Housing Market Channels of Segregation

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Abstract

Was the pattern of residential segregation that emerged in major US cities in the mid-twentieth century simply a reflection of white preferences? Or, was it due in part to constraints on the availability of homes to black families? In this paper, I draw on rich population data from the 1930 and 1940 censuses to answer these questions. I lay out a simple discrete choice model of residential choices by white and black families that depends on the local price of housing and on the fraction of black residents in each neighborhood. I show how the preferences of both race groups can be identified using information on the impacts of exogenous inflows of white and black residents to different neighborhoods. White and black rural inflows constituted a major source of inmigration to major cities during this time period; I construct a pair of novel instrumental variables for these inflows by connecting the distributions of white and black surnames in rural areas to earlier migrants living in different census tracts in 1930. The resulting structural estimates confirm that white families had a relatively high willingness to pay to avoid black neighbors, consistent with an important role for preferences in the evolution of neighborhood segregation. Combining white and black preferences, however, I also find strong evidence that black residents faced supply side constraints on their neighborhood choices. I conclude that about one half of the overall degree of neighborhood segregation observed in 1940 was due to the different preferences of white and black families, while a comparable share was due to implicit or explicit constraints on which neighborhoods black families could move into.

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1 Introduction

Higher rates of residential segregation are associated with worse educational outcomes for black children and persistent problems through adulthood, including lower employment and earnings.[1] Despite the wealth of findings on this correlation, 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, 1978). The role of white preferences in driving segregation has been corroborated by "white flight" following school desegregation efforts (e.g., Coleman, Kelly, & Moore, 1975; Reber, 2005) and by studies of rapid "tipping" of neighborhood racial shares in response to minority inflows (Card, Mas, & Rothstein, 2008). Recent research on the impacts of the Great Migration (Boustan, 2010; Shertzer & Walsh, 2016) suggest similar reactions throughout the twentieth century. 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.

Although detailed case studies have documented the existence of formal and informal constraints on the housing market options available to black families (see e.g. Ondrich, Stricker, & Yinger, 1998, 1999; Yinger, 1986), to the best of my knowledge, there has been no systematic attempt to quantify the separate contributions of "demand-based" explanations for segregation (i.e., explanations based on individualistic choices made by white and black families) from "supply-based" explanations (i.e., explanations based on institutions as well as extralegal threats of violence that restrict the choices available to black families). In part, the exercise has been hampered by the absence of credible identifying information that can make it possible to separate the effects of housing prices and neighborhood racial composition on the housing demands of white and black families. A related requirement is a modeling framework rich enough to specify the choices of black families *in the absence of any (non-price) constraints.* Indeed, state of the art models of housing choices (see e.g. Bajari & Kahn, 2005; Bayer, Ferreira, & McMillan, 2007; Bayer, McMillan, & Rueben, 2004) fit to contemporary data typically assume that each family can freely choose among housing units, given their incomes and preferences.

This paper attempts to provide a credibly identified, quantitative summary of the contributions of supply and demand based explanations for the patterns of racial segregation in large US cities in 1940, just before segregation became a permanent, entrenched fact of the American urban landscape. 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] I use the predictable component of these migrant inflows as a source of identifying variation that allows me to estimate simple structural models of the neighborhood preferences of white and black families, separating families into broad occupation groups.

[1] See e.g., Cutler and Glaeser, 1997; Massey and Denton, 1993; the 1966 Coleman Report; Chetty and Hendren, 2018a, 2018b; Chetty, Hendren, Kline, and Saez, 2014.

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

[3] Lieberson (1980), 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.

I then use the resulting estimates and the structure of the model to identify counterfactual neighborhood demands of black residents in the absence of non-price constraints. This allows me to quantify the components of observed segregation attributable to the differential preferences of whites and blacks (demand side) and the non-price constraints faced by black residents (supply side).

I begin my analysis by setting up a 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 under some additional assumptions, exogenous migrant demand shocks affect prices and the neighborhood black share. Crucially, the model also predicts that these effects materialize differently for more and less black neighborhoods, heterogeneity that ultimately provides part of my identifying variation.

The model provides a theoretical basis for using migrant demand shocks to perturb existing sorting equilibria and recover the preference parameters. Because migrants' endogenous neighborhood choices may reflect unobserved neighborhood changes, I develop shift-share instruments for inmigration from rural counties built on the fact that migrants are attracted enclaves of past migrants (Altonji & 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 based on *pre-1930* migrant settlement patterns are highly predictive of actual county-to-census tract flows in the 1935–40 period.

Instruments for rural migration in hand, I take the model to the data. I control for unobserved neighborhood heterogeneity by estimating a series of first-differenced regressions by census tract.[4] I show that the instruments' reduced form effects on white and black populations replicate predictions that one would expect from the model. These population effects similarly trace out corresponding changes in prices and neighborhood black share, which become the first stage estimates for the model.

I then estimate the choice parameters separately by broad occupation group using the linear instrumental variable approach developed by Berry (1994). These two-stage least squares (2SLS) estimates provide estimates of white and black willingness-to-pay for more or less black neighborhoods. Consistent with past findings of white aversion to more black neighborhoods, a typical white household would have to be compensated by a 1% lower house price for a 1 p.p. increase in the black share of the neighborhood to hold utility constant. At the same time, blacks seem to have no or weak preferences toward more black neighborhoods.

Nonetheless, for black families, these estimates reflect choices made among the restricted set of tracts where they were allowed to live. To quantify the effect of any non-price rationing on the allocation of black families to different neighborhoods, I have to specify the demand of black families in the absence of those restrictions, a task that is fundamentally unsuited to using only within-variation from the first-differenced regressions. To make progress, I assume a correlated random effects (CRE) structure that maintains the instruments' identification of the preferences over price and neighborhood black share. The CRE model imposes the assumption that the static component of neighborhood choice is a linear function of observable characteristics and an orthogonal unobserved component. Importantly, I allow this unobserved component to be correlated between races. This model allows me to predict counterfactual demand using the observed prices and white choice probabilities 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, a measure of statistical divergence between two distribu-

[4]Importantly, I include as one of my controls the sum of the population shares of rural migrants in each census tract as of 1930. The addition of this control variable addresses a commonly-raised concern that shift-share instruments may be inadvertently picking up differences in the shares of earlier migrants that are correlated with unobserved determinants of subsequent migration.

tions.[5] 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 supply-side explanations for segregation—and then comparing the counterfactual black demand to actual white demand—quantifying the contribution of demand-side explanations based on the responses to the prices and black resident shares observed in each neighborhood. This decomposition suggest that roughly half of segregation is explained by divergent preferences over the neighborhood's black share, and the remainder is driven by constrained supply.

In forthcoming work, I turn to aggregate evidence of housing market segmentation and its consequences for black residents. Abstracting from heterogeneity within cities, I compare the effects of an exogenous change in black population and white population on median black and white prices, respectively. Two facts emerge that are consistent to the within city analysis. First, an exogenous increase in black inmigration has a quantitatively large, statistically significant effect on average housing prices paid by blacks. In contrast, inflows of whites have no large or significant effect on housing prices for blacks. These results suggest that housing supply constraints caused materially higher prices for black households, as suggested by Cutler et al. (1999).

This paper contributes to several strands of literature. Most relevantly, this paper relates to empirical papers following Epple and Sieg (1999) that relate household equilibrium location choice to neighborhood quality and public good provision. In particular, Bayer et al. (2007) (henceforth, BFM) estimate models of equilibrium sorting similar to the one I present in this paper, identifying preferences over neighborhood characteristics using variation driven by households sorting across school district boundaries.[6] Using a similar approach, Bayer et al. (2004) report black and white preferences for segregation, but are careful to 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." This limitation is shared by virtually all recent papers that characterize equilibrium neighborhood choices. My paper attempts to separate the contributions of preferences and non-price constraints that limited the choices of black families to a subset of neighborhoods in the late 1930s.

Second, this paper relates directly to the expansive literature studying localized effects of migrants on labor markets, particularly those which utilizes the "past settlement" instrument.[7] The bulk of these papers 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 & Walsh, 2016). This paper shows that internal migrants are drawn to the locations of past migrants defined at the much finer county geography, which is suggestive of the importance of social networks in driving migration in addition to access to similar modes of transportation. A similar conclusion is reached in a recent study by Stuart and Taylor (2017) who use data on town of birth to study white and black migration flows over the course of the 20th century. While most of the research in immigration has focused on labor market effects, two studies in particular, Saiz (2003, 2010), utilize the housing demand variation driven by large inflows of immigrants to trace out housing supply curves.

Third, I relate to a smaller literature that studies housing supply and its determinants.[8] This literature

[5] Mora and Ruiz-Castillo (2010, 2011) develop methods for decomposing KL divergences between nests of groups (e.g. city vs. school district segregation) and along different dimensions (e.g income vs. race).

[6] One interpretation of their procedure is that they correct for unobserved selection in a hedonic model of house prices by (1) isolating the sample to school boundary areas and including boundary-specific fixed effects and (2) using the mean utility from a multinomial logit demand system as a control function, using interactions between housing and household characteristics and characteristics of houses in other neighborhoods as excluded instruments.

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

[8] DiPasquale's (1999) appropriately titled review "Why Don't We Know More About Housing Supply?" bluntly begins,

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 are connected to race.[9]

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 & Mullainathan, 2004; Clark, 2014; Olivetti & Paserman, 2015; Goldstein & Stecklov, 2016), while biologists and physical anthropologists trace divergences in gene distributions from the hereditary nature of surnames (see e.g. Zei, Guglielmino, Siri, Moroni, & Cavalli-Sforza, 1983; Piazza, Rendine, Zei, Moroni, & Cavalli-Sforza, 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.[10]

This paper is organized as follows. Section 2 presents the conceptual framework. It starts with a model of neighborhood choice where agents have preferences over the price of housing and the racial composition of the neighborhood, argues that model parameters can be identified using migration shocks, and shows how the predicted demands from a correlated random effects model can be decomposed. Section 3 develops the instrument by tracing the origins of migrants in the 1930 census using surname distributions and shows the predictive power of these instruments. Section 4 defines concepts in the full count census data that are crucial for the analysis. Section 5 presents preference parameter results and the decomposition results. Finally, section 6 concludes.

2 Conceptual Framework

In the first part of this section, I lay out a simple model of neighborhood choice, which I estimate directly in later sections. In this model, families have preferences that depend on the price of housing in a given neighborhood, the neighborhood black share, and a race-specific unobservable taste component that has both a fixed (time-invariant) component and a transitory (period-specific) component. In the empirical implementation described below, I define neighborhoods by census tracts and study the determinants of choice across tracts within different cities using a model with metropolitan area by time dummies, fit separately for families with a head in different occupation groups. For the purposes of describing the main features of the model, however, I begin by focusing on choices of white and black families from a single occupation group within a single city.

Decomposing the channels of segregation into preferences- and constraints-based explanations requires generating a counterfactual distribution of demand in the absence of supply constraints. To do so, I need to address three key issues:

1. identification of the key preference parameters parameters that govern choices of white and black families over neighborhoods with different housing prices and different shares of black residents,

"[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."

[9] A notable exception, Bayer, Casey, Ferreira, and McMillan (2017) use rich longitudinal data and find housing price premia for minorities.

[10] Massey, Alarcón, Durand, and González (1987), Munshi (2003) explore the strong ties that migrants retain with origin communities within states in Mexico.

2. specification of the unobserved component of black preferences for neighborhoods in which there were (essentially) no black residents in 1940,

3. linking a model of neighborhood choice by white and black families to overall segregation.

I discuss general identification issues in subsection 2.2. Then in subsection 2.3, I discuss a random effects specification of preferences that can be used to infer black preferences across all neighborhoods in a given city. Finally, in subsection 2.4, I show how I can use my fully specified model of preferences of black and white families to conduct a simple decomposition of the Kullback-Leibler divergence measure of segregation. This decomposition separates observed segregation into two components: one that summarizes the effect of constraints facing black residents (i.e., the effect of non-price rationing constraints); and the other that represents the effect of different preferences of white and black families.

2.1 A Model of Neighborhood Choice

The model presented in this section is related to the one presented by Bayer and Timmins (2005), Brock and Durlauf (2002) but with a specific functional form for the social interactions. I study partial equilibrium adjustments in this model rather than solve for the entire equilibrium, similar to the theoretical exercise in Cutler et al. (1999).

I begin by defining a city as a set of J neighborhoods $\mathcal{J}^*$, and householders i of race $r(i) \in \{B, W\}$ who have preferences over neighborhoods $j \in \mathcal{J}^*$ in time period t given by a linear indirect utility function:

$$\begin{aligned} v_{ijt} &= \delta_{r(i),jt} + \varepsilon_{ijt} \\ \delta_{rjt} &= \beta_r \ln P_{jt} + \gamma_r s_{jt} + \boldsymbol{\Phi_r' X_{jt}} + \alpha_{rj} + \xi_{rjt}, \end{aligned}$$

Here, the δ_{rjt} term is a race-specific population mean utilities for neighborhood j, $\ln P_{jt}$ is the price, s_{jt} is the black share, and $\boldsymbol{X_{jt}}$ is a vector of observable characteristics of the neighborhood. The α_{rj} and ξ_{rjt} terms represent time-invariant and time-varying unobservable components of race-specific demands for neighborhood j, respectively. Finally, ε_{ijt} is an i.i.d. error drawn from an extreme-value type I distribution, representing a component of demand that is specific to family i.

During the period of my data (1930–1940), there is extensive documentary evidence that certain neighborhoods in most cities were off-limits to black residents via formal prohibitions (e.g., steering and restrictive covenants) and also via informal threats of violence. I formalize this fact by allowing the choice set available to black families to be strictly smaller than the choice set available to whites. Specifically, let $\mathcal{J}_r \subseteq \mathcal{J}^*$ represent the set of neighborhoods "available" to a particular race and $J_r = |\mathcal{J}_r|$ be the size of the choice set. Households choose from available neighborhoods in each period that maximize their utility

$$D_{it} = \arg \max_{j \in \mathcal{J}_{r(i)}} v_{ijt}. \tag{1}$$

The independence of irrelevant alternatives (IIA) property is generic to logit models and allows analysts to obtain preference parameters among the set of choices available to agents. However, I am explicit about the choice set primarily because of its mapping into supply constraints. This representation allows households to have well-defined utility over all neighborhoods but can only make choices on those directly available to them, a distinction that will become useful in the counterfactual decomposition exercises.[11]

[11] An alternative, observationally equivalent formulation is that black households have "access" to all neighborhoods but have

Because I do not include any within group heterogeneity in utility, the extreme value assumption on ε_{ijt} gives the choice probabilities the convenient and well-known functional form of a multinomial logit

$$\pi_{rjt} = \frac{\exp \delta_{rjt}}{\sum_{k \in \mathcal{J}_r} \exp \delta_{rkt}} \tag{2}$$

for $j \in \mathcal{J}_r$ and 0 otherwise. Taking logs of equation (2) yields

$$\begin{aligned} \ln \pi_{rjt} &= -\theta_{rt} + \delta_{rjt} \\ &= -\theta_{rt} + \beta_r \ln P_{jt} + \gamma_r s_{jt} + \boldsymbol{\Phi_r'} \boldsymbol{X_{jt}} + \alpha_{rj} + \xi_{rjt}, \end{aligned} \tag{3}$$

where $\theta_{rt} = \ln \sum_{k \in \mathcal{J}_r} \exp \delta_{rkt}$ is the "inclusive value," the population mean utility, of agents given the available choice set and the prices and neighborhood black shares in each neighborhood.

Letting N_{rt} represent the total number of families in a given race group in a city in period t, the total number of housing units demanded by families in that race group is Q_{rjt}, where

$$Q_{rjt} = N_{rt} \pi_{rjt} \tag{4}$$

Summing across black and white families the total demand for housing in neighborhood j is:

$$Q^*_{jt} = Q_{Bjt} + Q_{Wjt}.$$

Finally, in the analysis below, I posit a generic upward sloping inverse supply curve that relates the price of housing in a neighborhood to the number of units supplied

$$\ln P_{jt} = S_{jt} \left(Q^*_{jt} \right).$$

2.2 Empirical Implementation

Berry (1994) shows one can replace $\ln \pi_{rjt}$ with the log of observed choice probabilities $\ln \hat{\pi}_{rjt}$ and estimate

$$\ln \hat{\pi}_{rjt} = -\theta_{rt} + \beta_r \ln P_{jt} + \gamma_r s_{jt} + \boldsymbol{\Phi_r'} \boldsymbol{X_{jt}} + u_{rjt} \tag{5}$$

using a simple specification that is linear in the log of the shares. The composite error term $u_{rjt} = \alpha_{rj} + \xi_{rjt} + (\ln \hat{\pi}_{rjt} - \ln \pi_{rjt})$ in this equation reflects the fixed and transitory components of race-specific neighborhood unobservables as well as sampling error in measuring the observed choice probabilities. Equation (5) is the main estimating equation for the paper.[12]

Careful consideration of the composite error u_{rjt} raises several important identification issues. A naive OLS estimation of equation (5) will lead to biased estimates due in part to omitted neighborhood amenities

very strong negative preferences for those neighborhoods $\alpha_{rj} \to -\infty$. As termed by Cutler et al. (1999), the threat of "collective action racism" in these neighborhoods serves as a de facto restriction on access. They make verbal note of the distinction between de facto and de jure constraints but ultimately the two are observationally equivalent in their model as in mine. Relatedly, some de facto constraints may not be so intense as to completely exclude black families from some neighborhoods. I am ultimately unable to capture these constraints.

[12]The existence of s_{jt} in equation (5) means that the inversion of the mean utilities into log market shares is not a closed form system of the system of simultaneous equations and thus is not a housing demand equation, per se. However, as pointed out by Bayer et al. (2004), *agents* can take the neighborhood share as exogenous since they have miniscule influence over the racial share of the neighborhood. Still, the *analyst* still must treat s_{jt} as endogenous in the presence of unobserved, aggregate shocks to the neighborhood.

and disamenities α_{rj}, which are likely correlated with the local price. Inclusion of tract fixed effects in a panel setting with at least two observations per neighborhood will eliminate this bias. Even with fixed effects, however, the presence of the transitory taste shocks ξ_{rjt} will lead to a similar positive correlation between the observed neighborhood shares and prices. Morever, since $s_{jt} = \frac{Q_{Bjt}}{Q_{Bjt}+Q_{Wjt}}$, the fraction of black residents in a neighborhood is mechanically correlated with the preference factors of whites and blacks, leading to potential biases.

Assuming a generic set of instruments $\boldsymbol{Z}_{jt}$, one can write a linear first stage system

$$\ln P_{jt} = a_1 + \boldsymbol{b}_1'\boldsymbol{Z}_{jt} + \boldsymbol{c}_1'\boldsymbol{X}_{jt} + e_{1jt} \tag{6}$$

$$s_{jt} = a_2 + \boldsymbol{b}_2'\boldsymbol{Z}_{jt} + \boldsymbol{c}_2'\boldsymbol{X}_{jt} + e_{2jt}. \tag{7}$$

Instruments for prices have seen much attention in empirical industrial organization, but these approaches are infeasible in my setting. The first commonly used instrument uses functions of other product characteristics available in the same market (e.g. Berry, Levinsohn, & Pakes, 1995). However, as Nevo (2001) points out, the inclusion of product (in my case, neighborhood) fixed effects will absorb most of this variation.

He instead uses a second common approach which takes variation in the prices of products in other markets as correlated, but exogenous. When estimating housing demand, BFM take a similar approach utilizing variation in housing quality that comes from faraway housing outside of school district boundary areas. There are two problems with applying this second approach in my setting. First, neighborhoods do not have clear analogs in other cities. Second, the goal of my exercise is to characterize housing demand and segregation in the entire city. Without being able to limit the geographic focus of neighborhoods within a city, equation (6) is subject to "endogenous effects" critiques of using leave-out-means from the peer effects literature (Manski, 1993).

Instead, in this paper, I use instrumental variables based on the predicted inflows of whites and blacks who have a particular interest in a given neighborhood driven by their social connections to the pre-existing residents of the neighborhood.[13] The availability of two instruments—one reflecting predicted inflows of whites, the other reflecting inflows of blacks—resolves the need to address the endogeneity of both neighborhood housing prices and the neighborhood share of black residents.

Intuitively, migrant shocks are relevant instruments because they increase the demand of the neighborhood, which should subsequently increase the price. Race-specific demand shocks affect the racial composition of the neighborhood. However, these initial shocks are met with feedback responses as the full system returns to equilibrium.

I show in a forthcoming appendix that migrants' effects on neighborhoods are heterogeneous with respect to the pre-existing black share of the population. In particular, black migrant demand shocks in relatively white neighborhoods lead to *decreases* in population and subsequent decreases in prices if whites have preferences for segregation $\gamma_W < 0$. This arises because the second-order feedback effect of white families leaving in response to a black migrant demand shock trump the first-order increase in population.

By contrast, in relatively black neighborhoods, there are few white families that leave in response to black demand shocks so prices increase. The model's predicted effects of white migrant shocks are symmetric. To capture this heterogeneity, I interact the instruments with the 1930 black share.

[13]In the context of the model, one can specify ε_{ijt} with two components according to Cardell (1997). One that reflects a draw specific to individuals of race r with the same origin o and a separate component that is individual specific. The shared first component will draw new migrants to particular neighborhoods.

2.3 Correlated Random Effects and Counterfactual Demand

Subsection 2.2 lays out the requirements to credibly identify β_r and γ_r for both black and white families. One can use fixed effects to absorb static unobserved quality differences across neighborhoods that reflect in prices and quantities and migration instruments to provide variation independent of time-varying unobservables. If it is a reasonable assumption, the independence of irrelevant alternatives (IIA) assumption of logit models—preference parameters can be determined by how agents interact given the choices they have—means that the existence of a constrained choice set for black residents $J_B \leq J$ poses no direct threat or adjustment to estimating model parameters.[14]

However, in order to quantify supply constraints, I need to be able to compare actual black demand to demand in the absense of those restrictions. An approach that only uses the within-variation of fixed effects models gives little guidance for what black utility might be in neighborhoods where there were no black residents because of supply constraints. In other words, estimating β_r and γ_r does not require parametric assumptions about α_{rj}, but quantifying segregation does.

In this section, I impose a correlated random effects structure to parameterize α_{rj}, which maintains similar identifying assumptions for β_r and γ_r. As I will detail further, the model I specify importantly allows the neighborhood unobservables for black and white residents to be correlated without requiring them to be the same. This structure allows me to use information from observable characteristics and the residuals from the models fit to white shares to extrapolate α_{Bj} and ultimately predict the black choice shares $\hat{\pi}_B^{CF}$ in neighborhoods with no black residents.

2.3.1 α_{rj} as a Correlated Random Effect

To draw the closest parallel to the fixed effects model I present in section 5.3, I impose a linear structure on α_{rj}:

$$\alpha_{rj} = \boldsymbol{A}_r' \bar{\boldsymbol{Z}}_j + \boldsymbol{C}_r' \bar{\boldsymbol{X}}_j + \psi_{rj},$$

where $\boldsymbol{A}_r$ and $\boldsymbol{C}_r$ allow the race-specific static characteristics of the neighborhood α_{rj} to correlate time-varying factors in the model.

I make the standard random effects assumptions:

1. $\boldsymbol{E}\left[\psi_{rj} | \bar{\boldsymbol{Z}}_j, \bar{\boldsymbol{X}}_j\right] = 0$, the static neighborhood unobservabled component of mean utility is conditionally mean zero,
2. $\boldsymbol{E}\left[\xi_{rjt} | \boldsymbol{Z}_{jt}, \boldsymbol{X}_{jt}, \alpha_{rj}\right] = 0$, the time-varying unobservable is conditionally mean zero,
3. ξ_{rjt} is serially uncorrelated, and
4. $\boldsymbol{E}\left[\xi_{rjt}^2\right] = \varsigma_r^2$, the neighborhood unobservables are homoskedastic.

I further assume cross-equation correlation between the black and white unobservables ψ_{Bj} and ψ_{Wj}:

$$\begin{pmatrix} \psi_{Bj} \\ \psi_{Wj} \end{pmatrix} \sim \mathcal{N} \begin{pmatrix} 0 & \sigma_B^2 & \sigma_{BW} \\ 0 & & \sigma_B^2 \end{pmatrix}. \tag{8}$$

[14] In this formulation, I continue to be agnostic between de jure (e.g. legal) and de facto (e.g. violenct) constraints.

Note that Assumption 2 is the same as an exclusion restriction for validity of a 2SLS regression with fixed effects.[15] The additional assumptions 1, 3, and 4 are used to recover A_r, C_r and the covariance structure specified in equation (8). Assuming no serial correlation in ξ_{rjt} means that all serial correlation in the composite error u_{rjt} must derive from the presence of a time-invariant unobservable α_{rj}.

Allowing a correlation between ψ_{Bj} and ψ_{Wj} allows me to predict counterfactual unobservables for black residents utilizing residual variation in the choice probabilities of white residents in those neighborhoods. Here, the homoskedasticity and normality assumptions are not crucial but produce a simple regression formula for using the white random effect to predict the black unobserved component, i.e.,

$$\boldsymbol{E}\left[\psi_{Bj}|\psi_{Wj}\right] = \frac{\sigma_{WB}}{\sigma_B^2}\psi_{Wj}. \tag{9}$$

It is worth considering what α_{rj} represents. Amenities valued equally among all households should be capitalized into price: in a spatial equilibrium model with homogeneous valuations of neighborhoods, this term should be zero.[16] Recalling that I perform my analysis separately by broad occupation, ψ_{rj} are race-specific deviations from of how individuals of a particular occupation group value neighborhoods. If all heterogeneity in neighborhood taste is driven by occupation, then $A_B = A_W$, $C_B = C_W$, and $\frac{\sigma_{WB}}{\sigma_B^2} = 1$, reflecting characteristics not included in the model such as average commute times. However, this formulation does not impose this restriction.

2.3.2 Extrapolation

I predict the log mean utilities $\widehat{\ln \delta_{rj}}$ for all neighborhoods $j \in \mathcal{J}^*$ by combining:

1. the instrument-identified parameters $\hat{\beta}_B$, $\hat{\gamma}_B$, and observed endogenous characteristics $\ln P_{j,1940}$, $s_{j,1940}$;
2. $\hat{A}_B$, $\hat{C}_B$, and observed exogenous characteristics $\bar{\boldsymbol{X}}_j$ and $\bar{\boldsymbol{Z}}_j$; and
3. the estimated random effect $\hat{\psi}_{Bj}$,
4. setting the time-varying unobserveable $\hat{\xi}_{Bjt} = 0$.

Finally, I renormalize by subtracting $\ln \sum_j \left(\exp \widehat{\ln \delta_{rj}}\right)$ from each predicted log choice probabilities, which becomes the estimate of $\hat{\theta}_{rt}$. This renormalization maintains the linear in log-odds property of the multinomial logit model and also has the probabilities sum to 1.

This approach is not without limitations, that I will discuss in subsection 2.5. However, one of the primary advantages of specifying a random effects variant of the Berry multinomial logit specification is that the choice model can be directly mapped into a model of segregation with terms that can be directly interpreted as contributions from supply side and demand side factors. I turn to this decomposition now.

2.4 A Decomposition Framework for Segregation

The estimates from the correlated random effects model allow one to ask quantify latent black demand for neighborhoods at prevailing prices in neighborhoods with no black residents. Intuitively, differences between

[15] Mundlak (1978) shows that correlated random effects models specified similar to the one I assume give numerically equivalent coefficient estimates for time-varying covariates that are not absorbed by the fixed effect. This numerical equivalence does not hold in my over-identified instrumental variable setting, the results are ultimately similar.

[16] In fact, the household-specific error ε_{ijt} should also be zero. See Kline (2010).

actual and counterfactual distributions of black demand are driven purely by the constraints. Correspondingly, differences between the latter and actual white demand are driven by preferences.

In this section, I lay out a framework that quantifies this intuition by decomposing the Kullback-Leibler divergence between two distributions. The divergence between black and white families' choices in a given city and time period can be written as

$$KL\left(\pi_B || \pi_W\right) = \sum_j \pi_{Bj} \ln \frac{\pi_{Bj}}{\pi_{Wj}},$$

where as before, π_{rj} is the probability mass function of the race r's multinomial choices. Just like the indices of dissimilarity and isolation, this measure quantifies how two distributions are different; however, its functional form lends itself very naturally to the multinomial logit model.

To incorporate the counterfactual black demand in decomposing actual segregation, I multiply and divide the term within the logarithm by $\hat{\pi}^{CF}$ so

$$\begin{aligned} KL\left(\pi_B || \pi_W\right) &= \sum_j \pi_{Bj} \ln \frac{\pi_{Bj}}{\hat{\pi}^{CF}_{Bj}} \frac{\hat{\pi}^{CF}_{Bj}}{\pi_{Wj}} \\ &= \sum_j \pi_{Bj} \left[\ln\left(\pi_{Bj}/\hat{\pi}^{CF}_{Bj}\right) + \ln\left(\hat{\pi}^{CF}_{Bj}/\pi_{Wj}\right)\right]. \end{aligned} \tag{10}$$

One can see immediately that the two terms that emerge reflect exactly the intuition from before: the first term reflects differences driven by an expansion of the choice set and the second reflects differences in preferences for different neighborhoods. Adding and subtracting $\log \hat{\pi}^{CF}$ is similar to the derivation of an Oaxaca decomposition where one adds and subtracts counterfactual predicted in a linear model. Because of the linear-in-log-share specification, a detailed decomposition of components attributable to different covariates immediately follows.

Replacing the actual probabilities with model predicted probabilities in this decomposition gives

$$KL\left(\hat{\pi}_B || \hat{\pi}_W\right) = \sum_j \hat{\pi}_{Bj} \left[\ln\left(\hat{\pi}_{Bj}/\hat{\pi}^{CF}_{Bj}\right) + \ln\left(\hat{\pi}^{CF}_{Bj}/\hat{\pi}_{Wj}\right)\right].$$

Using the predicted probabilities means that one can use the parameter estimates from the structural model in equation (5), which yields:

$$\begin{aligned} KL\left(\hat{\pi}_B || \hat{\pi}_W\right) = \sum_j \hat{\pi}_{Bj} \{ &\left(\theta^{CF}_B - \theta_B\right) \\ &+ \left[\left(\theta_W - \theta^{CF}_B\right) + \left(\alpha_{Bj} - \alpha_{Wj}\right)\right. \\ &\left. + \left(\beta_{Bj} - \beta_{Bj}\right) \ln P_j + \left(\gamma_{Bj} - \gamma_{Wj}\right) s_j + \left(\mathbf{\Phi'}_B - \mathbf{\Phi'}_W\right) \boldsymbol{X}_j\right] \}. \end{aligned} \tag{11}$$

The supply constraints contribution to segregation on the first line is summarized completely by the difference in the inclusive values $\theta^{CF}_B - \theta_B$ from expansion of the choice set—by construction, these two predicted distributions do not differ in their preference parameters. The second line is a detailed decomposition of the contribution of preferences to segregation. In particular, the $\left(\gamma_{Bj} - \gamma_{Wj}\right) s_j$ term, how segregation is driven by differences in preferences for more or less black neighborhoods, has been the focal point of the past literature.

2.5 Limitations of the Model

There are several important limitations to my procedure in capturing supply and demand contributions to segregation. First, I do not simulate a new sorting equilibrium for black and white families. In my approach, the simple model-based counterfactuals constructed from the random effects estimates hold constant $\ln P$ and s. It does not take into account second-order equilibrium adjustments (e.g. neighborhood tipping) that are likely important. But, capturing the first-order effects is the most straightforward way to clearly attribute contributions from supply and demand. Moreover, a full simulation of the new sorting equilibrium in absence of supply constraints will inevitably require knowledge of neighborhood supply curves and even stronger assumptions and parameterizations. While important, I leave these exercises for future research.

Second, my procedure relies on the structure of the model—particularly IIA—to accurately predict the latent black demand for otherwise unavailable neighborhoods $j \in \mathcal{J}^* \backslash \mathcal{J}_B$. Here, the threat to the validity of this speculative extrapolation exercise is that the model is incorrectly specified in those neighborhoods. External validity is always a lurking issue for models estimated via instrumental variables, but in this exercise, interpreting the extrapolated black neighborhood unobservable α_{Bj} merits additional discussion.

When supply constraints come from de jure restrictions, then the counterfactuals are clear: lifting supply constraints means legislating or effecting policy changes that abolish these restrictions. The modeling environment I provide in this paper treats the abolition of de facto restrictions coming from extralegal harassment and terrorism as similarly straightforward in a counterfactual world.

But, if organized violence is simply an extreme form of racism, these counterfactuals are essentially asking what would segregation look like if racism were "bounded above." A more complicated correlated random coefficients model could connect γ_W with the black neighborhood unobservable α_{Bj}, but ultimately counterfactuals generated from such a model will still rely on IIA. I leave such explorations for future work.

3 An Instrument for Inmigration

I now turn my attention to constructing an instrument for migration. The 1930's was a nadir for the first wave of the Great Black Migration, marking the tail end of nearly a quarter century of migration ending at the onset of the second World War. Nevertheless, there was substantial black and white migration during the 1930s. Table 1 reports the magnitude of gross migrant flows to the 48 major metropolitan areas with census tracts that form my main analysis sample.

The top panel shows that roughly half of black migrant flows were movements between cities, while the other half represented flows from rural counties, defined as those without any census incorporated places between 1910–1940. Most of these black rural migrants came from counties in the southern census region. By comparison, the bottom panel shows white migrant flows in greater absolute magnitude albeit with a smaller fraction represented by rural-to-urban migration.

Nonetheless, much of the migration to major cities for both blacks and whites was intraregional. Prior literature has focused on southern blacks leaving the south, but table 1 shows that roughly 60% of the rural-to-urban migration of southern blacks was within the south itself. White migration was also heavily within-region, the notable exception of the westward migration of whites from drought affected "Dust Bowl" regions in Texas, Oklahoma, and Kansas, notwithstanding.

In section 2, I motivated using migration shocks as a source of exogenous variation to perturb the sorting equilibrium. Figure 1 illustrates some of this variation, plotting black (purple from the left) and white (green from the right) rural county-to-census tract migrant flows from Texas and Oklahoma to Los Angeles County between 1935–1940. Origin counties are shaded in intensity based on the total rural-to-urban migrants to any destination.

The black flows to Los Angeles focus primarily on tracts in Watts and Compton with a high share of black residents in 1930 (red). But, there is dispersion: migrant flows are not perfectly correlated with the 1930 black share with some relatively high black share tracts getting fewer migrants than expected and vice versa.

The flow diagram also suggests that particular origin counties may have ties with particular tracts. Migrants from rural counties outside of Austin seem to be disproportionately directed toward tracts near Glendale and Pasadena. Meanwhile, migrants from rural counties outside Oklahoma City, seem to be particularly drawn toward Carson City and south Compton. I will shortly provide regression evidence that shows that counties do have particular ties to particular tracts.

Correspondingly, Figure 1 plots large directed flows of white migrants from rural Oklahoma. These migrant flows also show both dispersion and directedness. Notably, some counties in central Texas have large numbers of migrants, but relatively few are choosing to move to Los Angeles altogether.

The patterns illustrated in Table 1 and Figure 1 make a case for using granular county-level variation. But, directly applying the 1935–1940 county-level migrant flows measured from the retrospective component of the 1940 census is problematic because it is potentially subject to the same endogeneity that threatens panel OLS estimates of the preference parameters. This motivates using the shift-share instrumental variables approach common in the international migration literature—a neighborhood analog to the occupation partitions in the within-city analysis of Card (2001). This instrument uses past migrant location decisions to proxy for the predictable component of current migrants' decisions reflecting access to similar modes of transportation as well as social networks. However, origin counties of migrants prior to 1930 are conspicously absent in the data.

This section outlines how I utilize surname distributions to build a shift-share instrument. First, I describe the basic intuition of the instrument, which is similar in many respects to those used in the international migration literature. In the second subsection, I outline how I use surname distributions constructed from the 1910–1930 censuses to construct estimates of past migrants' choices. Finally, in the third subsection, I show that surname-constructed choice probabilities from the 1930 census are highly correlated with migration choice probabilities at the census tract level. I also show that these instruments provide independent variation and are not simply proxying for growing cities.

3.1 Requirements of an Instrument Using Past Settlement

In section 2, I dropped notational dependence on cities to focus purely on neighborhoods. In this section, I reintroduce necessary notational dependence on destination cities d to discuss migration.

Let $q_{j|rod}$ be the probability that a migrant of race r from origin o chooses neighborhood j conditional on being in city d, and let $p_{d|ro}$ be the probability that the migrant chooses city d. Let $inflow_{rdj}$ represent the total inflow of migrants of race group r who move to neighborhood j within city d and let $outflow_{ro}$ be the outflow of migrants of race r from origin o. Observed migrant flows can be written as:

$$inflows_{rdj} = \sum_{o} q_{j|rod} \times p_{d|ro} \times outflow_{ro}. \tag{12}$$

Two main sources of endogeneity can potentially arise from this accounting formula. First, even comparing the same cities and neighborhoods over time, migrants might be more likely to move to cities or neighborhoods that have housing supply shocks (e.g., a faster rate of conversion of older single family homes into multi-family apartments). In the context of equation (12), this would mean that $q_{j|rod}$ or $p_{d|ro}$ endogenously adapt to housing supply shocks.

One solution to this endogenous adaptation is to replace the q and p in equation (12) with probabilities based on the obseved settlement patterns of earlier migrants from thes ame origin and race group, $q^{past}_{j|rod}$ and $p^{past}_{d|ro}$, respectively. Specifically, to predict migrant flows from 1935–1940, I use the settlement patterns for migrants from each origin county who were observed living in larger cities in 1930—so "past" refers to migrants who had settled by 1930 in a particular urban area. As discussed in the next section, the 1930 census does not contain county of birth or residence at an earlier date, so I have to construct $q^{1930}_{j|rod}$ and $p^{1930}_{d|ro}$ based on clustered patterns of surnames.

A second concern is that potential migrants from a given origin may be tightly connected to a specific destination city. The simplest example are migrant flows to cities from rural counties on the outskirts of a city boundary. In this case, $outflow_{ro}$ may be partially endogenous to shocks in city d. To address this concern, one could use the outflows from origin o leaving out migrants who end up moving to city d, $outflow^{-d}_{ro}$. This flow measure is purged of endogeneity arising from demand-pull factors in city d. Combining these substitutions, I construct a predicted inflow of migrants of race group r from all origin counties to neighborhood j in city d between 1935–1940:

$$Z_{rjd} = \sum_{o} q_{j|rod} p_{d|ro} outflow^{-d}_{ro}. \tag{13}$$

where $outflow^{-d}_{ro}$ is based on the questions in the 1940 census that asks each person where they lived 5 years ago.

3.2 Past Migrant Flows Using Surname Distributions

3.2.1 An Overview of the Approach

In this section, I describe a series of steps I use to construct estimates of $q^{1930}_{j|rod}$ and $p^{1930}_{d|ro}$ based on counts of migrants who were observed in 1930 living in specific census tracts of larger cities in 1930. The 1910–1930 censuses have information on state of birth and current place of residence, as well as information on fullnames of all respondents. In brief, my procedure uses the fact that surnames were highly clustered in the early twentieth century. Thus, if one knew that a given black person was born in Texas and had a given surname, one could make an informed guess about their likely *county* of birth.

Throughout this section, I also temporarily drop the race group r subscript and the 1930 superscript. All counts and probabilities should be understood as referring to a specific race group observed in the 1930 census.

Let L_{od} represent the number of residents in city d who were born in origin county o and let M_{odj} represent the number of residents in city d and neighborhood j who were born in origin county o. If birth county data were available, one could easily write the city and neighborhood choice probabilities as:

$$p_{d|o} = \frac{L_{od}}{\sum_{d'} L_{od'}} \tag{14}$$

$$q_{j|od} = \frac{M_{odj}}{\sum_{j' \in \mathcal{J}_d} M_{odj'}}. \tag{15}$$

The key challenge is that none of these objects exist in the data.

3.2.2 Measuring Past Flows

I will show that surname distributions fill this gap. Throughout this section, I focus attention to $p_{d|o}$ because the procedure to construct $q_{j|od}$ is exactly analagous.

To summarize my procedure, I first assign a set of weights to each resident living in cities in 1930. The weights proxy the probability that an individual comes from a particular county. I generate weights by computing the fraction of non-migrant individuals living in the residents' state of birth who share the same last name and 10-year birth cohort, pooling data from the 1910–1930 censuses. Summing the origin-specific probabilities in a city gives an estimate of the origin-specific population.

Formally, let c index cells that identify unique combinations of an individual's last name, state of birth, and 10 year birth cohort, all information readily available in the 1930 census. Let $N_d(c)$ represent the total number of individuals in a cell c. Then a probabilistic measure of the population from origin county o becomes

$$\hat{L}_{od} = \sum_{c} N_d(c) \times \boldsymbol{Pr}\left(o | \underbrace{\text{surname, cohort, birth state}}_{c} \right), \tag{16}$$

which is a count of individuals weighted by the probability that they came from a particular county o.[17]

The next subsection 3.2.3 gives some background on common surnames and why they might provide information on county of birth. Next, subsection 3.2.4 describes how I use the population of non-migrants in each state to construct $\boldsymbol{Pr}(o|c)$. Finally, I analyze whether these variables succeed in providing granular information that can be used to construct county-to-county flows.

3.2.3 Signal in Surnames

Researchers in biology and physical anthropology (e.g., Zei et al., 1983; Piazza et al., 1987; Zei et al., 1993) have treated surnames as alleles traditionally transmitted via male lineage to measure patterns of genetic drift—i.e., migration. Several facts about black and white surnames in the early 20th century are suggestive that these same patterns hold in the mid-20th century United States. The observation that immigrants move to enclaves of past migrants is not a feature unique to recent waves of immigration to the United States, and as a result, native born whites descendents of European migrants from the late 19th and early 20th centuries should be clustered and not totally dispersed (Tabellini, 2018).

For blacks, last names were often imposed by slave masters in the antebellum era, ultimately making it unlikely that surnames carry any signal that can connect former slaves and their descendants to their ethnic origin countries in West Africa. Nonetheless, 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 reflecting emancipation (e.g. Freeman) or their occupation (e.g. Smith). The empirical question remains of whether common black surnames are clustered and provide signal of county of origin.

[17] One can derive the same estimate for $p_{d|ro}$ by using Bayes's rule with an independence assumption $\boldsymbol{Pr}(o,d|c) = \boldsymbol{Pr}(o|c)\,\boldsymbol{Pr}(d|c)$ and assuming that the geographic distribution of non-movers reflects the birth locations of movers.

3.2.4 Constructing Surname Distributions

To construct the distributions $\boldsymbol{Pr}(o|c)$ used in equation (16), I pool data from the 1910–1940 censuses separately by state. First, I limit the sample to non-migrants by only keeping individuals who are living in their state of birth. Second, I only keep individuals born in the prior 10 years in the 1920–1940 censuses. This way, the distributions for a particular birth cohort only come from a single census.

Most individuals have a common last name, and so this analysis relies on common last names providing a signal of birth location. I do not rely on using uncommon names to find unique match on individual characteristics. I define names as being common if at least one person in each decade between 1900–1940 has the last name. Individuals with uncommon last names are pooled into a single category according to this definition.[18] At this point, I discard individuals born between 1930–1940.

Finally, I define cells analogously to equation (16) and construct the fraction of individuals in each state, surname, birth cohort cell living in each county. These fractions are my estimate for $\boldsymbol{Pr}(o|c)$.

I provide two pieces of evidence that last names provide a strong signal of county of birth, focusing on shares constructed using cells without incorporating birth cohort to analyze the predictive power of last names by themselves. First, 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 fashion among whites, but are clustered nonetheless.

Second, I aggregate these case studies to quantify the distinctiveness of the each last name. I systematically compare the county shares $\boldsymbol{\varphi}_o$ of surname ℓ in each state to the county shares leaving out the surname $\tilde{\boldsymbol{\varphi}}_\ell$. I form a Pearson χ^2 test statistic for each last name:

$$\chi^2_\ell = N_\ell \sum_o \frac{(\varphi_{\ell o} - \tilde{\varphi}_{\ell o})^2}{\varphi_{\ell o}}$$

where N_ℓ is the number of individuals with last name ℓ. 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 1, and the null hypothesis of this test is that individuals who have surname ℓ have the same geographic distribution of those who do not. In 1930, 99.4% and 99.6% of black and white individuals have a surname with a p-value that the computer cannot distinguish from zero.[19]

3.2.5 Flow Probabilities

I now substitute the constructed $\boldsymbol{Pr}(o|c)$ into equation (16) to generate $\hat{\boldsymbol{L}}_{od}$. I use these destination populations to construct flow probabilities according to equation (14), and having already assigned individuals to census tracts in 1930, I do the same for equation (15). Next, I provide visual and regression evidence that the surnames have strong predictive power using the actual flows between 1935–1940 constructed from the retrospective question in the census. Figure 3 plots the log of the 1935–1940 county-to-tract flow probabilities against the corresponding measure from the 1930 census for both blacks and whites, restricting the sample to the 25% of rural counties with the largest outflows. A clear positive slope emerges.

[18] One question that arises is why limit oneself to surnames and utilize first names, finer age categories, and respondent's gender to in principle generate a better version of $\hat{L}_{od}$. This only makes sense if, for example, a first name contains signal of one's origin of birth, having already conditioned on surname and birth cohort. However, in practice, doing so generates small cells and thus either requires assigning more individuals to the "uncommon" binned category or placing parametric structure on $\boldsymbol{Pr}(o|c)$.

[19] I.e., 2.2×10^{-308} for double floating precision on the machines where I perform the analysis.

Table 2 quantifies these relationships in regressions of the 1935–1940 flow probability on the surname constructed probability, weighting each observation by the total rural-urban outflows from the origin county. The first column shows that the surname constructed shares are highly predictive of actual migrant choice probabilities.

The auxiliary analysis in column (1) is sufficient to generate an instrument for migration, but in columns (2)–(5), I estimate the same models with increasing number of fixed effects. In column (2), I include destination tract fixed effects. Heterogeneity across the black share of neighborhoods provides an important source of identifying variation in this paper, and the inclusion of tract fixed effects suggests that black migrants are not driven by neighborhood characteristics such as share of black households.

In columns (3)–(4), I include state of origin by destination metro area fixed effects. Using only this within variation, the persistent predictiveness of the surname constructed shares shows that migrants from the same county are not simply chosing the same cities as past migrants, the focal point of the cross-city comparisons in previous work. Migrants choose the same neighborhoods.

Finally, in column (5), I include state of origin by destination census tract fixed effects. These highly saturated regressions have two implications. First, neighborhoods have strong connections to origin places *within region*, which are not likely to be purely driven by similar access to transportation networks. Second, the distributions of surnames allows me to exploit migrant variation generated by outflows from rural counties to cities within the same region, and indeed the same state. The surname-constructed flow probabilities' strength is strong evidence of familial and kinship relationships that underly the motivation behind the past-settlement instrument.

4 Data and Definitions

This paper uses the full count 1910–1940 decennial censuses digitized by IPUMS and Ancestry.com (Ruggles et al., 2018). In this section, I address definitional questions that arise when implementing the strategy outlined in section 2.

4.1 Families and Neighborhoods

The first immediate issues is how one defines a neighborhood, which I define as census tracts according to their definition in the 1940 census. Because census tracts were first developed in 1934, they are not readily available in the 1930 census data. Therefore, I assign households in 1930 to 1940 census tracts using a procedure based on street addresses documented in the appendix.

The second immediate issue that arises is how to define the decision making unit in the model. I analyze the collective decisions of family units, defined as households with a male head between the ages of 18–50 with a cohabiting wife and at least one child. Furthermore, I exclude analysis of families living in group housing. Overall, families were less likely to live in group housing (e.g., hotels, the YMCA, institutionalized settings, etc.), where data on housing costs is generally not available.

Even by limiting the analysis to families, there may still be taste heterogeneity among the agents. Papers in empirical industrial organization have found that in models of differentiated products, allowing for taste heterogeneity can have a dramatic effect on the conclusions one draws (see e.g. Berry et al., 1995; Petrin, 2002).[20] To overcome these concerns yet retain parsimony of the choice models, I group families based

[20]Because they only observe a single market share for each product, these papers often have to apply sophisticated method of methods estimators to include taste heterogeneity in their models and overcome ecological fallacies. I do not face this same

on broad occupation groupings for the household head. Finally, when constructing the observed choice probabilities, I exclude consideration of tracts where there are fewer than 10 families in the same race and occupation grouping.

Table 3 reports details of the 1940 subset of households that I use to construct the shares. The top panel shows that of the 9 million black and white households living in one of the 48 major cities with census tracts in 1930, 3.5 million households are families by my definition. Roughly 6% of families in cities are black families. Black household heads are clustered in three broad occupation groups that constitute 86% of families—laborers, service workers, and operators. Men in these relatively low-skilled occupations include longshoremen, cooks, janitors, cooks, deliverymen, and valets.

By contrast, less than 40% of white household heads are employed in one of these occupations, and a majority of them are operators, a group that also includes apprentices in blue collar professions. A comparable 23% are blue collar craftsmen, and the remaining 40% of white family men are white collar professionals.

Having generated coarse groupings of families, I summarize the characteristics of neighborhoods of the median and white black resident in table 4. The top panel reports characteristics of housing, particularly the cost and ownership status of units. A typical white resident lives in a tract with a median price of roughly \$3,500 (roughly \$63,000 in 2018 dollars), while the neighborhood of the median black resident is \$800 less. This masks tremendous differences in the home ownership rate between neighborhoods. The typical white person lives in a neighborhood with double the homeownership rate of the typical black person. Using a composite price index that combines contract rent and self-reported house prices into a single measure (described in detail in the next subsection 4.2), the less than 30% price gap balloons to more than 40%. Focusing on employed white people in black occupations, that gap narrows (~25%), but is still sizeable.

The bottom panel reports characteristics of the people living in these neighborhoods. A stark contrast emerges in terms of the black share of neighborhoods of the median white and black family: roughly 50% of white people living in major cities live in neighborhoods with essentially no black people, but the median black person lives in a predominantly black neighborhood, a fact that does not change when again limiting to whites in low-skill occupations. These differences overshadow smaller differences in neighborhood employment shares.

4.2 Defining the Price of the Neighborhood

The 1930 census was the first where measures on housing costs were solicited.[21] Because census tracts have differing shares of renter and owner households, simply using the median rent or the median house price within a neighborhood likely does not consistently capture the cost of the neighborhood. In an extreme case, there are some neighborhoods with no owner-occupied or renter-occupied units. To avoid issues of composition, I create a create a single cost index that utilizes information on both the neighborhood rents and house prices by converting rents into home price equivalent units.

More formally, I stipulate that each house is defined by a latent cost, which translates proportionally into either a house price or a contract rent. This in turn implies a proportional relationship between a house's

challenge because I am able to construct shares using the microdata.

[21]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.

inherent price and contract rent, $HomeValue_{it} = \rho MonthlyRent_{it}$.[22]

To estimate ρ, I compare units at the same address that convert from rental to ownership status and vice versa between 1930 and 1940. Operationally, I construct a longitudinal dataset of housing units where the 1930 address could be matched on housing number and street name to a 1940 address documented in a forthcoming appendix. I then construct a single dependent variable that stacks owner-occupied home values and renter-occupied rents into $Y_{it} = (1 - Owner_{it}) \times \log Monthly\_Rent_{it} + Owner_{it} \times \log HomeValue_{it}$ and estimate a regression model:

$$Y_{it} = c_{a(i)} + d_{j(i),t} + (\log \rho)\, Owner_{it} + \varepsilon_{it} \tag{17}$$

where $c_{a(i)}$ are address fixed effects and $d_{j(i),t}$ are census tract by year fixed effects, which absorb both changes in the overall price level and tract-level variation in housing cost growth. Thus, $\widehat{\log \rho}$ captures the average change in housing costs from addresses that experience conversions of housing from owner-occupied to renter-occupied. Estimates in the appendix suggest that $\log \rho = 4.8$, which means annual contract rent payments are roughly one tenth of the self-reported value of the home.

5 Empirical Implementation and Results

5.1 Econometric Issues

Utilizing migrant flows as an exogenous source of variation to identify the model parameters carries with it several econometric issues. First, the static model in section 2 suggests a panel IV regression identified using time-varying instruments. However, the instruments laid out in section 3 are static. These shift-share instruments in the international migration literature shift changes rather than levels of the endogenous variable.

To obtain parameter estimates of β and γ, I utilize the equivalence of fixed effects and first-differenced regressions with two time periods and adapt a first differenced version of equation (5)

$$\Delta \ln \hat{\pi}_{rj} = -\Delta\theta_r + \beta_r \Delta \ln P_j + \gamma_r \Delta s_j + \boldsymbol{\tilde{\Phi}'_r X_j} + \Delta u_{rj} \tag{18}$$

and instrument for the changes in the endogenous variables $\Delta \ln P_j$ and Δs_j. Thus, identification arguments for these parameters ask whether changes in the residual neighborhood choice probability Δu_{rj} are correlated with the set of instruments $\boldsymbol{Z}_j$, conditional on controls $\boldsymbol{X}_j$.[23]

An immediate question relates to what constitute valid controls $\boldsymbol{X}_j$. Allowing neighborhood choices to agnostically evolve according to controls is not well-motivated by the model, but in many empirical settings as well as in mine, controls improve the empirical performance of the estimators. In particular, the procedure of matching addresses to census tracts in 1930 is subject to measurement error. I will outline the controls I use and argue their necessity in my empirical specification.

[22] In a frictionless world, a no-arbitrage condition suggests that rental profits from risk-neutral landlords in perfect competition should be equivalent to interest income. Simply using the prevailing bank lending rates during the 1930s to scale home values (roughly 4–7% according to Basile, Landon-Lane, and Rockoff, 2010) is problematic because I do not observe costs facing landlords and thus would tend to overstate ρ.

[23] Converting the first differenced model to a fixed effects model is tantamount to utilizing as time-varying instruments and controls $\boldsymbol{Z}_j$ and $\boldsymbol{X}_j$ interacted with a dummy variables for the observation being in 1940.

5.1.1 Controlling for the Sum of Shares

The first set of controls I include relate generally to shift-share instruments. In a forthcoming appendix, I show that in a linear representation of rural outflows, shift-share migration instruments in the spirit of Altonji and Card (1991), Card (2001) have two components: the share-weighted sum of origin push factors and the share-weighted sum of a constant, or the sum of shares. Rhetorical justification for shift-share instruments often focuses on the former. Endogeneity concerns focus on the latter. Critics worry that the shares are potentially related to unobserved omitted variables that determine the outcome of interest.[24][25] I include the sum of shares as a control variable to partially alleviate this concern.

5.1.2 Controlling for 1930 Characteristics

The second set of controls relates to limitations of using migrant demand shocks as instruments for a neighborhood choice model. In the instrument set, I include both black and white shift-share demand shocks as well as the demand shocks interacted with the 1930 black share as instruments. These interactions are necessary: as I will show, the model's predicted heterogeneous effects on the neighborhood black share materializes empirically. As such, I include a main effect for the 1930 tract black share as a control variable. I also include the 1930 tract population and the 1930 median log housing cost as controls, which improve the power to detect the migrants' effects on prices in the first stage regressions.

From the perspective of the model specified in changes in equation (18), one can include any predetermined lagged characteristic, including both the sum of shares and the lags of the endogenous variable, under the assumption of sequential exogeneity. That is, the unobserved determinants of 1940 choice probabilities are unrelated to the 1930 characteristics, conditional on the tract fixed effect.[26] More directly, identification of β and γ relies on the unobserved *changes* in neighborhood choice being uncorrelated with the instrument set conditional on 1930 characteristics.

In fact, Wooldridge (2010) suggests that these characteristics can even be included as instruments in the context of the static model. However, the impetus for including lagged endogenous variables as controls is that 1930 prices and black share are measured with error, driven in part to the procedure I implemented to reconstruct the 1940 census tracts in 1930. In turn, measurement error in the change in the endogenous variable is mechanically negatively correlated with measurement error in the control.

5.1.3 Identification Amid Measurement Error

Both the main effects of the demand shocks and the interactions with the 1930 black share are likely to have a mechanical unconditional correlation with the endogenous variables. The latter is clear because of the lag of the endogenous variable is in the term. But, even the former is subject to this problem. The origin shares used in equation (13) are constructed with the same census tract construction procedure and may in turn produce similar correlated measurement error. In sum, estimation of the model parameters relies in part on the controls' ability to absorb correlated measurement error between the endogenous variable and the instruments.

[24] In my setting, these concerns are not without merit. In the aforementioned appendix, I show that both the black and white sums of shares are unconditionally strong predictors of population growth of both black and white residents across cities, suggesting that the sum of shares can easily proxy for growing cities generally.

[25] Identification issues related to the shares is a matter of continued debate for Bartik style instruments. See e.g. Goldsmith-Pinkham, Sorkin, and Swift (2018).

[26] I show this formally in a forthcoming appendix.

5.2 Reduced Form and First Stage Effects of Migration

5.2.1 Population Effects

In this section, I present reduced-form, qualitative effects of black and white migration on neighborhoods. To do so, I estimate basic ordinary least squares (OLS) regressions of the form

$$\Delta Y_j = a_{m(i)} + \sum_r \boldsymbol{b}_r' \boldsymbol{Z}_j + \boldsymbol{c}_r' \boldsymbol{Z}_j \times s_j + \boldsymbol{G}' \boldsymbol{X}_j + \varepsilon_j \tag{19}$$

where $\alpha_{m(i)}$ is a metropolitan area fixed effect and $\boldsymbol{X}_j$ is a vector that includes the black and white sum of shares, the tract 1930 population, and the 1930 median housing cost as controls. The model suggests that a black migrant is likely to have different effects in relatively black and relatively white neighborhoods. Thus, I report results both with and without interacting the instruments with s_j. As I will show, there is important heterogeneity along the gradient of 1930 black share.

Table 5 presents the relationships between changes in black, white, and total population and the instruments. The coefficients are not directly interpretable since they reflect not only the effect of migrant inflows but also measurement error that arises from the last name procedure, mismeasurement in county outflows, and the leave-out procedure mechanically scaling down the magnitude of the instrument. Nonetheless, qualitatively, columns 1 and 2 show that black and white migrant shocks are associated with black and white populations for the average tract and smaller declines in white and black populations.

However, these effects by themselves mask tremendous heterogeneity. Columns 4–6 report models where the instruments have been interacted with the 1930 black share. The second panel of the table reports linear combinations of the coefficients to produce implied effects in relatively white and relatively black neighborhoods. Whereas column 2 reports estimates for a typical tract, the estimates in column 4–5 suggest that white residents leave more rapidly than black residents enter, in these neighborhoods. The bottom panel of the table reports joint tests of significance among all the coefficients. The first row labeled "All Instruments" tests the joint significance of all coefficients in the top panel of the table, while the second two rows test the joint significance of Z_B and Z_W and their interactions, respectively. Consistent with strong heterogeneity, the F-statistic from the Wald joint test of significance on the black instrument increases from 0 to 27 between columns 2 and 5.

Relative to black demand shocks, white demand shocks appear to have less predictive power in general reflecting white rural migration being less directed than black migration during this period. Nonetheless, even in a relative sense, white demand shocks do not seem to have a qualitatively important impact on tract black populations operating only to change white populations.

5.2.2 First Stage Regressions

Table 6 mirrors Table 5 except that it reports coefficients of regressions for housing cost and neighborhood black share. Similar important heterogeneity can be seen across the gradient of black share of neighborhoods. Because of scale, regressors have been divided by 1,000 before estimation.

Consistent with the model, costs fall in response to black migrant shocks in relatively white neighborhoods and increase in relatively black neighborhoods. Additionally, neighborhood minority share evolves in exactly the way one would expect: black migrants increase the black share in relatively white neighborhoods but have no effect in relatively black neighborhoods, and vice versa for white migrants. Interestingly, though white migrants had a consistently positive effect on the neighborhood total population, white migrants seem to have a negative effect on housing costs. Though they do not produce nearly as much variation as the black demand, white demand shocks are nonetheless always statistically significant at conventional levels.

5.3 Estimates of Preference Parameters

5.3.1 Estimation Procedure

I estimate equation (5) in first differences via two-sample two-stage least squares (2SLS) in order to keep the first stage estimates the same across all samples. Because there are many neighborhoods with few or no black residents, the sample of tracts used for the second stage can be considerably smaller when estimating the black preference parameters versus when estimating white preference parameters. These smaller samples can be particularly meaningful when estimating the interaction terms in the first stages.

The two-step procedure, however, poses no particular threat to the second stage estimation under the I.I.A assumption of the multinomial logit model. I report robust standard errors derived for two sample 2SLS according to the procedure suggested by Pacini and Windmeijer (2016), which also incorporates the potential covariance in first stage and reduced form parameters induced by the partially or completely overlapping samples.

5.3.2 2SLS Estimates of Parameters Governing Prices and Racial Composition

Table 7 reports estimated preference parameters over housing costs for black households in panel A and white households in panel B. Column (1) estimates the model on shares pooling the location choices of households in all occupation, column (2) focuses on heads of household who are in low-skill occupations typical of black workers, and column (3) estimates parameters pooling blue- and white-collar workers.

The estimates of the model are consistent with households having downward sloping demand. Interestingly, white household utility appears to be somewhat more sensitive than black households to price.

Starker contrasts emerge in the preferences over neighborhood black share. My preferred estimates for black residents are in column (2) where I construct location shares using households in the three broad occupation groups that represent most black households. These estimates suggest that black households have no particular affinity for more or less black neighborhoods. The pooled estimates that include families of higher-skilled black men in column (1) are potentially confounded by taste heterogeneity for certain neighborhoods, but if anything point to black households having an affinity for black neighbors.

Corresponding estimates for white households are consistent with a prior literature that find that white households have a high willingness to pay to avoid growing minority shares. Interpreting these results through the model, in the bottom panel, I report elasticities that reflect how households would need to be compensated for a 1 p.p. increase in the neighborhood black share to keep utility constant. For white households, these estimates sugges that a 1 p.p. increase in the black share would need to be offset by an approximately 0.7–1% decline in house prices to keep white households indifferent.

5.4 Estimates of the Correlated Random Effects

Table 7 speaks to the prior literature and by using migrant shocks, estimates preferences that do not confound potential supply and demand factors. However, these analyses by themselves are not able to quantify segregation. As outlined in section 2.3, I first present parameter estimates from a correlated random effects model. I then use these counterfactual distributions directly in a decomposition of the KL divergence, which I use as a measure of segregation.

5.4.1 Estimation Procedure

Direct estimation of a CRE version of the model in equation (5) is infeasible in my setting. The demand shocks are suitable instruments for the model in changes in equation (18), but the a CRE model requires instruments for the 1930 levels of $\ln P$ and s.

However, under the identification assumptions laid out before, the 2SLS regressions in first differences give consistent estimates of β and γ. Thus, a consistent estimator for u_{rjt} is

$$\hat{u}_{rjt} = \ln \hat{\pi}_{rjt} - \hat{\beta}_r \ln P_{jt} - \hat{\gamma}_r s_{jt}. \tag{20}$$

To obtain the parameters of the CRE model, I can then estimate a cross-sectional OLS regression pooling the two periods

$$\ln \hat{u}_{rjt} = \vartheta_{rdt} + \underbrace{\boldsymbol{\Omega_r' X_j} + \boldsymbol{\Upsilon_r' Z_j} + \psi_{rj}}_{\alpha_{rj}} + \xi_{rjt} \tag{21}$$

where $\boldsymbol{X}_j$ includes the sum of shares and the 1930 total population.

Identification of the variance components in equation (8) comes from the residuals

$$\hat{e}_{rjt} = \psi_{rj} + \xi_{rjt}.$$

This residual has two components. Using the three assumptions in equation (8) in section 2.3, one can write the full variance-covariance matrix of the errors:

$$\boldsymbol{Var}\begin{pmatrix} e_{Bj,1930} \\ e_{Bj,1940} \\ e_{Wj,1930} \\ e_{Wj,1940} \end{pmatrix} = \begin{pmatrix} \sigma_B^2 + \varsigma_B^2 & & & \\ \sigma_B^2 & \sigma_B^2 + \varsigma_B^2 & & \\ \sigma_{BW} + \varsigma_{BW} & \sigma_{BW} & \sigma_W^2 + \varsigma_W^2 & \\ \sigma_{BW} & \sigma_{BW} + \varsigma_{BW} & \sigma_W^2 & \sigma_W^2 + \varsigma_W^2 \end{pmatrix}$$

where $\boldsymbol{Cov}\left\{\xi_{Bjt}, \xi_{Wjt}\right\} = \varsigma_{BW}$. The coefficients I need for the counterfactuals are σ_B^2, σ_W^2, and σ_{BW} to plug into equation (9). The population variance-covariance matrix directly maps into sample covariances of the regression residual. That is

$$\hat{\sigma}_r = \frac{1}{N-K} \sum_j \hat{e}_{rj1930} \cdot \hat{e}_{rj1940}, \tag{22}$$

$$\hat{\sigma}_{BW} = \frac{1}{2N-K} \sum_j \left(\hat{e}_{Bj1930} \cdot \hat{e}_{Wj1940} + \hat{e}_{Bj1940} \cdot \hat{e}_{Wj1930}\right). \tag{23}$$

I compute the variance and covariance components using the sample of tracts where there are both white and black residents for a given occupation group.[27]

5.4.2 Estimates of Random Effects and Variance Components

Table 8 summarizes the estimated correlated random effects parameters. The top panel reports estimates of the random effects variance among different occupation groups of households. The first line in each row reports the raw variance estimate, and the second line in each row reports the correlation of the composite

[27]Utilizing the full sample of neighborhoods for white residents has no substantial effect on the variance estimates. Results available upon request.

residuals used to estimate the covariance. For example, the first row in column (2) reports a random effect variance $\hat{\sigma}_B^2 = 0.331$ and a sample correlation $\boldsymbol{Corr}\left[\hat{u}_{Bj1930}, \hat{u}_{Bj1940}\right]$ of 0.735. The first two rows across the sample suggest that neighborhood unobservables are highly correlated across periods, which implies that static characteristics of the neighborhood explain a large portion of the variance in unobservable neighborhood choice.

Interestingly, the white and black unobservables σ_{BW} are strongly *positively* correlated. Ex ante, the opposite result is equally plausible. For instance, one can imagine that neighborhoods that have better schools for whites would have worse schools for blacks, reflecting educational resource inequality growing with the white unobservable. This does not seem to be the case. In the sample of tracts where there are both black and white households, the probability that a black family choose a neighborhood grows with the probability that a white family chooses the neighborhood, conditional on the neighborhood's black share and price.

Extending this analysis to include observables, the bottom panel reports the model implied covariances between α_{Bj} and α_{Wj}. The first line in each row reports the raw covariance, and the second line divides this covariance by the variance of α_{Wj}. This gives the interpretation of a regression coefficient where the dependent variable is the component indicated by the label in the row, and the the independent variable is α_{Wj}.

Focusing on the group of households in black occupations in column (2), one can see that α_{Bj} has a strong positive correlation with α_{Wj}. The implied regression coefficient suggests that a one unit increase in the log odds for white households driven by α_{Wj} corresponds to a 0.8 increase in the log odds for black households.

The second row focuses only on the components that are driven by the observable covariates. The implied regression coefficient suggests that almost 90% of the variation in the implied 0.8 coefficient is driven by observable characteristics.

Altogether, this analysis could have very easily shown that among neighborhoods with both white and black families, unobservables drive segregation by being negatively correlated. This does not seem to be the case. The between-race correlation of the random effects seems to suggest that the random effect can be most accurately thought of a shared amenity rather than amenities and disamenities that are race-specific.

5.4.3 Overall Decomposition

Using the CRE model in conjunction with the underlying multinomial logit I generate model predicted mean utilities $\widehat{\log\delta}$ and the implied inclusive value to make the choice probabilities sum to 1 according to the procedure described at the end of section 2.3.2. I then replace the terms in equation (2.4) to decompose the KL divergence into components interpretable as driven by supply and demand factors.

Table 9 reports the results of the decomposition using these predicted choice probabilities. The top panel of the table presents the overall divergence, and the bottom panel presents each component. In each row, the second line is the fraction of the total divergence explained by the component.

The first line in the bottom panel compares the choice probabilities of black households to those of counterfactual black households. The latter group, by definition has the same exact preference parameters, which I interpret as driven by constrained supply. The second line is the remainder and compares the counterfactual demand to white demand. Here, because the counterfactual is extrapolated to include all neighborhoods, there are no supply constraints.

The results in this table consistently show that roughly one of observed segregation within an occupation group is driven by supply. The accumulated results to this point are consistent with a supply based explanation. If segregation were driven purely by preferences, the willingness of white households to pay to avoid black families would be capitalized into price—one should expect that white families are concentrated in expensive all white neighborhoods. This is partly true. Recall from table 4 that white neighborhoods tend to be more expensive than black neighborhoods.

However, the observed price gap is not large enough to fully deter black families from moving into those neighborhoods. Lifting the constraints through the counterfactual exercise shows that black families would move to those neighborhoods without those prohibitions.

6 Conclusion

The analysis of this paper suggests that roughly one half of observed segregation in 1940 can be explained by divergent preferences over neighborhoods. I estimate parameters of a multinomial logit demand model identified using information from migrant demand shocks. To avoid migrant demand shocks being correlated with neighborhood unobservables, I utilize the predictable component of migration by connecting residents in 1930 to rural origin counties using surname distributions.

Structural estimates suggest that white households willingness-to-pay to avoid a 1 p.p. increase in black neighbors is roughly 1% of the house value. While preferences over the black share of the neighborhood diverge between races, they seem to converge on everything else: between races, the implied price elasticities of demand with respect to housing are roughly the same, and unobservable neighborhood characteristics are highly correlated.

The measurement of these preference parameters in conjunction with neighborhoods with essentially no black residents are highly suggestive of supply constraints driving a large share of segregation. Constructing counterfactual demands from the parameter estimates and incorporating them in the decomposition of the KL divergence suggests the share of segregation explained by formal and informal constraints is comparable to the preference based explanations.

Was the persistent concentration of high poverty black neighborhoods in inner cities the inevitable consequence of decentralized, individualistic decisions of households? Boustan's (2010) research suggests that suburbanization in the latter half of the 20th century was driven in large part to white flight. While my partial equilibrium model does not account for dynamics, it does suggest state dependence on the neighborhood black share, implying that at least some of post-war white flight has origins in supply-driven segregation prior to the second World-War.

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7 Figures

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

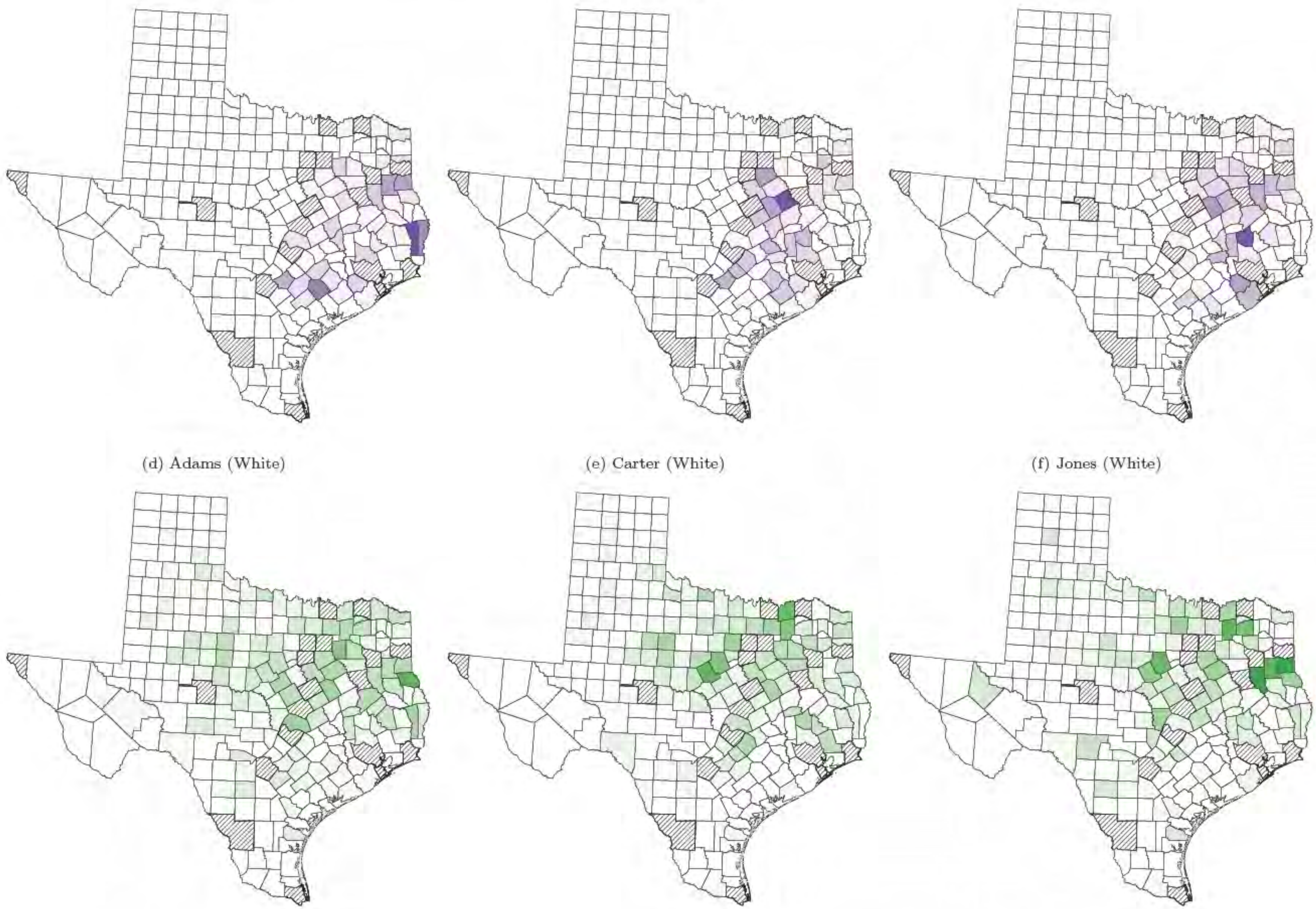
[a] Black flows plotted in purple, and white flows plotted in green.

[b] Origin counties shaded in purple and green with the intensity corresponding to the total county outflows of blacks and whites to major cities with census tracts, respectively. Cross-hatched counties are urban counties.

[c] Census tracts in Los Angeles shaded in red according to the tract share of black residents in 1930.

[d] Flows bundled via algorithm documented in Graser, Schmidt, Roth, and Brändle (2017) using software from https://github.com/dts-ait/qgis-edge-bundling.

Figure 2: Comparison of Three Common Last Names in Texas



(a) Adams (Black) (b) Carter (Black) (c) Jones (Black)

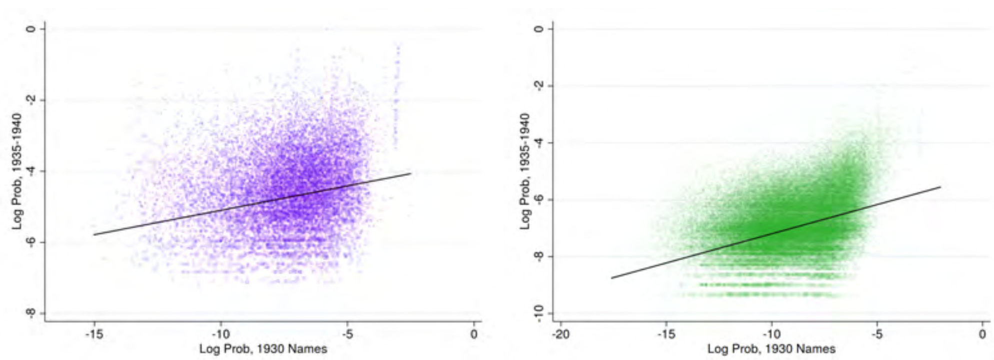
(d) Adams (White) (e) Carter (White) (f) Jones (White)

[a] The first row of figures plots the residential share of non-migrant blacks. The second row of figures plots the distribution for whites.

[b] Cross-hatched counties are urban counties.

Figure 3: Current and Surname-Constructed Flows Probabilities for Counties in the Top Quartile of Outflows

(a) Black (b) White



[a] Each point is an origin county-destination tract pair.

[b] The vertical axis measures the log of the 1935–1940 flow probabilities from the 1940 census, and horizontal axis represents the log of the probabilities estimated from the surname procedure in the 1930 census. See text for details.

[c] The size of each point is weighted by the total race-specific migrant outflows from the origin county. The sample of points come from rural counties in the top quartile of race-specific outflows for display purposes.

8 Tables

Table 1: Migrant Inflows to 48 Major Cities with Census Tracts by Census Region, 1935–1940 (Thousands)

(a) Black

	All	South	West	Midwest	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

	All	South	West	Midwest	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

[a] Rural counties are those without a census incorporated place. See text for details.

[b] Flows are from a retrospective question in the 1940 census asking about respondents' location five years prior.

[c] All flows including the total only include individuals for whom an origin county could be ascertained.

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

(a) Black

	(1)	(2)	(3)	(4)	(5)
Past Flowrate	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)
Past Flowrate	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

[a] The unit of observation is an origin county-destination census tract pair.
[b] Regressions weighted by total rural-to-urban origin county migrant outflows.
[c] Robust standard errors clustered by origin county reported in parenthesis.

Table 3: Occupation Distribution by Race, 1940

	Black	White
All Households	789,140	8,358,405
...with employed male head of household, age 18–55,	488,045	5,350,075
... with wife and at least one child	212,624	3,342,510
... in tracts with at least 10 with same occ. $\times$ race	207,701	3,340,763
Broad Occupation Shares		
"Black" 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

[a] The top panel reports counts of households living in one of 48 tracted metropolitan areas in 1940.

[b] 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 4: Neighborhood Characteristics of Median Black and White Families, 1940

	All	White	White (Black Occs)	Black
Characteristics of Neighborhood Housing				
Median Housing Cost	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				
Black Share	0.00289	0.00195	0.00180	0.730
Mean Household Size	3.607	3.590	3.677	3.763
Median Household Income	1,500	1,551	1,500	979
Share Employed (Head)	0.704	0.711	0.690	0.636
Share Employed in Black Occs. (Head)	0.280	0.269	0.305	0.401
Average Years of Education (Head)	8.357	8.506	7.949	7.050
Sum of Weights	33,283,800	29,920,195	9,771,394	3,237,710

[a] Each column reports a weighted median of tract characteristics where weights are the number of families described by the column labels.
[b] Black occupations include laborers, service workers, and operators.
[c] Housing cost combines both home values and rents into a single measure. See text for details.

Table 5: Reduced Form Effects of Migrants on Population

	(1) Black	(2) White	(3) Total	(4) Black	(5) White	(6) Total
Coefficient Estimates						
Z_B	8.856	-0.813	7.958	21.06	-31.24	-10.46
	(2.284)	(2.152)	(2.186)	(5.934)	(5.080)	(5.395)
Z_W	-2.093	4.436	1.976	-1.866	3.461	1.218
	(0.431)	(1.804)	(1.855)	(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	6132	6132	6132
Wald F-statistics and p-values						
All Instruments	21.39	3.372	6.678	24.73	15.33	7.683
	⟨0.000⟩	⟨0.034⟩	⟨0.001⟩	⟨0.000⟩	⟨0.000⟩	⟨0.000⟩
Black Effects	15.03	0.143	13.25	6.895	27.05	9.693
	⟨0.000⟩	⟨0.705⟩	⟨0.000⟩	⟨0.001⟩	⟨0.000⟩	⟨0.000⟩
White Effects	23.62	6.046	1.135	9.602	5.250	7.780
	⟨0.000⟩	⟨0.014⟩	⟨0.287⟩	⟨0.000⟩	⟨0.005⟩	⟨0.000⟩

[a] Robust standard errors reported in parentheses, p-values reported in angular brackets.
[b] The dependent variables are tract decadal changes in black, white and total population, respectively.
[c] Z_B and Z_W are black and white demand shocks. See text for details.
[d] 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.
[e] The Wald test for "All Instruments" tests the joint significance of all coefficients in the top panel. "Black Effects" and "White Effects" test Z_B and Z_W and their interactions (if applicable), respectively.

Table 6: First Stage Regressions

	(1) Cost	(2) Share	(3) Cost	(4) Share
Coefficient Estimates				
$Z_B/1,000$	0.188	0.102	-1.486	2.899
	(0.275)	(0.141)	(0.437)	(0.365)
$Z_W/1,000$	0.0789	-0.147	0.0518	-0.0679
	(0.168)	(0.0426)	(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	6132	6132
Wald F-statistics and p-values				
All Instruments	0.329	6.427	19.76	35.51
	⟨0.719⟩	⟨0.002⟩	⟨0.000⟩	⟨0.000⟩
Black Effects	0.470	0.525	15.51	44.60
	⟨0.493⟩	⟨0.469⟩	⟨0.000⟩	⟨0.000⟩
White Effects	0.222	11.97	4.698	3.392
	⟨0.638⟩	⟨0.001⟩	⟨0.009⟩	⟨0.034⟩

[a] See the table notes a, c, d, and e from table 5.

[b] The dependent variables are tract decadal changes in median log housing cost and neighborhood black share, respectively. See section 4.2 for details on construction of housing costs.

[c] Z_B and Z_W are divided by 1,000 before estimation for reporting.

Table 7: Preference Parameters for Broad Occupation Groups

(a) Black

	(1) Pooled	(2) Black Occ	(3) Other Occ
Log Housing Costs	-1.228	-1.906	-0.284
	(0.575)	(0.553)	(0.452)
Black Share	0.887	-0.0113	0.350
	(0.701)	(0.704)	(0.639)
Tracts	1196	1087	490
Elasticity	0.722	-0.00593	1.230
	(0.879)	(0.368)	(4.092)

(b) White

	(1) Pooled	(2) Black Occ	(3) Other Occ
Log Housing Costs	-3.542	-4.109	-2.743
	(0.950)	(1.026)	(0.828)
Black Share	-2.473	-3.982	-2.134
	(1.011)	(1.109)	(0.928)
Tracts	6049	5750	6015
Elasticity	-0.698	-0.969	-0.778
	(0.165)	(0.143)	(0.187)

[a] Robust standard errors adjusted for two-step procedure according to Pacini and Windmeijer (2016) reported in parentheses. First stage coefficients are reported in table 6.

[b] Reported elasticities are the percentage change in housing costs needed to offset a 1 p.p. increase in the black share and keep an average household indifferent to the neighborhood. Standard errors are computed using the delta method.

[c] "Black occupations" are laborers, service workers, and operators.

Table 8: Scaled Covariances of Correlated Random Effects

	(1) Pooled	(2) Black Occ.	(3) Non-Black Occ
Estimated Covariances and {Correlations}			
σ^2_B	0.416	0.494	0.235
	{0.742}	{0.776}	{0.703}
σ^2_W	1.153	0.855	0.855
	{0.724}	{0.775}	{0.820}
σ_{BW}	0.367	0.449	0.153
	{0.390}	{0.538}	{0.262}
Covariances, Raw and [Implied Regression Coefficents]			
α_{Bj}	0.315	0.650	0.145
	[0.198]	[0.531]	[0.128]
$\left(A_B\bar{\boldsymbol{Z}}_j + C_B\bar{\boldsymbol{X}}_j\right)$	-0.0523	0.201	-0.00774
	[-0.0328]	[0.164]	[-0.00683]
σ_{BW}	0.367	0.449	0.153
	[0.231]	[0.367]	[0.135]
Tracts	1118	915	396

[a] The top panel reports estimates of the variance components of the permanent neighborhood unobservable from a correlated random effects model. The first line in each row is the point estimate of the variance, and the second line in each row is the correlation between the two residuals from which the variance is estimated. For example, the first line in the first row is the covariance between the 1930 and 1940 black residuals, and the second line is the correlation coefficient. See text for details.

[b] σ_B and σ_W are estimated from the covariance between the 1930 and 1940 black and white residual, respectively. σ_{BW} is a pooled covariance of the 1930 black residual and 1940 white residual and 1930 white residual and 1940 black residual. The correlation coefficient for the latter is an average of the two estimates.

[c] All covariances are estimated on the subset of tracts for which there are both black and white residuals.

[d] The bottom panel reports the covariances between α_{Bj} and α_{Wj}, both raw, and scaled by the variance of α_{Wj}. The scaled covariances have the interpretation of a regression coefficient.

Table 9: Decomposition of KL Divergence

	(1) Pooled	(2) Black Occ.	(3) Non-Black Occ
Divergence	116.7	105.1	129.5
	[1]	[1]	[1]
$\pi_{Bj} \ln \left(\pi_{Bj}/\hat{\pi}_{Bj}^{CF}\right)$	55.60	49.94	76.02
	[0.476]	[0.475]	[0.587]
$\pi_{Bj} \ln \left(\hat{\pi}_{Bj}^{CF}/\pi_{Wj}\right)$	61.14	55.16	53.53
	[0.524]	[0.525]	[0.413]

[a] The top line reports the actual divergence from the black multinomial distribution to the white distribution. The second and third line reports the divergence between the actual black distribution and a counter-factual distribution computed via the random effects model and the divergence between the counter-factual distribution and the white distribution.

[b] The first row in each line reports the component of the Kullback-Leibler divergence. The second row in each line reports the share of the actual divergence explained by that component.

[c] The sample of tracts over which the divergence is calculated are those with some white residents. Probabilities are renormalized to sum to 1 according to a procedure outlined in the text.