Housing Market Channels of Segregation

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Abstract

This paper quantitatively decomposes forces driving racial segregation in major U.S. cities in 1940. It estimates models of neighborhood demand for White and Black families, identifying preferences over price and racial composition using exogenous inflows of White and Black rural migrants to different neighborhoods. The results confirm that White families had a high willingness to pay to avoid Black neighbors. However, an analysis of cities' segregated equilibria finds that implicit or explicit constraints on Black families' choices explain about half of neighborhood racial segregation observed in 1940. The early constraints on Black households' neighborhood choices drive the persistence in segregation across cities between 1960–2010.

JEL codes: C31, C33, C35, J15, R21, R23, R31

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1 Introduction

Higher rates of residential segregation are associated with a variety of negative outcomes from worse educational outcomes in childhood to lower employment and earnings in adulthood.[1] Despite the wealth of findings, researchers have been cautious in their recommendations for policy. Cutler and Glaeser (1997), for example, conclude, "[i]t may be that widespread social changes in attitudes toward minorities and housing choices will be required before equality of outcomes can finally be achieved."

Implicitly, this caution derives from the prevailing view that segregation is an indelible feature of cities driven by the preferences of Whites to avoid neighborhoods with a substantial presence of minorities (Schelling 1971; Schelling 1978). The role of White preferences in driving segregation has been corroborated by "White Flight" following school desegregation efforts (e.g., Coleman, Kelly, and Moore 1975; Reber 2005) and by studies of rapid "tipping" of neighborhood racial shares in response to minority inflows (Card, Mas, and Rothstein 2008). Recent research on the impacts of the Great Migration suggest similar reactions throughout the twentieth century (Boustan 2010; Shertzer and Walsh 2016). Nonetheless, in their landmark study of the rise of Black-White residential segregation over the twentieth century, Cutler, Glaeser, and Vigdor (1999) argued that segregation first arose as a coordinated effort to constrain the housing supply to Black residents.[2] It was only reinforced in the latter half of the century by the decentralized decisions of White residents who fled inner city neighborhoods with growing minority shares.

Researchers have conducted case studies on individual housing supply constraints (see e.g. Ondrich, Stricker, and Yinger 1998; Ondrich, Stricker, and Yinger 1999; Yinger 1986), but the combined systemic effect of non-market constraints on segregation requires predictions of neighborhood demand. For instance, the specific effect of restrictive covenants prohibiting Black residents depends on the extent to which Black families would have lived in restricted neighborhoods. However, the absence of restrictive covenants gives no indication of whether other, harder-to-measure constraints (e.g. threatened or actualized violence) interfered with residents' choices. To the best of my knowledge, there has been no analysis able to separately measure the degree of segregation driven by non-price constraints from market forces and unconstrained sorting. This requires both identifying variation that can credibly measure households' preferences for the racial composition of the neighborhood and an empirical framework that can capture agents making decisions from a restricted choice set. Indeed, state of the art models of housing choice such as Bayer, Ferreira, and McMillan (2007) fit to contemporary data typically assume that each family can freely choose among all available housing units.

This paper aims to provide a credibly identified, quantitative summary of the contributions of market- and non-market based explanations for the patterns of racial segregation in large US cities in 1940, just before cities became further segregated coinciding with the second wave of the Great Migration. Over the previous decade, many cities had experienced large influxes of White and Black rural migrants—many of whom followed the path of earlier migrants from specific origin counties (e.g., counties near the Mississippi River Delta) to specific destinations (e.g., the South Side of Chicago).[3] The predictable component of these migrant inflows provide identifying variation for simple structural models of the neighborhood preferences of low-skilled, Black and White families. I then use the resulting estimates to predict counterfactual neighbor-

[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. Ananat (2011) argues that the correlations are causal. Chyn and Katz (2021) provide a useful review of evidence on neighborhoods' effects more broadly.

[2] Recently, Rothstein (2017) has underscored the role of government policies in promoting and enforcing racial segregation.

[3] Lieberson (1980) and Wilson (1987) argue that rural Black migrants received focused animosity from Whites in the early part of the 20th century. Anti-immigrant settlement subsided following following the legislated curtailments of migration from Europe and Asia, but competition from Black migrants from rural counties drew the ire of urban White residents.

hood demands of Black residents in the absence of non-price constraints. This allows me to quantitatively decompose observed segregation into (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 variation in these measures across cities to revisit explanations for racial segregation's long-run persistence.

More specifically, I begin my analysis by setting up a parsimonious multinomial logit model of neighborhood choice where families have preferences over the local price and Black share of the neighborhood. This model is the basis of my empirical analysis. I show that equilibrium perturbations arising from rural inmigration can identify the preference parameters of the demand model. The model motivates using shift-share instruments built on the fact that migrants are attracted to enclaves of past migrants (Altonji and Card 1991; Card 2001). To overcome the lack of origin county information in the data, I connect migrants living in census tracts in 1930 to origin counties on the basis of their last name. I show that surname distributions are highly clustered and provide a strong signal of one's county of birth within a state. The surname-predicted flows based on pre-1930 migrant settlement patterns are highly predictive of actual county-to-census tract flows.

Instruments for rural migration in hand, I estimate a series of first-differenced regressions by census tract. The instruments' reduced form effects on White and Black populations replicate the rich predictions that one would expect from the simple model. Correspondingly, the population effects similarly trace out changes in prices and neighborhood Black share, the first stage estimates for the choice model. I then estimate the choice parameters separately by broad occupation group using the linear instrumental variable (IV) approach developed by Berry (1994), providing estimates of White and Black willingness-to-pay for more or less Black neighborhoods. Consistent with past findings of intense White aversion to more Black neighborhoods, a typical White household would have to be compensated by a 1% lower house price for a 1 percentage point increase in the Black share of the neighborhood to hold utility constant. At the same time, Blacks seem to have no or weak affinity toward more Black neighborhoods.

Quantifying the effect of non-price rationing on the allocation of Black families to different neighborhoods requires predicting demand of Black families in an unconstrained equilibrium. Using within-neighborhood variation accounts for a broad class of neighborhood unobservables for the IV strategy and estimating parameters governing how households trade off between the price and racial composition of a neighborhood. However, unobserved neighborhood amenities themselves are an important component of neighborhood demand. Longitudinal data allows me to model residual explanations for demand (i.e. the value of local amenities) using correlated random effects (CRE). The CRE model attributes serially correlated demand across decade to preferences for permanent neighborhood characteristics. I find that Black and White preferences for local amenities are positively correlated, suggesting that local amenities are not a major driver of segregation. More importantly, the covariance between the Black and White random effects allows me to use residual explanations for White demand to predict Black demand. I use the model estimates to predict counterfactual demand in all-White neighborhoods.

Finally, I compare the actual distribution of Black and White demand by extending decomposition methods of Kullback and Liebler's (1951) relative entropy. Specifically, I decompose segregation between Blacks and Whites by first comparing 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—and then comparing the counterfactual Black demand to actual White demand—quantifying the contribution of decentralized neighborhood preferences based on the responses to the prices and Black resident shares observed in each neighborhood. Aggregating across cities, the decomposition suggests that roughly half of segregation is explained by divergent preferences over the neighborhood's Black share, and the remainder is driven by constrained choices.

The quantification supports the conclusions of existing scholarship that highlight the role of White households' neighborhood preferences in driving observed segregation. At the same time, it renews the importance of non-market constraints as a complementary explanation. However, one consequence of that line of research 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. Segregation today may be a legacy of historical constraints, and widespread improvements in attitudes may not lead to integration. To assess this possibility, I use variation in segregation and my model-based measure of constraints 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. First, it applies equilibrium sorting models following Bayer, Ferreira, and McMillan (2007) (henceforth, BFM) to the analysis of racial residential segregation. Existing work on segregation has typically considered its consequences, estimating models where the unit of observation is a city and some measure of segregation is the main regressor of interest. Understanding segregation's determinants has been more indirect. Cutler, Glaeser, and Vigdor (1999) infer the drivers of segregation from its effects on house prices, and the implicit link between segregation and studies of population effects (e.g. Boustan 2010; Card, Mas, and Rothstein 2008) are largely qualitative.[4] The fundamental empirical challenge is reconciling the effect of neighborhood-level institutions on city-level segregation. Aggregating formal constraints is not straightforward, and comparing segregation across cities says little about the unmeasurable non-market forces driven by informal White collective action (Cutler, Glaeser, and Vigdor 1999).

This paper estimates neighborhood demand to address the ecological tension that arises from linking constrained neighborhood choices to aggregate segregation. The primary contribution of the paper is implementing a research design that allows structural neighborhood demand relationships to accommodate non-market constraints, in the process addressing several shortcomings inherent to how existing housing demand approaches identify preferences for neighborhoods' racial composition. Identifying demand models with racial preferences requires resolving two simultaneity problems—upward sloping supply and a reflection problem driven by endogenous social interactions (Manski 1993)—which cannot both be resolved with even randomly assigned cost shifters. Consistent with theory, my identification strategy in essence infers preferences from choice probabilities changing in response to external migrants perturbing the equilibrium. In addition to addressing a litany of static unobservable characteristics (Nevo 2001), using within-neighborhood variation crucially allows me to estimate Black residents' preferences from the subset of neighborhoods where they live.

In contrast, existing approaches fit models that make identifying restrictions that rationalize equilibrium behavior in the cross-section. For instance, BFM treat neighborhood race shares as exogenous and use characteristics of adjacent neighborhoods as instruments for price.[5] Wong (2013) addresses endogenous social interactions by augmenting neighborhood characteristics with variation in initial conditions driven by

[4] A notable exception is Caetano and Maheshri (2021) who infer drivers of segregation using simulations informed by a neighborhood demand model.

[5] In the industrial organization literature, oligopolistic markups are supply shifters. Conditional on observables, mean characteristics proxy for the presence of close substitutes, which in turn proxy for markups (Berry, Levinsohn, and Pakes 1995). Applying similar identification arguments to housing assumes that oligopolistic firms exert market power to increase the price of housing in a neighborhood.

historical settlements. Caetano and Maheshri (2021) use lagged neighborhood characteristics when moving frictions generate temporary disequilibria. In each case, the instrument sets are themselves a product of equilibrium, and however strong or weak, the identification assumptions fundamentally cannot distinguish when households are choosing among a restricted set of housing. 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." By assumption, choices reflect agents' revealed preference selections from a choice set that includes all local housing, precluding any role for constraints.

Second, this paper relates to the expansive literature studying localized effects of migrants on labor markets, particularly those which utilizes the Card (2001) "past settlement" instrument.[6] 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.

Third, the paper relates to a smaller literature that studies housing supply and its determinants.[7] This literature has primarily sought to better understand the connections between supply and construction, government policy, and housing durability, but less is known about whether the determinants of housing supply—or its restrictions—are connected to race.[8]

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 explore how highly localized nature of social networks transmits correspondingly into highly localized housing demand pressure by neighborhood.[9]

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

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

[7]DiPasquale's (1999) appropriately titled review "Why Don't We Know More About Housing Supply?" bluntly begins, "[v]irtually every paper written on housing supply begins with some version of the same sentence: while there is an extensive literature on the demand for housing, far less has been written about housing supply."

[8]A notable exception, Bayer et al. (2017) use rich longitudinal data and find housing price premia for minorities.

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

demand to decompose segregation across cities. Finally, section 7 concludes.

2 Conceptual Framework

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. However, rather than study segregation across cities in the aggregate, I analyze π_{rjt} directly.

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 more formal prohibitions (e.g., restrictive covenants) and also via de facto constraints such as informal threats of violence. $\mathcal{J}_{rc} \subseteq \mathcal{J}_c^*$ denotes the set 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} (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 $\hat{\pi}_{Bjt}^{CF}$ in their absence, $\mathcal{J}_{Bc} = \mathcal{J}_c^*$. To predict counterfactual choices, I make two assumptions about preferences:

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,[10] 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).[11]

The choice shares follow the convenient and well-known functional form of a multinomial logit:

$$\pi_{rjt} = \frac{\exp \delta_{rjt}}{\sum_{j' \in \mathcal{J}_r} \exp \delta_{rj't}}$$

[10] See section 3.3 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.

[11] 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.

for $j \in \mathcal{J}_{rc}$ and 0 otherwise. Substituting and taking logs yields a linear regression model (Berry 1994):

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

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 living in a city given the choices available to them.

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

2.2 defining non-market constraints;

2.3 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;

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

2.5 and decomposing an aggregated measure of segregation, the Kullback-Leibler divergence, using the predictions of the choice model to separately summarize the contributions of preferences- and constraints-based explanations for segregation.

2.2 Constraints and non-market forces

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

Their distinction between constraints ("collective action racism") and market forces ("ports of entry" and "decentralized racism") is not meant to suggest conceptually distinct preferences of the local White population. Rather, the classification implies that some of segregation is mediated through prices, and some depends on whether and how White preferences manifest in formal and informal institutions that enforce segregation. Teasing apart those forces is the objective of the paper.

There are several challenges inherent to understanding the consequences of neighborhood choice restrictions on segregation. First, some formal de jure restrictions can be measured (e.g. restrictive covenants, racial zoning laws), but informal de facto restrictions (e.g. implicit threats of violence) cannot. Second, for even those that can be measured, restrictions are unlikely to be randomly assigned either within cities or across them. Third, restrictions do not operate in isolation. Absent random assignment, exclusion from a neighborhood may simultaneously reflect both legal restrictive covenants and intimated violence and cannot conceptually be attributed to a single factor. Both de jure and de facto restrictions have the same observable effect on choices of excluding Black families from certain neighborhoods; but, an analysis of a single measurable constraint in isolation gives little indication of what others may be present.

The framework developed in this section lays out how this paper overcomes these challenges. I infer Black demand for neighborhoods with no Black residents by observing how their choices change among the limited set of unrestricted neighborhoods. Relative to other applications of housing demand models, the crucial difference in my approach is that I do not rationalize choices in a cross-sectional equilibrium. Instead, I consider how much of cross-sectional choices can be explained by a demand model that uses within-neighborhood variation.

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

This section discusses identification of β_r and γ_r. To facilitate exposition, I decompose ξ_{rjt} into a permanent component ($\bar{\xi}_{rj}$) (which I return to in Subsection 2.4) and a transitory component ($\tilde{\xi}_{rjt}$) so $\xi_{rjt} = \bar{\xi}_{rj} + \tilde{\xi}_{rjt}$. A naive OLS estimation of neighborhood demand in equation 1 will yield biased estimates for several reasons. First, more attractive neighborhoods with higher $\bar{\xi}_{rj}$ are likely to be more expensive neighborhoods. Second, neighborhood price is simultaneously determined by the specified housing demand relationship and unspecified housing supply. Prices changing to clear the market generate a correlation between $\tilde{\xi}_{rjt}$ and $\ln P_{jt}$. Third, the neighborhood Black share has a mechanical relationship to the choice probabilities, and its simultaneity issue mirrors "endogenous effects" confronted by the literature on peer effects (Manski 1993).

Longitudinal data allow me to absorb static characteristics of the neighborhood $\bar{\xi}_{rj}$. First differencing equation 1 yields:

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

The first-differenced, cross-sectional relationship alleviates some concern about omitted variable bias. But, credible identification of the demand relationship requires two instruments that predict *changes* (rather than levels) in price and racial composition to resolve concerns about simultaneity. To measure how households trade off between the price and racial composition of a neighborhood, one would ideally use instruments derived from an experiment whose treatment arms randomly "drop" people of different races into different neighborhoods. Such an experiment mechanically changes the neighborhood racial composition. It also changes the local housing supply available to incumbents. Identification comes from inferring preferences governing price and neighborhood racial composition by observing how choices change in response to migrants. I use shocks of Black and White migrants as instruments to approximate this thought experiment and perturb the preexisting equilibrium.

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

2.3.1 Definition of the past settlement instrument and instrument exclusion

Observed inmigration M_{rjt} cannot be used as an instrument because migrants choose neighborhoods for the same unobservable reasons that residents do. 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.

Consider individuals that share the same race that also come from the same rural county of origin, social network groups indexed by g. I decompose immigrant inflows into

$$\begin{aligned} M_{rjt} &= \sum_g M_{rgjt} \\ &= \sum_g \pi_{rgjt} \times M_{rgt}^c \end{aligned}$$

Abusing notation slightly, the first line decomposes immigrant inflows M_{rjt} into the sum of group-specific inflows M_{rgjt}. The second line decomposes group-specific inflows into the group-specific probability of choosing neighborhood $\pi_{rgjt} \equiv \Pr\left[D_{it} = j | r(i), g(i), c(j), t\right]$ and the immigrant inflow to the city $M_{rgt}^{c(j)}$.

To construct the instrument, I use past neighborhood choice shares of immigrants $\hat{\pi}_{rgj0}$ to proxy for affinities for ethnic enclaves. Second, I generate predicted flows from origin g to destination city c. The first element of the product is the probability that past migrants chose *city* c, $q_{rgc0} = \Pr\left[c(D_{it}) = c | r(i), g(i), t\right]$.[12] The second element of the product is total migrant flows from origin g leaving out destination c, M_{rg}^{-c}. Together, $\hat{M}_{rg}^c = q_{rgc0} M_{rg}^{-c}$ proxies for push factors that shift the probability that migrants leave their origins but are unrelated to changing neighborhood amenities $\Delta\tilde{\xi}_{rj}$. Combining these elements, the instrument for neighborhood inflows is

$$Z_{rj} = \sum_g \hat{\pi}_{rgj0} \times \hat{M}_{rg}^c.$$

Migrant enclaves emerge naturally from the location choice model and provide a reasonable basis for using the past settlement instrument for identification. To link the model to the instrument, I assume the following:

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 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).*

Assumption 3 implies Assumption 1: ε_{ijt} is distributed according to the extreme value type I distribution. Accordingly, $\ln \pi_{rgjt} = \ln \pi_{rjt} + \eta_{rgjt}$, and η_{rgjt} is a group-specific deviation from the log probabilities in equation 1. Further decomposing η_{rgjt} into a permanent and transitory component, $\eta_{rgjt} = \bar{\eta}_{rgj} + \tilde{\eta}_{rgjt}$, the permanent component $\bar{\eta}_{rgj}$ reflects an affinity to previously-established immigrant enclaves.

The necessary condition for the instrument's exclusion restriction is that conditional on covariates, neighborhoods that are connected to origin counties experiencing shocks are not systematically those whose amenities are increasing or decreasing $\boldsymbol{E}\left[Z_{rj}\Delta\xi_{rj} | \boldsymbol{X}_j\right] = 0$. That is, connectedness to shocked rural counties is conditionally uncorrelated with *changes* in amenities. Two features of the data and design lend credibility to the model's identifying assumption. First, using longitudinal data and estimating the models in first differences addresses a broad array of static unobservables that may confound structural interpretations of cross-sectional comparisons (Nevo 2001). Second, the instrument is derived from past settlement decisions combined with migrant outflows that exclude the destination city, ameliorating concerns that migrants are intentionally deviating toward neighborhoods with improving amenities rather than independently perturbing the equilibrium.

One potential threat to identification occurs if neighborhoods connected to shocked rural counties are systematically those experiencing changes to amenities. In order to isolate variation from shocked rural

[12] q_{rgc0} are typically the shares used in the literature on immigrants' effects on wages.

counties, I derive a simple measure of connectedness—the sum of shares—to control for potential omitted variable bias from the shares driven by differential exposure. By controlling for the sum of shares, I make comparisons between census tracts that are equally connected to rural counties but are differentially connected to shocked rural counties. Assumption 3 is sufficient to establish identification.

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

I include a Black migrant and White migrant sum of shares control in all the neighborhood regressions.[13]

The sum of shares is proportional to the value of the instrument if each origin sent the same number of migrants. Thus, the identifying variation comes specifically from those origins that are shocked. The identification argument is tantamount to assuming that origin-specific *deviations* from Black and White neighborhood choice probabilities are independent of *changes* in unobservables driving neighborhood choices. So, conditional independence would be violated if neighborhoods connected to shocked origins experience unobservable changes in preferences $\Delta\xi_{rjt}$ that are systematically higher than those connected to unshocked origins. One way this could manifest is if migrants have a causal effect on local amenities that are not capitalized into price. The IV model interprets migrants' causal effects on neighborhood choice probabilities exclusively via price and the neighborhood black share.

Using migrants to perturb local equilibria yield several theoretical advantages over existing approaches that use characteristics of adjacent neighborhoods for identifying variation. Berry, Levinsohn, and Pakes (1995) argue that competing product characteristic means proxy for market concentration. Products closer to the market average face more competition and have lower markups. Products further away are more unique and have higher markups. Supplier markups are excludable from the demand relationship. The instrument's validity relies on product mean observables proxying for market average markups rather than market average unobservables.

The approach of using characteristics of adjacent neighborhoods for identifying variation is premised on the same logic. Clusters of housing reflect a local "market." However, the identification argument yields strong empirical predictions. For instance, the reasoning implies that all else equal, the price of a large house surrounded by large houses is *lower* than the price of the same large house surrounded by small houses as a result of greater competition among developers of large housing. Under the identifying assumption, large houses cannot cluster around a local unobservable amenity (e.g. parks), which would violate the exclusion restriction even if households do not have direct preferences for having neighbors with large houses. Similarly strong assumptions are required for using adjacent neighborhood characteristics to infer households' preferences for neighborhoods' racial composition (Angrist 2014).

The migrant research design bypasses these issues by inferring preferences from within-neighborhood variation. The first difference specification absorbs permanent characteristics of neighborhoods that would include the variation used for identification in other applications. In this setting, the structural relationship is confounded if neighborhoods experiencing *changes* in local amenities are those that are connected to rural counties experiencing large outflows. Controlling for overall connectedness (including counties not experiencing large outflows) ameliorates those concerns.

[13] 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*.

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

Migrant shocks change the local racial composition. But, how do migrants affect prices?

The basic requirement for instrumental variables to identify the parameters of the demand relationship is that they shift equilibrium prices and neighborhood racial composition without being systematically related to the unobserved reasons underlying neighborhood choices. The theory generates reduced form predictions of migrants' equilibrium effects that guide the estimation of the first stage relationships. For example, Black 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—or place other restrictions on how housing can vary with other factors.

Proposition 2 in Appendix C formally derives theoretical predictions of the effects of an origin outmigration shock. Leaving the formal notation in the appendix, 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.

Migrants' offsetting effects have separate implications for using migrant shocks as instrumental variables.[14] The model predicts, reassuringly, that Black migrant shocks increase the neighborhood Black share and a White migrant shocks decrease the neighborhood Black share. However, because price effects are traced out by the overall demand, migrants' effects on prices may be ambiguous.

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

[14] 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.

and increases in White neighborhoods. However, population and price effect heterogeneity crosses from positive to negative at most once.

Thus, under particularly intense racial preferences, the average effect of a Black migrant shocks may be ambiguous because they reflect both population increases in Black neighborhoods and population decreases in White neighborhoods. Countervailing effects ultimately cancel out. 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. $a_{1c(j)}$ and $a_{2c(j)}$ are city-specific intercepts that capture city-specific trends in prices and Black shares. The coefficients on the excluded instrument set—the summed migrant shocks' main and effects interacted with the baseline Black share—reflect a combination of the preference parameters of interest and the housing supply relationship.[15] The error terms e_{1j} and e_{2j} in the first stage regression specifications in equations 3 and 4 capture higher order non-linearities, measurement error, and departures from migrants' mean effects driven by neighborhood heterogeneity in the supply elasticity.

$\boldsymbol{X}_j$ is a vector of neighborhood controls, which include the sum of shares described previously. I include a main effect for the baseline 1930 Black share in the neighborhood regressions so that the interaction terms with the 1930 Black share $Z_{rj} \times s_{j0}$ captures migrants' heterogeneous effects developed in Proposition 2. In doing so, I remain agnostic about how neighborhood amenities may evolve with different initial Black shares.[16] Finally, I estimate all models including the local price and population of the neighborhood in 1930 as controls to increase statistical precision. With controls, the linear estimating equations for each race becomes

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

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

2.4 Correlated random effects and predictions of household valuations of local amenities

The previous section discussed how migrant shocks help identify how households trade off between the local price of housing and the neighborhood racial composition. Racial preferences intuitively play a role in driving segregation, but measuring β_r and γ_r, however credible the identification, gives limited indication of how much observed segregation is actually driven by those preferences. After all, location choices may be partially driven by race-specific preferences over housing characteristics or other amenities (BFM; Wong

[15] In my empirical implementation, the coefficients also reflect measurement error since I generate proxies for past migrants' decisions π_{rgj0} using surname distributions.

[16] Caetano and Maheshri (2021) use lagged neighborhood race and ethnic shares for identifying variation.

2013). Where before it was a nuisance parameter, the residual mean utilities ξ_{rjt} are a conspicuous third pillar in predicting both demand and corresponding explanations for segregation.

From a practical standpoint, constructing the counterfactual requires mapping the estimates of equation 5 in changes back to equation 1 in cross-sectional levels. In other applications of multinomial logit demand models, ξ_{rjt} are tautologically measured from empirical regression residuals. There, the role of the residual is taken as given (or for new products, imputed to be the mean—zero) when constructing counterfactuals. Predictions are largely driven by observable characteristics.

In contrast, my setting faces two challenges. First, constraints forced Black residents into a limited set of neighborhoods. The residual is simply not measurable for Black households in most neighborhoods. Second, I lack a rich set of observable amenities via which I could reasonably forecast ξ_{rjt} out-of-sample. While tastes over amenities may differ across races, divergent preferences only translate into segregation to the extent that those preferences are (negatively) related to one another. Were they directly measurable, one could simply regress ξ_{Bjt} on ξ_{Wjt}. But because they are incidental parameters, relating regression residuals may reflect correlated estimation error instead of a structural correlation between race-specific valuations of amenities.

I take advantage of the panel data in my setting and cast ξ_{rjt} as a correlated random effect. This strategy interprets serial correlation in the residual as indicative of latent unobserved amenities that may be potentially correlated between races. Importantly, that correlation allows me to use White choice probabilities to predict Black demand in off-limits neighborhoods.

Formally, I define $u_{rjt} \equiv -\theta_{rct} + \xi_{rjt}$. Under the identifying assumptions in Section 2.3, the consistent 2SLS estimates of $\hat{\beta}_r$ and $\hat{\gamma}_r$ allow me to obtain consistent estimates of u:

$$\begin{aligned} \hat{u}_{rjt} &= \ln \hat{\pi}_{rjt} - \hat{\beta}_r \ln P_{jt} - \hat{\gamma}_r s_{jt} \\ &= -\theta_{rc(j)t} + \xi_{rjt} + \underbrace{(\hat{u}_{rjt} - u_{rjt})}_{\tilde{u}_{rjt}}. \end{aligned} \tag{6}$$

$\hat{u}_{rjt}$ reflects both race-specific valuations of amenities ξ_{rjt} and estimation error $\tilde{u}_{rjt}$. Recall the decomposition $\xi_{rjt} = \bar{\xi}_{rj} + \tilde{\xi}_{rjt}$. Consider the projection of $\bar{\xi}_{rj}$ onto the instrument and covariate set:

$$\bar{\xi}_{rj} = \boldsymbol{F}_r' \left[\boldsymbol{Z}_j', \boldsymbol{X}_j'\right]' + \psi_{rj}.$$

Substituting back into equation 6 yields

$$\hat{u}_{rjt} = -\theta_{rct} + \boldsymbol{F}_r' \left[\boldsymbol{Z}_j', \boldsymbol{X}_j'\right]' + \psi_{rj} + \tilde{\xi}_{rjt} + \tilde{u}_{rjt}, \tag{7}$$

a linear regression model where the inclusive value θ_{rct} is absorbed by city-time fixed effects. To predict 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. $\begin{pmatrix} \psi_{Bj} \\ \psi_{Wj} \end{pmatrix} \sim \mathcal{N}\begin{pmatrix} 0 & \sigma_B^2 & \sigma_{BW} \\ 0 & , & \sigma_B^2 \end{pmatrix}$

Normality is not strictly required, but Assumption 5 is sufficient to produce a simple linear prediction

$$\boldsymbol{E}\left[\psi_{Bj}|\psi_{Wj}\right] = \frac{\sigma_{BW}}{\sigma_W^2}\psi_{Wj}. \tag{8}$$

Having parameterized and subsequently purged $\hat{u}_{rjt}$ of the variation used for estimation of $\hat{\beta}_r$ and $\hat{\gamma}_r$, assumption 2 attributes the remaining serial correlation in choice probabilities to the presence of a permanent unobserved factor. Subsequently, the estimated cross-decade, cross-race correlation in the residuals reflect the relationship in Black and White residents' preferences for that unobserved factor rather than the fact that preferences for amenities cannot be directly measured.

2.5 Decomposing segregation

The demand framework developed in Sections 2.3 and 2.4 summarizes two of the three channels laid out in Cutler, Glaeser, and Vigdor (1999). Segregation may reflect White neighborhood preferences: White households who are willing to pay more may price Black households out of White neighborhoods. Segregation may reflect Black neighborhood preferences: Black households have no desire to live in White neighborhoods either because they prefer to live in neighborhoods with higher Black share or because they prefer different local amenities. Nevertheless, in essence, segregation is defined as White neighborhood choices being negatively related to Black neighborhood choices. Absent non-market constraints, divergent choices are divergent revealed preferences.

However, Black choices were constrained. Without accounting for that, any demand model that tries to rationalize the observed equilibrium patterns will naturally predict segregation. Given segregation's strong correlation with social issues to this day, it bears asking how much of segregation at the time reflects institutional and extralegal non-market forces. The framework developed in Sections 2.3 and 2.4 allows me to consider the counterfactual without Black restrictions—where segregation purely reflects choices under market forces.

I first construct the counterfactual. In the same spirit as McFadden (1974), I construct neighborhood mean utilities for Black residents in all neighborhoods. Applying the demand parameters and holding fixed the characteristics of those neighborhoods, predicted unnormalized mean utilities are given by:

$$\hat{\delta}_{Bjt} = \hat{\beta}_B \ln P_{jt} + \hat{\gamma}_B s_{jt} + \hat{\xi}_{Bjt}$$
$$\hat{\xi}_{Bjt} = \hat{\boldsymbol{F}}_B' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j'\right]' + \hat{\psi}_{Bj}$$

I obtain counterfactual choices by subtracting from the mean utilities the counterfactual inclusive value $\hat{\theta}_{Bc}^{CF} = \ln \sum_{j\in\mathcal{J}_c^*} \left(\exp \widehat{\delta}_{Bj}\right)$, which forces the choice probabilities in each city to sum to 1:

$$\widehat{\ln \pi_{Bjt}^{CF}} = -\hat{\theta}_{Bc}^{CF} + \hat{\delta}_{Bjt}.$$

I then decompose the Kullback-Leibler (KL) divergence, defined as

$$KL_c\left(\boldsymbol{\pi}_{Bct}||\boldsymbol{\pi}_{Wct}\right) \equiv \sum_{j\in\mathcal{J}_c^*} \pi_{Bjt} \ln \frac{\pi_{Bjt}}{\pi_{Wjt}},$$

which is a simple summary measure of 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.

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

$$KL_c = \underbrace{\sum_{j \in \mathcal{J}^*_c} \pi_{Bjt} \left(\ln \pi_{Bjt} - \widehat{\ln \pi^{CF}_{Bjt}} \right)}_{\text{non-market forces}} + \underbrace{\sum_{j \in \mathcal{J}^*_c} \pi_{Bjt} \left(\widehat{\ln \pi^{CF}_{Bjt}} - \ln \pi_{Wjt} \right)}_{\text{market forces}}. \tag{9}$$

The decomposition of the KL divergence yields two comparisons. The first expression compares actual Black choices to Black choices in an unrestricted counterfactual, quantifying the role of constraints in driving segregation.[17] The second expression compares unrestricted Black choices to White choices, measuring the extent to which divergent choices actually reflect divergent preferences.[18]

The question at the core of the decomposition is whether model parameters that summarize the revealed preferences of Black residents in neighborhoods where they lived can be reasonably used to predict where they would live if housing were only rationed by prices. But, therein lies a paradox of prediction. If Black families can be found in relatively few neighborhoods—prima facie evidence of non-market barriers—the model predictions are necessarily more extrapolative even if those decisions likely reflect constrained choices. If Black families can be found in relatively more neighborhoods, the model summarizes decisions over a broader array of choices. There is less extrapolation but also necessarily fewer constraints.

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.

3.1 Households i

I analyze qualitatively similar households for two reasons. First, I focus specifically on preferences for the neighborhood's racial composition as a driving force in segregation. The framework in Section 2 is set up to quantify those trade offs rather than differences in class and income.

However, the framework assumes that individual heterogeneity only enters the demand relationship via ε_{ijt}. This has the benefit of allowing for simple, straightforward, and tractable linear IV regression models collapsed to neighborhoods. Identifying variation at the neighborhood level suggests defining outcomes at the neighborhood level. But, whether or not I can safely aggregate away individual idiosyncrasies ultimately depends on whose decisions I am modeling. The assumption may be violated if, for example, households in higher and lower income occupations have different demand elasticities. In that case, the estimate of β_r will only reflect an average elasticity if the variation in demand elasticities are also orthogonal to the identifying variation—i.e., if migrant shocks perturb neighborhoods independently for households across the income

[17] Substituting, this simplifies to an average difference in the estimated inclusive values $\sum_{j \in \mathcal{J}^*_c} \pi_{Bjt} \left(\ln \pi_{Bjt} - \ln \hat{\pi}^{CF}_{Bjt} \right) = \sum_{j \in \mathcal{J}^*_c} \pi_{Bjt} \left(\theta_{Bc(j)} - \hat{\theta}^{CF}_{Bc(j)} \right)$, weighted by the Black choice probabilities.

[18] Also substituting, the second expression can be further decomposed to reflect detailed differences in the estimated parameters between Blacks and Whites.

distribution. The rural migrants whose effects I study were generally very poor. A technical literature in industrial organization has developed modeling and estimation techniques to overcome this ecological inference problem, especially in circumstances where choice data are divorced from demographic information that would allow focusing a simpler demand analysis on a homogeneous population (Berry, Levinsohn, and Pakes 1995).

I construct choices from a homogeneous population. First, I focus on 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.

3.2 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.[19]

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 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.

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

3.3 Neighborhood Price Indices P_{jt}

Neighborhoods do not have prices—houses do.[20]

A natural measure of the price of a neighborhood is its median. However, I only observe self-reported prices from owner-occupied dwellings. Similarly, I only observe monthly rents for renter-occupied dwellings. Simply using the median rent or house price within a neighborhood would not consistently capture its cost when the share of owner- and renter-occupied homes changes from neighborhood to neighborhood and over time.[21] I create single cost index that combines the two household level measures. This requires predicting a dwelling's value based on its rent (or equivalently, its rent based on its price).[22]

I stipulate that monthly rents proxy for home value in a simple multiplicative way $\delta HomeValue_{it} = MonthlyRent_{it}$. I use a longitudinal dataset of a subset of housing units where the 1930 address could be exactly matched to a 1940 address on house number and street name. I then stack owner-occupied home values and renter-occupied rents into a single dependent variable $Y_{it} = (1 - Owner_{it}) \times \ln MonthlyRent_{it} + Owner_{it} \times \ln HomeValue_{it}$. Substituting the assumed relationship yields $Y_{it} = \ln MonthlyRent_{it} + \ln \delta \times Owner_{it}$.

Resembling a potential outcomes framework, comparing average log rents and average log home values would yield unbiased estimates only if homeownership were uncorrelated with the underlying value of the home. To mitigate omitted variables bias, I compare the same dwellings that convert from rental to ownership status between 1930 and 1940 and vice versa. Specifically, I estimate panel regression models of the form

$$Y_{it} = c_{addr(i)} + d_{j(i)t} + \ln \delta \times Owner_{it} + e_{3it}$$

where $c_{addr(i)}$ are a set of address fixed effects and $d_{j(i)t}$ are tract by time fixed effects. I estimate $\widehat{\ln \delta} = 4.8$.[23]

With this estimate, I impute the log value of a home as $\ln P_{ht} = (1 - Owner_{it}) \times \left(\ln MonthlyRent_{it} + \widehat{\ln \delta} \right) + Owner_{it} \times \ln HomeValue_{it}$. I then define the neighborhood price index as the median $\ln P_{jt} \equiv Med_j \left[\ln P_{ht} \right]$.

3.4 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

[20] 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.

[21] The 1930 census was the first where measures on housing costs were solicited. Non-farm households, "[families] or any other group[s] of persons, whether or not related by blood or marriage, living together with common housekeeping arrangements in the same living quarters" (Ruggles et al.) were surveyed on their monthly contract rent or the estimated value of their home for renter-occupied housing and owner-occupied housing, respectively. For owner occupied housing, the value of the home is self-reported and represents an estimate unless the house was recently purchased. For renter occupied housing that was provided as in-kind compensation of labor, enumerators estimated the rent paid for similar housing.

[22] The literature on estimating costs of living faces a similar problem when trying to understand difference in tax incidence between homeowners and renters and how much to weight house prices in measures of inflation. Two theoretically equivalent approaches—the user cost method and the rental equivalence method—attempt to define and predict homeowner's opportunity cost (the "rent" they pay themselves) of living in the home of value P_{ht}. The former (see e.g., Díaz and Luengo-Prado 2012; Díaz and Luengo-Prado 2008; Poterba and Sinai 2008) attempts to account for all the practical (e.g. maintenance) and financial (e.g. mortgage) costs of living in a house for a year. The latter (see e.g., Poole, Ptacek, and Verbrugge 2005) attempts to estimate how much income homeowners are forgoing by choosing to live in the home instead of renting it to the market based on its characteristics. Differing in objective, I do not use an estimate from the literature, but my methodology is more closely related to the latter.

[23] This implies an equivalent annual rent of roughly $12 \exp(-4.8) \approx 10\%$ of the home value. This estimate is somewhat higher than user cost and rental equivalence estimates from the literature of roughly 5–7% (Díaz and Luengo-Prado 2008; Poterba and Sinai 2008). These estimates come from sophisticated calibrations using aggregated data in more recent decades, which could account for many of the differences.

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. The median neighborhood for low-skilled Whites had 14% lower prices and 11% lower rents than among Whites overall, and 29% of residents lived in owner-occupied housing. Black families lived in neighborhoods where the local price of housing was about 20% lower than low-skilled Whites, driven in part by lower home ownership rates in those neighborhoods.

Correspondingly, Black neighborhoods were generally poorer with lower income, lower employment rates, and lower education levels. However, the typical White family lived in a neighborhood with practically no Black people. The typical Black family's neighborhood was 73% Black.

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

In this section, I detail how I use variation from migrant enclaves to estimate the models laid out in Section 2.3. Section 2.3 describes a thought experiment where random population shocks of Black and White residents perturb existing neighborhood equilibria. Migrant inflows approximate that thought experiment. As an illustration, 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.

While Black migrant flows concentrate toward Watts and Compton, areas with a relatively high share of Black residents, 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 interestingly, migrants from Texas are drawn to cities other than Los Angeles.

However, these migrant flows are computed from self-reports on 1935 county of residence from the 1940 census. Some of their directedness may reflect not only affinities for enclaves of past migrants but also unobserved changes of neighborhood amenities that occurred between 1930 and 1940.

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 2.3.2, 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 2.3.1 require granular neighborhood variation. A diverse set of rural origin counties provide that variation.[24]

The conceptual framework in Section 2 focused on neighborhood choices conditional on living in a city c. Migrants come from outside the city. I denote the joint probability that migrants of race r and origin g choose both a neighborhood j in a city c by $\pi q_{rgj0} = \pi_{rgj0} \times q_{rgc0} = Pr[j, c|r, g]$. Thus, the definition of the past settlement instrument from Section 2.3.1 is $Z_{rj} = \sum_g \pi_{rgj0} \times \hat{M}^c_{rg} = \sum_g \pi q_{rgj0} M^{-c}_{rg}$. The key ingredient to construct the past instrument are the location probabilities of past migrants in the base period 1930.

The principal data challenge in my setting is that county of birth is unavailable prior to the 1940 census. Here, I develop a procedure for using surname distributions to recover a prediction for past settlement probabilities. I first use Bayes's Rule to relate the problem of predicting where migrants go to a problem of predicting where residents came from. Second, I show that surname distributions strongly predict the locations of rural non-migrants. Finally, I show that the migration choices of city residents in 1930 inferred by their surnames strongly predicts the decisions of those who emigrated between 1935–1940.

4.1.1 Where did city residents come from?

Consider the statistical population of migrants of race r and origin g living in a city. Denote neighborhood population counts with Q's and city population counts with N's. Were g directly observable, I could generate a simple estimate of the group's neighborhood choices by dividing the population of the group in neighborhood j by the population of the group in the city $\hat{\pi}_{rgj0} = \frac{Q_{rgj0}}{N_{rgc0}}$. In 1930, neither the numerator nor the denominator are directly available.

But, predicting where migrants go is related to predicting where residents came from. Applying Bayes's rule,

$$\pi q_{rgj0} = \frac{\Pr[g|r, j, c]}{\Pr[g|r]} \Pr[j, c|r],$$

omitting notation for the base period. The geographic distribution of each race $\Pr[j, c|r]$ can be estimated. The missing data problem fundamentally arises from not having granular information on where resident migrants came from $\Pr[g|r, j, c]$.

However, even though they are computed from self-reports, the probabilities are typically aggregated anyway. Microdata on each individual's origin is not strictly necessary. Origins themselves are only proxies for the social connections within immigrant communities that allow migrants' choices to be predicted over time. As such, other measures of connectedness can link origin shocks to destination neighborhoods.

To see this formally, let ℓ index groups that share certain observable characteristics (like the same surname). Expanding using the law of total probability, $\Pr[g|r, j, c] = \sum_\ell \Pr[g|r, j, c, \ell] \Pr[\ell|r, j, c]$. Unrelated to the identifying assumptions of the demand model in Section 2.3.1, I make two approximations about ℓ to recover the first term:

[24] I define rural counties as those that did not have an incorporated place. Granular county level variation offers several advantages over using state of birth alone, which is directly available in the census. First, appendix table A.2 shows a large portion of rural-to-urban migration was within region. Second, anecdotes suggest that migrants' kinship networks were highly localized (Wilkerson 2011). State level variation proxies for this more local variation, consistent with the flows depicted in figure 1 and analysis in table 2.

1. Conditional on resident's race r and group characteristics ℓ, birth origins are independent of city and neighborhood choices: $Pr[g|r, j, c, \ell] = Pr[g|r, \ell]$

2. The conditional distribution of birth counties is the same for the population of migrants as non-migrants $Pr[g|r, \ell] = Pr_{NM}[g|r, \ell] \equiv \varphi_{r\ell g}$,

yielding

$$Pr[g|r, j, c] \approx \sum_{\ell} \varphi_{r\ell g} Pr[\ell|r, j, c]$$

and

$$\widehat{\pi q}_{rgj0} \approx \frac{\sum_{\ell} \varphi_{r\ell g} Q_{r\ell j0}}{\sum_{\ell} \varphi_{r\ell g} \sum_{c} N_{r\ell c0}}. \tag{10}$$

$Q_{r\ell j0}$ is measurable using data on city residents. I estimate the probabilities $\varphi_{r\ell g}$ using data on non-migrants in rural counties. This expression mirrors the natural estimator for the choice probabilities except with approximations in place of the origin-specific populations $\hat{Q}_{rgj0} \approx \sum_{\ell} \varphi_{r\ell g} Q_{r\ell j0}$.

Note that these are not additional identifying assumptions of the model in Section 2, only approximations that allow me to make out-of-sample prediction using the population of non-migrants. Using surname distributions as proxies is not likely to introduce omitted variables that are related to unobserved changes in neighborhood amenities. Violations of these approximating assumptions manifest in worse predictions for county of origin—potentially problematic for instrument relevance, which I test in Section 4.2.2—but not necessarily biased estimates for the parameters of the neighborhood demand model. Next, I describe how I estimate $\varphi_{r\ell g}$ using surname distributions.

4.1.2 Surname distributions

Researchers in biology and physical anthropology (e.g., Zei et al. 1983; Piazza et al. 1987; Zei et al. 1993) have treated surnames as analogous to genetic alleles. Traditionally transmitted patrilineally, they measure patterns of genetic drift—i.e., migration.

Several facts about the early 20th century United States suggest that Black and White surnames are similarly clustered. 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).

I begin by constructing cells ℓ, grouping individuals who share the same race, state of birth, 10-year birth cohort (e.g. born between 1911–1920), and surname. Each city resident in 1930 must belong to a cell, and each rural non-migrant must also belong to a cell. As such, I focus on common surnames, defined as those that are present in each of the four decadal censuses between 1910–1940. I group the remainder into a single category of "uncommon" surnames.[25] Since surname distributions can drift, I use the nearest relevant census between 1910–1930 to measure the surname distributions for each birth cohort. Specifically, I use the 1930 census to measure the surname distributions for those born between 1921–1930, the 1920 census for those born between 1911–1920, and the 1910 census for those born before that.

[25] Incidentally, this category also includes uncommon misspellings and uncommon transcription errors.

The question of whether surnames provide granular signals of county of origin or simply noise is an empirical one. 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. The same corresponding surnames are not clustered in exactly the same patterns among Whites but are clustered nonetheless.

I aggregate these case studies to quantify the distinctiveness of each last name. Focusing on the surname distributions generated from the 1930 census, I compare the surname distribution for a given surname $\boldsymbol{\varphi}_{r\ell}$ to those leaving out the surname $\boldsymbol{\varphi}_{r,-\ell}$. I test the equality of each of these multinomial distributions for each of these state-surname combinations by generating a Pearson χ^2 test statistic $\chi^2_{r\ell}\left(\boldsymbol{\varphi}_{r\ell}, \boldsymbol{\varphi}_{r,-\ell}\right) = Pop_{r\ell}\sum_g \frac{(\varphi_{r\ell g}-\varphi_{r,-\ell,g})^2}{\varphi_{r\ell g}}$, where $Pop_{r\ell}$ is the number of individuals with last name ℓ. The null hypothesis of this test is that individuals who have surname ℓ have the same geographic distribution of those who do not. This test statistic is distributed according to a χ^2 distribution with degrees of freedom equal to the number of counties in the state minus one. The tests are statistically significant, evidence that surnames are highly predictive of geography. In 1930, 99.4% of Black non-migrants and 99.6% of White non-migrants had a surname with a p-value indistinguishable from zero.[26]

4.1.3 From surnames to migrants

The Pearson χ^2 test provides statistical evidence that surnames are clustered and not randomly allocated according to the geographic distribution of population in a state. However, the IV model's identification arguments do not hinge on being able to predict origins. They rest on whether surname-predicted probabilities $\widehat{\pi q}_{rgj0}$ generated by plugging in estimates of $\varphi_{r\ell g}$ from equation 10 contain signal about group-specific preferences for particular neighborhoods.

Recall that county of origin is available for city residents who migrated between 1935–1940 from the 1940 census. I assess whether the choices of these migrants can be predicted using the probabilities constructed from surname distributions in 1930. To that end, I perform a series of regression analyses on migrant flows separately for White and Black migrants. The unit of analysis is an origin (rural county)-destination (urban census tract) flow. I use as the dependent variable choice probabilities of migrants between 1935–1940, which are directly estimable from the 1940 census. The regressor is $\widehat{\pi q}_{rgj0}$ constructed via surname distributions. 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. However, the identification arguments in Section 2.3 and Appendix B 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. Rather, the R^2 improves more substantially

[26] The smallest double floating point precision number is 2.2×10^{-308}.

by including county of origin by destination city fixed effects, in part reflective of more local proximity to 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. Even in a very saturated regression, the probabilities generated from 1930 residents' surnames combined with non-migrant surname distributions strongly predicts later neighborhood decisions. Because the specification includes county of origin by destination city fixed effects, this pattern is not likely to be driven by proximity to transportation networks. Instead, the regression analyses are highly suggestive of 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

The previous section outlines how I measure past migrants' choices using surname distributions. Measurement in hand, I generate the instruments $Z_{rj} = \sum_g \widehat{\pi q}_{rgj0} M_{rg}^{-c}$, where I directly measure leave-one-out outflows from origin g to the other 45 cities M_{rg}^{-c} using information in the 1940 census on location in 1935. 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 offsetting effect may decrease the 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 Migrant effects on population

The theory in Section 2.3.2 and Proposition 2 posits a simple supply relationship that increases with the neighborhood's population. Changes in population trace out changes in price, generating the regression specification in equation 3. One concern is that the instruments were constructed from surname distributions instead of measured directly, introducing noise. For the instruments to be relevant for the model predictions, there must be enough explanatory variation to (1) predict population changes along the spectrum of baseline 1930 Black share s_{j0}, (2) conditional on the included covariates used for identification.

I estimate regression models analogous to equation 3, except I replace the dependent variable with the neighborhood's change in Black, White, and total population. Table 3 reports each model's coefficient estimates. The coefficients reflect a combination of hitherto unknown model parameters (see Appendix C) and noise associated with using surname distributions to predict migrant shares. In particular, the signal-to-noise of Black surname distributions may differ from White surname distributions. Accordingly, I interpret these results only qualitatively and do not compare the magnitude of coefficient estimates between Z_{Bj} and Z_{Wj}.

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 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.[27] 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. Recall in Section 2.3.2, I assumed a housing supply relationship that depends on the local neighborhood population. As a result, migrants' predicted price effects are closely linked to their effects on neighborhood population. Most of the predictions discussed theoretically in Section 2.3.2 and empirically in section 4.2.1 are borne out in the price results in column 2. 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 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.

[27] 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.

4.3 Estimates of β_r and γ_r

The equilibrium predictions in Section 2.3.2 come from two structural relationships: race-specific housing demand in equation 1 and a neighborhood-specific housing supply relationship. The section estimates the parameters governing choices over prices and racial composition specified by the former. I do not parameterize or estimate the latter. Assuming supply slopes upward generates intuitive implications corroborated by the reduced form patterns in Section 4.2.1, but I do not impose the assumptions as identifying restrictions.

Rather, I simply estimate the demand relationships, remaining empirically agnostic about how the slope of supply varies from neighborhood to neighborhood. With only one linear structural equation, straightforward 2SLS estimation of equation 5 recovers the demand parameters by inverting a reduced form system of linear equations that combines (1) the conditional correlations of choice probabilities with the migrant demand shocks with (2) the equilibrium associations of neighborhood Black share and price from Section 4.2.2 as first stage regressions. In doing so, I interpret changes in choice probabilities associated with migrant shocks to only reflect residents' revealed preferences over equilibrium changes in price and neighborhood racial composition.

While quantifying their impact is an objective of this paper, constraints in Black housing choice pose a practical hurdle: the estimation samples for the Black and White demand models are limited to the tracts where I observe them. Thanks to the multinomial logit's IIA assumption, I can construct the outcome using the subset of tracts where I observe Black and White families. Rather than having different first stage relationships for each demand model, I use identifying variation from all available tracts by estimating the model parameters using two-sample 2SLS. The first stage regressions are the same as those reported in Table 4, estimated on the full analysis sample of census tracts. The second stage regressions are estimated on the subset of choices.[28] I report heteroskedastic robust standard errors according to Pacini and Windmeijer (2016).

Table 5 reports the coefficient estimates, panel A for Black families and panel B for White families. Column 1 reports estimates where I construct the choice probabilities from the choices of families headed by males in low-skilled occupations. I focus primarily on these families for the remainder of the analysis because 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.

Low-skilled Black families do not seem to exhibit particularly strong preferences for neighborhood racial composition. Low-skilled White families have intensely negative preferences for Black neighbors. One quantitative way of summarizing the trade off is via a utility-constant, compensated semi-elasticity $\frac{\gamma_r}{\beta_r}$. Whereas for low-skilled Black families, a one percentage point increase in the local Black share keeps families relatively indifferent, the same effect must be compensated by nearly a 1% decrease in the local price of housing to keep similarly situated White families indifferent.

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.

Consistent with the findings in other research, White families unsurprisingly had a high willingness to

[28] 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.

pay more to avoid Black neighbors. The analysis of the equilibrium in the next sections asks whether they had to pay more to avoid Black neighbors.

5 Correlated random effects and predictions of household valuations of local amenities

The previous section argues that all else equal, White families had strong preferences for White neighborhoods. However, Black and White neighborhoods may not be equal. Even absent direct preferences for the racial composition of the neighborhood, differing preferences over local amenities can drive differing choices, arising in segregation.

In the spirit of BFM, preferences in my model reflect both physical characteristics as well as social interactions—a direct preference for living next to or avoiding Black neighbors.[29] After adjusting for prices and neighborhood racial composition, (potentially constrained) choices reflect households' utility value of the physical characteristics of the neighborhood. The IV regressions of the previous section are necessary to measure households' value of the neighborhood's physical characteristics.

The model formalizes the assumptions that permit an out-of-sample prediction of preferences for neighborhoods that were not selected independently—they had no Black residents.[30] Under its simple structure that parallels BFM, the model residuals are summary measures of how much average households value the same physical characteristics. Those valuations need not be the same across races, but they may be correlated. The principal challenges are with measurement. In this section, I first measure the race-specific average value of neighborhoods' physical characteristics. I then assess whether those valuations are correlated between races in the neighborhoods where I observe both. Finally, I predict Blacks' valuations out-of-sample in White neighborhoods.

5.1 Measuring the amenity value of neighborhood characteristics

For each race and broad occupation group, I begin by residualizing the choice probabilities $\hat{u}_{rjt} = \ln \hat{\pi}_{rjt} - \hat{\beta}_r \ln P_{jt} - \hat{\gamma}_r s_{jt}$ using the estimates of β_r and γ_r measuring how households tradeoff between price and racial composition of a neighborhood from the previous section. These residual measures reflect both race-specific valuations of neighborhood amenities $\xi_{rjt} = \bar{\xi}_{rj} + \tilde{\xi}_{rjt}$ as well as estimation error $\tilde{u}_{rjt}$.

Section 2.4 details the procedure to separate Black and White residual preferences from estimation error. Stacking the dependent variable $\hat{u}_{rjt}$ across both 1930 and 1940, I estimate the regression models of equation 7 on the same sample of tracts used to produce $\hat{\beta}_r$ and $\hat{\gamma}_r$, using as predictors the Black and White migrant shocks, the connectedness controls, 1930 neighborhood population, and city by decade fixed effects to absorb

[29] In BFM's setup, houses and neighborhoods are essentially defined as a collection of observable and unobservable characteristics that are capitalized into the price. One of their insights is that after adjusting for prices, choices themselves are a summary measure for how much an average household values those characteristics—a mapping from indirect utility to revealed preference to price and vice versa. Their demand estimation is equivalent to using a multinomial logit as a control function to selection correct a hedonic pricing model. Heterogeneous households have idiosyncratic preferences for heterogeneous houses and self-select accordingly. BFM show that adjusting choices by prices is equivalent to adjusting prices by choices to measure the average value of the housing stock and neighborhood.

[30] My approach diverges from BFM's in objective. BFM aim to decompose choices and prices into average partial effects of different observable characteristics with the intent of holding the others constant. Accordingly, they project choice-adjusted prices onto observable characteristics. The estimated parameters measure the average partial effect of each of those covariates on price. In this paper, I do not consider counterfactuals where neighborhoods have different characteristics. In my setup, the direct objective of the CRE parameters summarizing the physical aspect of neighborhoods is not causation but rather prediction: particularly, how Black households value the characteristics of White neighborhoods.

the inclusive value. I denote the coefficient estimates on observable predictors by $\hat{F}_r$, and the residuals of these auxiliary regression models by $\widetilde{\xi u}_{rjt}$.

According to the assumptions laid out in Section 2.4, 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

$$\hat{\sigma}_r^2 = \frac{1}{J-K}\sum_j \widetilde{\xi u}_{rj0} \cdot \widetilde{\xi u}_{rj1} \tag{11}$$

$$\hat{\sigma}_{BW} = \frac{1}{2J-K}\sum_j \left(\widetilde{\xi u}_{Wj0} \cdot \widetilde{\xi u}_{Bj1} + \widetilde{\xi u}_{Wj1} \cdot \widetilde{\xi u}_{rj0}\right), \tag{12}$$

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.3 summarizes the estimates of the variance components.

The parameters estimated in this section summarize the joint distribution of race-specific residual preferences but are not directly interpretable. The CRE structure has two related objectives: (1) to understand whether amenities drive segregation in neighborhoods where Black and White residents do live and (2) to predict counterfactual Black demand in neighborhoods where Black residents were excluded. The next section explores the first objective.

5.2 Do amenities drive segregation?

Using the parameter estimates, I generate predictions of race-specific preferences for neighborhood characteristics $\bar{\xi}_{rj}$ from the combination of the observable and unobservable components:

$$\begin{aligned}
\hat{\xi}_{rj} &= \hat{F}_r' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j'\right]' + \hat{\psi}_{rj} \\
\hat{\psi}_{rj} &= \boldsymbol{E}\left[\psi_{rj} | \widetilde{\xi u}_{rj0}, \widetilde{\xi u}_{rj1}\right] \\
&= \frac{\hat{\sigma}_r^2}{\hat{\tau}_r^2}\left(\frac{\widetilde{\xi u}_{rj0} + \widetilde{\xi u}_{rj1}}{2}\right),
\end{aligned}$$

where $\hat{\tau}_r^2 = \frac{1}{2J-K}\sum_j \widetilde{\xi u}_{rjt}^2$, the pooled estimate of the residual variance (including estimation error). The observable components are the predicted values from the regression. The unobservable component is the usual random effects prediction: an average of the residuals shrunk according to the ratio of the signal (measured from the serial correlation) to the overall residual variance.

Focusing on low-skilled occupation groups, Figure 3 plots the joint distributions of the race-specific correlated random effects. Panel a plots the composite predicted effect $\hat{\xi}_{rj}$, panel b plots the component due to observables $\hat{F}_r' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j'\right]'$, and panel c plots the joint distribution of the shrunken average residuals. The relationship in each graph is upward sloping, suggesting that White and Black families fundamentally value amenities in the same way. In particular, the unobservable component exhibits both spread and a strong positive correlation. Thus, a substantial amount of the overall variation in $\hat{\xi}_{rj}$ is driven by those unobservables, highlighting their especially important role in my setting where I lack rich observable characteristics to make predictions. Neighborhoods differ along a plethora of different dimensions, but those idiosyncracies matter for segregation only to the extent that they systematically manifest in different choices.

Positively correlated demand residuals in mixed neighborhoods push against the idea that segregation reflects differing Black and White residents' tastes for parks, schools, or local businesses. The bottom panel of Appendix Table A.3 reports raw and scaled covariances of $\bar{\xi}_{Bj}$ and $\bar{\xi}_{Wj}$.

This section asked whether Black and White residents have systematically different preferences over the same neighborhood idiosyncracies. The analysis suggests that they do not. Focusing on White residual demand as a summary measure for neighborhoods' characteristics, the next section asks whether all-White and mixed neighborhoods are fundamentally different.

5.3 Amenities in White neighborhoods

Are White neighborhoods substantively different from mixed neighborhoods? Qualitatively, low-skilled Black and White families appear to value the same local amenities. But, quantifying counterfactual Black demand for all neighborhoods requires predicting Black families' value of those amenities for housing in White neighborhoods. The estimated CRE parameters summarize the joint distribution of $\bar{\xi}_{Bj}$ and $\bar{\xi}_{Wj}$ in mixed neighborhoods. Whether those parameters are useful for out-of-sample predictions of $\bar{\xi}_{Bj}$ depends on whether I can reasonably compare the unobservables of mixed neighborhoods to all-White neighborhoods.

Do the distributions of estimates of $\bar{\xi}_{Wj}$ share the same support? Disjoint support weakens the case that the correlation of Black and White residual preferences estimated in mixed neighborhoods in Section 5.1 can reasonably approximate the unobserved correlation in all-White neighborhoods. That is not the case. Figure 4 plots the marginal distributions of $\bar{\xi}_{Wj}$ in both Black and White neighborhoods. The distributions share similar support. Mixed tracts exhibit somewhat more spread than all-White tracts over all of the components, but the marginal distributions are otherwise remarkably similar.

Predicting Black demand in White neighborhoods To produce counterfactual Black demand, I predict Black valuations of amenities out-of-sample using equation 8

$$\begin{aligned}\hat{\psi}_{Bj} &= \frac{\hat{\sigma}_{BW}}{\hat{\sigma}^2_W}\hat{\psi}_{Wj} \\ &= \frac{\hat{\sigma}_{BW}}{\hat{\tau}^2_W}\left(\frac{\widetilde{\xi u}_{Wj0} + \widetilde{\xi u}_{Wj1}}{2}\right).\end{aligned}$$

The equation modifies the estimate $\hat{\psi}_{Wj}$ by replacing $\hat{\sigma}^2_W$, the cross-decadal covariance in the White residual, with $\hat{\sigma}_{BW}$, the average cross-decadal covariance in the residuals across race. Following Section 2.5, I use these predicted valuations to construct counterfactual mean utilities and counterfactual choices. I use the counterfactual choices to decompose segregation in the next section.

6 Decomposing Segregation

Section 4 identified how low-skilled Black and White households trade off between the price and racial composition of a neighborhood using migrant-driven neighborhood perturbations. Section 5 used those estimates to (1) adjust choices and recover households' implicit valuation of local neighorhood amenities; (2) summarize the joint distribution between Black and White valuations; and (3) use those summary parameters to predict Black valuations out of sample. The section concludes by combining the ingredients to construct counterfactual Black demand at prevailing prices absent constraints.

Following the procedure laid out in the conceptual framework in Section 2.5, this section uses the counterfactual to decompose the KL divergence KL_c. The KL divergence is an average. It measures the average distance between the Black and White probabilities of choosing a neighborhood for specifically Black families. 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.[31]

In the context I study, those choices do not need to correspond to purely market forces. I split the distance between Black and White choices into two distances, using as an intermediate the counterfactual predicted Black demand from Section 5. The first distance in equation 9 is between actual and counterfactual Black choices. Counterfactual Black families are meant to have the same preferences as actual Black families. They differ only in the neighborhoods available to them. Thus, the first distance measures the influence of non-market constraints on the KL divergence. The second distance is between counterfactual Black choices and actual White choices. I assume that White choices are unconstrained. Hence, the second distance measures the influence of preferences on the KL divergence.

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, because neighborhoods where low-skilled Whites lived were more expensive, the model also does not predict that an integrated equilibrium is compatable with the estimated preferences. In column 3, the decomposition suggests that preferences mediate the remaining 100 log points—roughly half—of observed segregation through prices.

Both segregation and constraints vary across city and region. 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). Perhaps reflecting less "necessity" for residential segregation where explicitly racist policies ensured separation in schools and public life, equilibria in cities like Birmingham, Nashville, and Savannah were characterized by somewhat fewer constraints.

[31] This measure is closely related to a version of the common index of isolation, which is also a mean. The isolation index uses as a characteristic the White share of the neighborhood. It measures the average neighborhood White share for Black families.

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,[32] 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.[33]

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 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.[34] I estimate two sets of regression models:

$$KL_{ct} = a_t + b_t KL_{c,1940} + e_{ct} \tag{13}$$

$$KL_{ct} = c_t + d_{1t} Constraints_{c,1940} + d_{2t} Preferences_{c,1940} + u_{ct}, \tag{14}$$

where constraints and preferences are measured via the decomposition and reported in appendix table A.4.[35]

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

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

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

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

[35]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 $d_{1t} = d_{2t}$.

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 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 and applies that model to explain the segregated equilibria in major US cities in 1940. The analysis in Section 4 interprets households' changing neighborhood choices in response to surname-predicted migrant perturbations as reflecting underlying racial preferences. Investigating the determinants of segregation, the model estimates find no strong role of Black racial preferences and confirm the important role of White racial preferences. Summarized in the estimated compensated semi-elasticity, each percentage point increase in the neighborhood Black share must be compensated by a 1% decrease in the price to keep White households indifferent. Section 5 characterizes households' residual neighborhood preferences using correlated random effects. The positive correlation between the residual explanations of Black and White choices suggest that race-specific amenities are not likely to be a strong driver of segregation.

Simply, White households are willing to pay more for neighborhoods that are more White. All-White neighborhoods are generally more expensive. Culminating in Section 6, this paper asks the extent to which the observed distribution of neighborhood prices can support cities' observed equilibria given the choices rationalized by the demand model. The analysis shows that the equilibria that prevailed in US cities in 1940 are generally not consistent with a fully decentralized equilibrium. The quantitative decomposition analysis of Section 6 shows that constraints explain roughly half of segregation across cities in my sample. But like segregation itself, the model-derived measure of constraints varies dramatically across cities. Using that variation, I show that segregation in the second half of the twentieth century is more persistent when driven by constraints in 1940.

Segregation is path dependent. 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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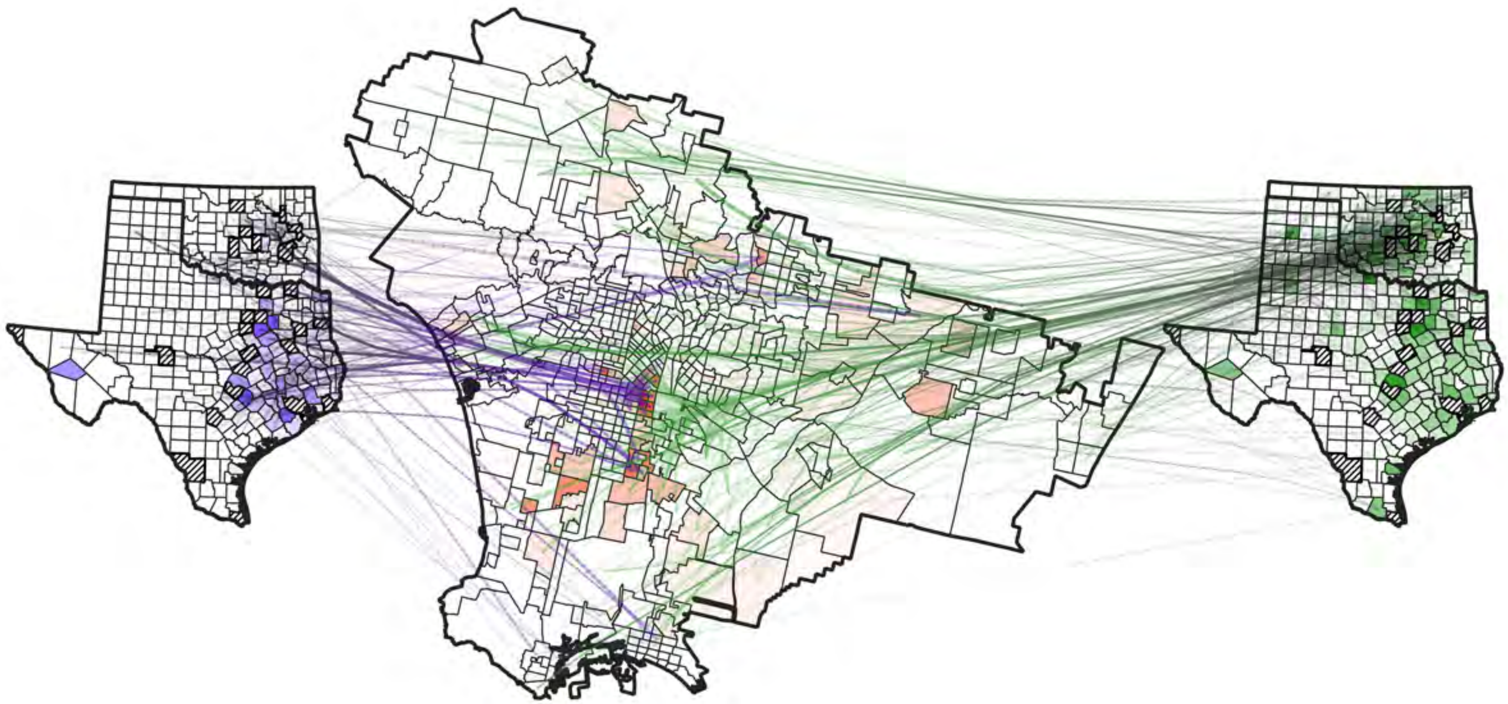
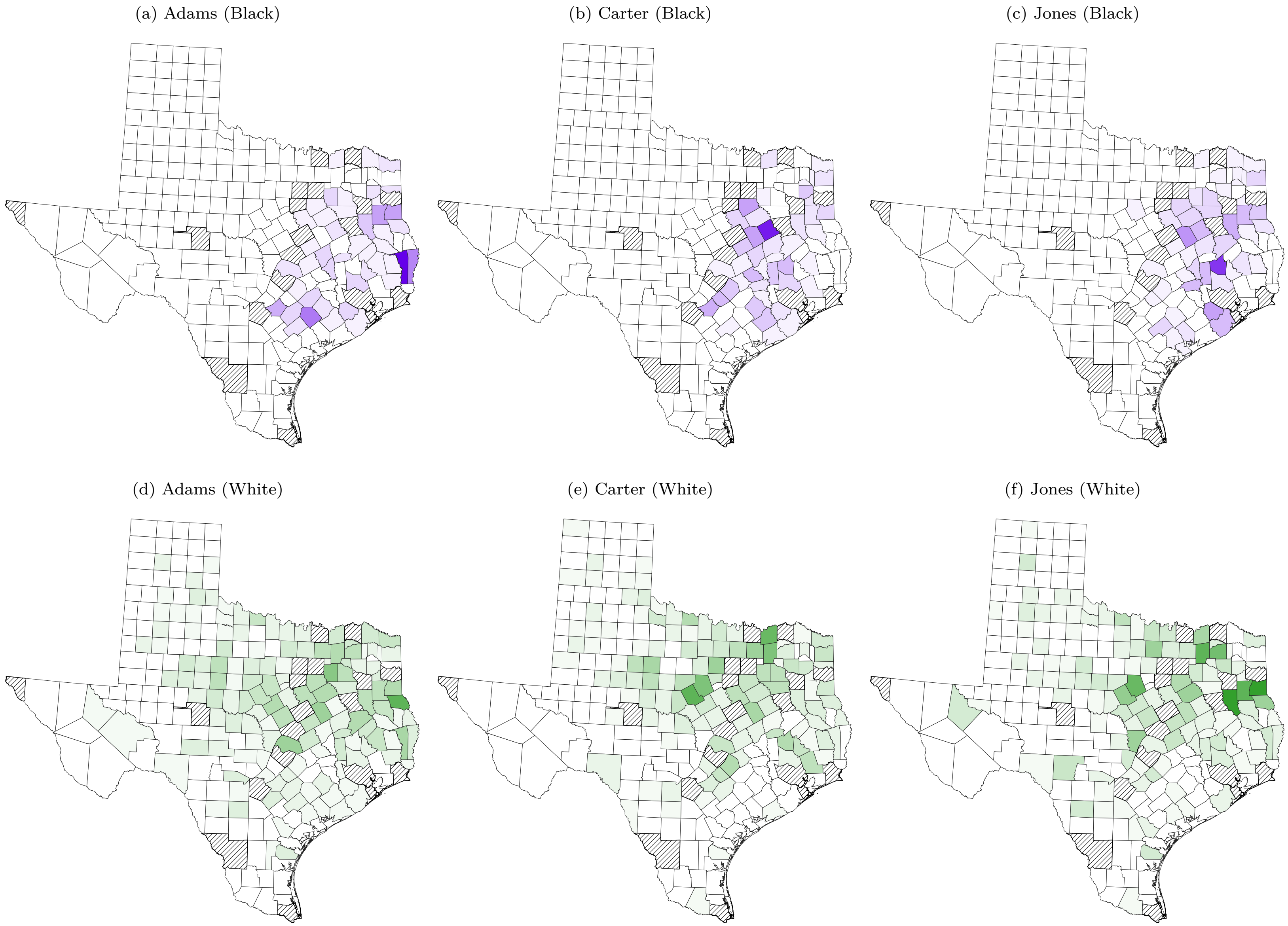
8 Figures and Tables

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.

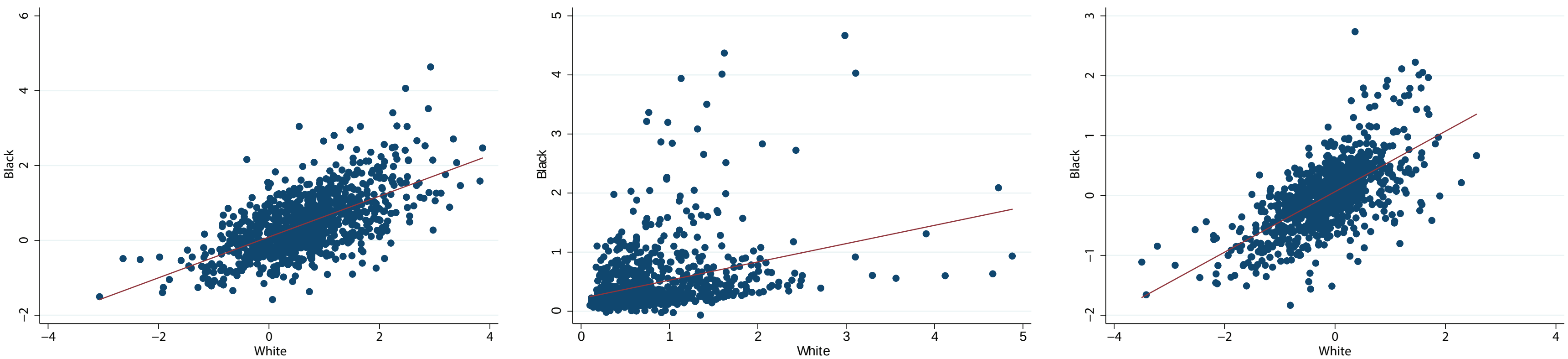
Figure 2: Geographic Distribution of Three Common Last Names in Texas



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: Joint Distribution of Black and White Residual Demand, Low-skilled Workers

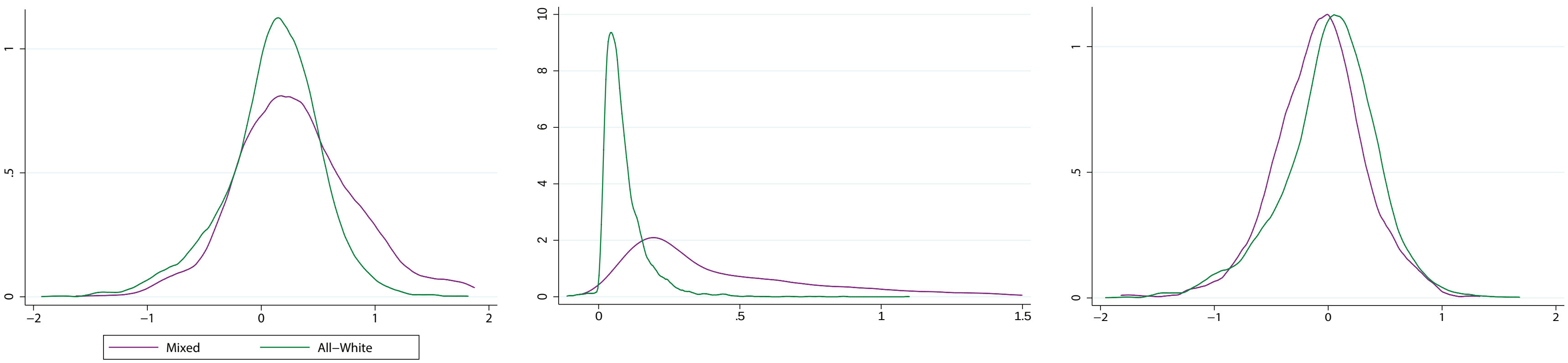
(a) Composite $\bar{\xi}_{rj}$ (b) Observables $F_r' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j' \right]'$ (c) Unobservables ψ_{rj}



This figure plots the joint distribution of components of low-skilled Black and White residual demand estimated in section 5. The samples for each figure are the mixed neighborhoods where both White and Black families lived. The vertical axis of each figure measures the component for low-skilled Black families and the horizontal axis measures the component for low-skilled White families. Panel a plots the joint distribution of the total composite estimate, $\bar{\xi}_{Bj}$ against $\bar{\xi}_{Wj}$. Panel b plots the components of the prediction from the observable covariates. Panel c plots the unobservable shrunken residual. See the text in section 5 for details.

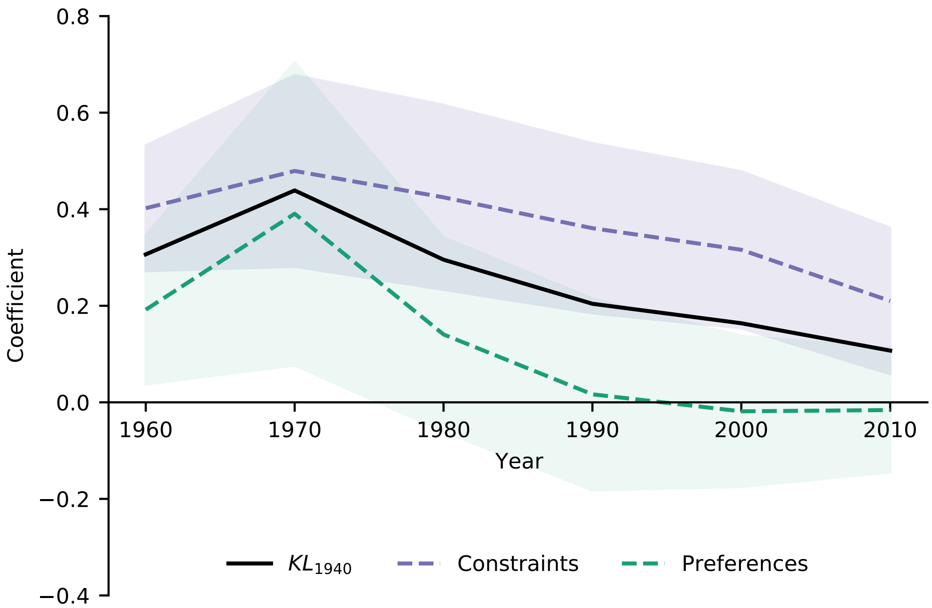
Figure 4: Marginal Distributions of White Residual Demand in Mixed and All-White Neighborhoods, Low-skilled Workers

(a) Composite $\bar{\xi}_{rj}$ (b) Observables $F_r' \left[Z_{Bj}, Z_{Wj}, \boldsymbol{X}_j' \right]'$ (c) Unobservables ψ_{rj}



This figure plots the marginal distributions of components of White residual demand estimated in section 5. Plotted in purple is the distribution of White residual demand in mixed neighborhoods where both Black and White families lived. Plotted in green is the distribution of White residual demand in all-White neighborhoods. Panel a plots marginal distribution of the total composite estimate, $\bar{\xi}_{Bj}$ against $\bar{\xi}_{Wj}$. Panel b plots the component of the prediction from the observable covariates. Panel c plots the unobservable shrunken residual. See text for details.

Figure 5: The Origins of Modern Segregation



This figure plots the coefficients of equations 13 and 14 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.4. 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 3.1 for details. Median neighborhood price combines both home values and rents into a single measure. See section 3.3 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 4.1.2 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
	⟨0.000⟩	⟨0.000⟩
Black Effects	15.51	44.60
	⟨0.000⟩	⟨0.000⟩
White Effects	4.698	3.392
	⟨0.009⟩	⟨0.034⟩

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 3.1 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) Overall	(2) Constraints	(3) Preferences	(4) Constraints	(5) 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 9, 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.4 for decompositions of all 46 cities.

A Appendix Tables and Figures

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: Migrant Inflows to 46 Major Cities with Census Tracts by Census Region, 1935–1940 (Thousands)

(a) Black

	(1) All	(2) South	(3) West	(4) Midwest	(5) Northeast
Total	250	105	18	55	72
From rural counties	116	69	4	22	22
in the South	110	68	3	19	20
in the West	1	0	1	0	0
in the Midwest	4	0	0	3	0
in the Northeast	2	0	0	0	2

(b) White

	(1) All	(2) South	(3) West	(4) Midwest	(5) Northeast
Total	3,960	767	929	952	1,311
From rural counties	1,087	344	308	297	138
in the South	440	315	49	49	28
in the West	180	5	165	6	4
in the Midwest	355	19	90	235	11
in the Northeast	112	6	4	6	96

These tables report the magnitude of flows between 1935–1940, computed from a retrospective question in the 1940 census asking about respondents' location five years prior. The top panel reports flows of Black migrants and the bottom panel reports flows of White migrants.

Table A.3: 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.4: 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. Columns 2 and 3 decompose the KL divergence into constraints and preferences explanations, respectively. See text in section 6 for details.

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 $Q_{rgj0} \sim Binom\,(M_{rg}, \pi_{rgj0})$. By iterated expectations, $\boldsymbol{E}\,[Q_{rgj0}|\pi_{rj0}] = M_{rg}\pi_{rj0}\boldsymbol{E}\,[\exp\eta_{rgj0}]$.

For large numbers of *migrants* M_{rg}, $\hat{\pi}_{rgj0} \xrightarrow{d} \mathcal{N}\,[\pi_{rgj0}, \pi_{rgj0}\,(1-\pi_{rgj0})]$ by the central limit theorem. Thus, one can view, $\{\hat{\pi}_{rgj0}\}\,|\pi_{rj0} \overset{iid}{\sim} \mathcal{N}\,[\pi_{rj0}\boldsymbol{E}\,[\exp\eta_{rgj0}]\,, \pi_{rj0}\boldsymbol{E}\,[\exp\eta_{rgj0}]\,(1-\pi_{rj0}\boldsymbol{E}\,[\exp\eta_{rgj0}])]$. 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 $\Pr[\cdot]$,

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

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

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

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:

$$
\begin{aligned}
\frac{\partial Q_W}{\partial N_{Bg}} &= Q_W\frac{\partial \ln \pi_W}{\partial N_{Bg}}\\
&= (1-s)\left\{\left(\beta_W\lambda - \gamma_W s\right)\frac{\partial Q_W}{\partial N_{Bg}} + \left[\beta_W\lambda + \gamma_W(1-s)\right]\frac{\partial Q_B}{\partial N_{Bg}}\right\}\\
\left[1-\beta_W\lambda(1-s)+\gamma_W s(1-s)\right]\frac{\partial Q_W}{\partial N_{Bg}} &= \left[\beta_W\lambda + \gamma_W(1-s)\right](1-s)\frac{\partial Q_B}{\partial N_{Bg}} \qquad (15)
\end{aligned}
$$

and

$$
\begin{aligned}
\frac{\partial Q_B}{\partial N_{Bg}} &= \pi_{Bg} + Q_B\frac{\partial \ln \pi_B}{\partial N_{Bg}}\\
&= \pi_{Bg} + s\left\{\left(\beta_B\lambda - \gamma_B s\right)\frac{\partial Q_W}{\partial N_{Bg}} + \left[\beta_B\lambda + (1-s)\gamma_B\right]\frac{\partial Q_B}{\partial N_{Bg}}\right\}\\
\left[1-\beta_B\lambda s-\gamma_B s(1-s)\right]\frac{\partial Q_B}{\partial N_{Bg}} &= \pi_{Bg} + \left(\beta_B\lambda - \gamma_B s\right)s\frac{\partial Q_W}{\partial N_{Bg}}. \qquad (16)
\end{aligned}
$$

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 15 and 16.

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

Proof. For simplicity, define:

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

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. $\frac{\partial Q_B}{\partial N_{Wg}} = \mu(s)\left[s\left(\beta_B \lambda - \gamma_B s\right)\right]\pi_{Wg}$

3. $\frac{\partial Q}{\partial N_{Wg}} = \mu(s)\left(1 - \gamma_B s\right)\pi_{Wg}$

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:

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

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* $b_{1W} > 0$, $c_{1B} < 0$, $\tilde{e}_{1W} = O\left(\left(s-\frac{1}{\gamma_B}\right)^2\right)$, *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

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

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

Similarly,

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

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

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

Corrrespondingly,

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

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).[36]

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 $(\beta_r \ln P_{ht} + \varsigma_{rht})/\rho$.

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

[36] 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.

location of the house price distribution G_{jt}. I proxy for the mean $\boldsymbol{E}_{rjt}\left\{\exp\left[\left(\beta_r \ln P_{ht} + \varsigma_{rht}\right)/\rho\right]\right\}$ with $\boldsymbol{Med}_{jt}\left\{\exp\left[\left(\beta_r \ln P_{ht}\right)/\rho\right]\right\}$. Since monotonic transformations commute with the median operator, substituting yields

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

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 2.3 discusses the first force. Unobserved neighborhood amenities and simultaneously determined supply drives a correlation between price and ξ_{rjt}, discussed in section 2.3.[37] 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 2.3 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.

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,

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

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.