjt} + \rho \boldsymbol{E}_{rjt}[\vartheta_{rjt}] + \tilde{\vartheta}_{rjt}$$

The distribution of $\ln P_{ht}$ is empirically measurable. But, neither the joint distribution of $(\ln P_{ht}, \varsigma_{rht})$ nor the parameters β_r or ρ are directly observable. I assume that the identifying variation shifts the location of the house price distribution G_{jt}. I proxy for the mean $\boldsymbol{E}_{rjt}\{\exp[(\beta_r \ln P_{ht} + \varsigma_{rht})/\rho]\}$ with $\boldsymbol{Med}_{jt}\{\exp[(\beta_r \ln P_{ht})/\rho]\}$. Since monotonic transformations commute with the median operator, substituting yields

$$\begin{aligned} \ln \pi_{rjt} = & -\theta_{rct} + \beta_r \boldsymbol{Med}_{jt}[\ln P_{ht}] + \gamma_r s_{jt} + \underbrace{\xi_{rjt}}_{(1)} \\ & + \underbrace{\rho \ln Q_{jt}}_{(2)} + \underbrace{\tilde{\vartheta}_{rjt}}_{(3)} + \underbrace{\rho\left(\ln a_{rjt} - \ln \boldsymbol{Med}_{jt}\{\exp[(\beta_r \ln P_{ht})/\rho]\}\right)}_{(4)}. \end{aligned}$$

The first line resembles the cross-sectional regression equation 1, but the residual continuing onto the second line now reflects four forces instead of one:

1. race-specific valuations of neighborhood amenities;
2. the size of households' choice sets (the supply of housing);
3. independent sampling error associated with the neighborhood inclusive values;
4. and approximation error.

Section 2.2 discusses the first force. Unobserved neighborhood amenities and simultaneously determined supply drives a correlation between price and ξ_{rjt}, discussed in section 2.2.[29] The second force is also driven by supply. Because more choice gives households more utility, supply is also an omitted variable in the demand relationship. The third force is assumed to be independent sampling error.

Since I estimate the IV regressions laid out in section 2.2 in first differences, the new threat to identification would arise if the *changes* in the approximation error were systematically correlated with connections to shocked rural counties. This would arise, for example, if migrants had a direct effect on the distribution of housing stock quality ς_{rht}, the skewness of the local house price distribution F_{jt}, or the relationship between the two.

[29]In this formulation, the inverse supply relationship in appendix C is defined as a location shift of the distribution. Denoting the supply curve as $G(Q_{jt})$, $\ln P_{ht} \sim F_{jt}(x - G(Q_{jt}))$. The theoretical arguments in appendix C apply if migrants only change the location and not the shape of the local house price distributions.

E Data Appendix

E.1 Constructing Tracts in 1930

To construct the 1940 census tracts using 1930 addresses, I construct three datasets of source street addresses with corresponding census tracts in the 1940 census: one with the reported house number (e.g. 6789), one with the house number truncated at the 10's digit (e.g. 6780), and one with the house numer truncated at the 100's digit (e.g. 6700). For each dataset, I restrict attention to streets that appear on at least two pages of census forms, and when a single address corresponds to multiple census tracts, I take the tract that corresponds to the largest number of households.

With each of these datasets, I construct a pairwise Levinshtein ratio, a measure that captures the fraction of the source word that has to be edited to match the target word, between each source street in each city in 1940 and each target street in the same corresponding city in 1930. After excluding matches with a ratio of less than 0.8, I take the source street name with the highest ratio as the match. Having matched the street, I turn to matching the target house number. For a given street, I attempt to match the house number in each source dataset and keep the match that maintains the most digits of accuracy.

Due to the nature of the problem, it is not possible to assess how much measurement error is introduced by matching street names. However, one can see how often using the most common census tract for a given house number will lead to one to infer an incorrect census tract in the 1940 census. In 6 million unique addresses, the unconditional misclassification rate is roughly 1% for exact house numbers (driven by breaking ties and taking the most common), 5% for house numbers recorded up to the 10s digit, and 10% for house numbers recorded up to the 100s digit.

E.2 Measuring the KL Divergence, 1960–2010

The primary measure of segregation that I analyze in this paper is the KL divergence between low-skilled Black and White families in 1940. I use microdata to define low-skilled families and construct counts and probabilities at the census tract level. To the best of my knowledge, microdata with census tract information is not publically available in subsequent decades.

I use data made available by Manson et al. (2020) to construct tract counts and measures of the KL divergence in subsequent decades. Unfortunately, these measures are not the same definitions of Black and White low-skilled families that I define in section 3. Below, I detail the population counts that I use to approximate the definitions that I use to estimate my model:

1960: The number of non-White and White married couples

1970: The number of husband-wife Black and White families

1980: The number of families with Black and White heads of household

1990: The number of married-couple families with Black and White heads of household

2000: The number of married-couple families with heads of household that are Black alone or White alone

2010: The number of married-couple families with heads of household that are Black alone or White alone

Like the 1940 measures, I estimate the tract choice probabilities excluding tracts with fewer than 10 families.