Race, Class, and Location in Neighborhood Migration:
A Multidimensional Analysis of Locational Attainment*

Lincoln Quillian
Northwestern University

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Address correspondence to Lincoln Quillian, Department of Sociology, Northwestern University, 1810 Chicago Avenue, Evanston, IL 60208.
E-mail: l-quillian@northwestern.edu.

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What factors uphold persistent neighborhood racial segregation in American metropolitan areas? Data on migration among neighborhoods provides a key resource to address this question, but the use of this data has been limited because dominant approaches to studying migration represent destinations by a single characteristic, often neighborhood percentage white. Instead of viewing migration as a process of attainment on a single dimension, in this article migration is analyzed as a sorting process along multiple dimensions. Black and white migration is analyzed as guided by neighborhood racial composition, housing prices, neighborhood income level, geographic distance, and characteristics of the origin neighborhood. The model is estimated with data from the Panel Study of Income Dynamics, 1997-2009, using a conditional logit discrete-choice model. For whites, neighborhood racial composition is the strongest driver of neighborhood mobility decisions that produce segregation, and its influence weakens little after accounting for the other dimensions of neighborhood sorting For blacks, a significant part of race-sorting in mobility reflects the influence of correlated conditions like price and distance. Counterfactuals applied to the model suggest that direct neighborhood race effects and geographic distance are the largest contributors to segregated patterns of mobility, and that segregation in neighborhood mobility is over-determined by the overlap of multiple neighborhood attributes.

Race, Class, and Location in Neighborhood Mobility: A Multidimensional Analysis of Locational Attainment

Despite a slow decline, racial residential segregation remains a defining social fact of American metropolitan life. In the year 2010, nearly 59% of black households and 48% of Latino households in metropolitan areas would need to relocate to achieve an even spatial distribution across neighborhoods relative to white households (Logan and Stults 2011). Segregation on the basis of race remains much higher than segregation on the basis of socioeconomic status.

Racial segregation persists despite the frequent churning of households among neighborhoods. With more than 15% of households relocating each year (Ihrke and Faber 2012), segregation would decline rapidly were households to move to destinations randomly: Neighborhoods remain segregated because migration remains segregated. Aided by the availability of panel datasets, the flows of migration that produce segregated neighborhoods have been well documented. Less is known, however, about what explains these migration flows.

In this paper I argue that an important barrier to better understand the “why” behind migration flows has been the failure of studies of migration to employ a sufficiently realistic model of the factors guiding migration. The problem rests in the way dominant approaches to modeling migration in sociology, such as locational attainment models, characterize destinations based on one continuous attribute such as percentage white or median income or based on a small number of categories. These approaches fail to capture the fact that neighborhoods are bundles of many attributes that matter simultaneously in migration: households are concerned about neighborhood racial composition, but also neighborhood economic level, location, price, and other attributes of neighborhoods.

This omission has had two consequences. First, empirical studies corresponding to major theoretical debates about the relative importance of neighborhood race and neighborhood class (economic level) in accounting for segregated migration have not benefited from analyses of data on actual migration, because methods of migration analysis could not incorporate neighborhood race and neighborhood class together. Instead, sociologists have had to rely on more indirect methods of addressing race-class debates with attendant drawbacks. Second, studies of neighborhood migration have mostly not examined the role of other bundled neighborhood attributes in producing segregated migrations streams, including predictors that are critical in the migration literature, such as distance.

Correspondingly, my analysis focuses on addressing two major research questions. First, what is the importance of race and class factors in accounting for the migration streams that uphold segregation? Second, what is the role of distance, as a basic factor guiding migration, in upholding racially segregated space? The first question has been the subject of much work, but with significant limitations caused by lack of a sufficiently realistic model of migration. The second question has been only indirectly considered by a handful of studies, despite the fact that in theories of migration distance is the most basic factor structuring migration patterns.

This manuscript addresses these questions by employing a discrete-choice modeling approach in the place of the regression approaches that have been dominant in the locational attainment literature: the resulting model of locational attainment is multidimensional, in that it recognizes the bundling problem of neighborhood attributes and allows for simultaneous influence of neighborhood race, neighborhood class (or economic level), distance, and other attributes in guiding migration. The discrete choice approach is a variation on methods available for some time in the technical literature on methods for migration analysis (McFadden 1978) and recently discussed in an account of methods to analyze migration by Bruch and Mare (2012).

BACKGROUND

Knowledge of the migration flows that produce racially segregated neighborhoods has increased tremendously over the past 20 years. Two streams of migration have been established as especially important to maintaining racial residential segregation. First, whites tend to avoid neighborhoods with more than small percentages black and Latino residents: exit is higher and entry is much lower as the share black or Latino increases. Second, blacks and Latinos move into predominately white neighborhoods at lower rates than whites, but not extremely infrequently, and also move out of predominately white neighborhoods frequently (Crowder 2000, Quillian 2002; South, Crowder, and Pais 2008; Crowder, Pais, and South 2012).

What accounts for these patterns of migration? Theoretical debates in sociology have focused on the relative importance of race and class (or socio-economic status) factors. The race explanations emphasize prejudices, stereotypes, and discrimination as key factors driving segregated migration. The class explanations emphasize racial gaps in income and affluence as factors that produce racially segregated migration streams. These explanations are more complicated than they may initially seem, because race and class are attributes of both individuals and of neighborhoods, and thus there are multiple race and class theories.

In the remaining discussing, I focus especially on white and black migration, because my data will not allow me to consider migration separately for Latinos or other race and ethnic groups. I also focus on destination selection rather than out-migration. Racial selectivity in destinations after moving is far more important than differential patterns of moving out in producing segregation (Ellen 2000; Quillian 2002).

Race and Class in White Avoidance

One of the most consistent results of migration studies is that the rate of white entry to a neighborhood drops sharply as the share black or Hispanic increases (Ellen 2000, Quillian 2002). What reasons drive white avoidance? The major debate in this area has contrasted the "pure-race" versus "racial proxy" hypothesis (Harris 2001, Krysan et al. 2009, Swaroop and Krysan 2011). The "pure-race" hypothesis suggests white mobility is grounded in prejudices or inaccurate stereotypes about blacks and Hispanics. The "racial-proxy" hypothesis suggests that apparent white aversion for black and Latino neighborhoods represents the desire to avoid low-income neighborhoods, or the social problems more often found in low-income neighborhoods, rather than black and Hispanic neighbors per se.[1]

Data on white migration would be logically used to address this debate. But it has not because typical approaches to analyzing migration lack a way to separate neighborhood race, neighborhood class, and other neighborhood conditions as factors driving white migration. Studies in this literature have instead analyzed data on housing prices or survey evaluations to address reasons for white avoidance.

One approach uses the economic technique of hedonic price analysis to estimate preferences for neighborhood race and class composition. In theory, housing prices reflect preferences for characteristics of housing and neighborhoods, which drive demand; preferences can then be estimated by regressing price on relevant housing and neighborhood characteristics. Most studies using this approach have found neighborhood race effects on prices sharply decline under controls, supporting the racial proxy hypotheses (Harris 1999; Chambers 1992; Kiel and Zabel 1996; Bayer, Ferreira, and

[1] An additional useful distinction is between white evaluations that are based on pure prejudice and those based on inaccurate stereotypes about black neighborhoods (see Ellen 2000). We group these theories together, since both theories have mostly similar implications for why whites avoid black neighborhoods that are clearly distinct from

MacMillan 2007).[2] A weakness of the hedonic approach is that discrimination in housing markets can create barriers that distort the relationship between neighborhood preferences and prices, and housing audit studies indicate that discrimination is present in housing markets (Turner et al. 2002).

A second approach has analyzed survey data asking white respondents about their satisfaction with their neighborhood of residence (or related evaluative questions about their neighborhood). Satisfaction ratings are then regressed on neighborhood racial composition, neighborhood class level, and other conditions to estimate their effects. Swaroop and Krysan (2011), Baybeck (2006), and Stipak and Hensler (1983) find persisting effects of neighborhood racial composition on white neighborhood satisfaction after controls for neighborhood class, supporting the pure-race hypothesis. In contrast, Taub, Taylor, and Dunham (1984), Ellen (2000), and Harris (2001) find that neighborhood class measures account for lower neighborhood satisfaction of whites as share black in their neighborhood increases, supporting the proxy hypothesis. One weakness with this approach is the self-selected nature of neighborhood residence. Households who have a preference for a characteristic are more likely to live in a neighborhood with that characteristic, a selection that is likely to attenuate slopes of predictors of satisfaction to an unknown degree.

A third approach relies on evaluations of hypothetical neighborhoods. The hypothetical neighborhood is described on a survey, including its racial composition and income level. Respondents are asked to rate its desirability. Hypothetical neighborhood studies find persisting effects of racial composition on ratings of neighborhood desirability when neighborhood income level and other factors are controlled (St. John and Bates 1990; Farley et al., 1994; Emerson, Yancey, and Chai 2001; Krysan et

[2] Relatedly, Sermons (2000) and Bayer, Ferreira, and MacMillan (2007) use conditional logit models (mixed with a hedonic model in the case of Bayer, Ferreira, and MacMillan) to estimate white preferences for non-white neighbors in San Francisco. Sermons' results support the pure-race interpretation, while Bayer, Ferreira, and MacMillan's results support the racial proxy hypothesis. See pages 13-15 for more discussion of these studies.

al. 2009).[3] The weakness of the hypothetical neighborhood approach is the lack of realism in simulating neighborhood evaluations made in buying or renting. Thoughts and feelings experienced when hearing a vignette about a hypothetical neighborhood, or (in case of Krysan et al. 2009) seeing a video vignette, are likely not the same as visiting an actual neighborhood, and the time scale over which the decision made is very different in the survey from actual situations. In a study comparing an actual hiring decision and a parallel survey vignette, Pager and Quillian (2005) found little correspondence between survey evaluations and real decisions revealed through an audit, suggesting that survey hypotheticals may not accurately portray responses in complex decision contexts.

In my review, eight studies find more support for the racial proxy hypothesis, and nine studies find more support for the racial prejudice hypothesis. There has been no clear winner in this contentious debate. Moreover, these studies all use somewhat indirect methods that require significant, often difficult-to-test assumptions. An important missing piece to this debate has been analyses of actual white mobility that can separate neighborhood race and class as influence on mobility.

Race and Class in Black Migration

Migration by black households is to more diverse racial destinations than it is for white households. Black households do migrate into predominately white neighborhoods with some regularity: from 1979 to 1990, about 10% of all black moves were to neighborhoods that were less than 10% black, and 23% of black moves were to neighborhoods less than 30% black (Quillian 2002). On the other hand, black households still move to highly black neighborhoods far out of proportion to the presence of black

[3] Krysan et al. (2009) showed respondents brief videos of a neighborhood manipulated to assign visual cues about the class and race level of the neighborhood.

neighborhoods in the population. In addition, studies find that black households appear relatively likely to move back to black neighborhoods from white origin neighborhoods on subsequent migration.

Explanations of black neighborhood migration have focused on the trio of preferences, class, and race. The preference explanation is that black migration reflects desire for own-race neighbors and racial community, the class explanation is that black migration reflects racial income gaps combined with racial differences in housing prices, and the race explanation is that race reflects racial discrimination in housing markets that may tend to steer black and Latino households toward black neighborhoods of destination.

Subsequent work has mostly rejected the preference explanation, at least in strong form. Survey analyses that ask for racial preferences consistently show that black and Latino households prefer neighborhoods that are highly racially diverse (Clark 1991; Farley et al. 1978, 1994; Bobo and Zubrinsky 1996).[4] Further, on surveys almost all black households say they would move into any neighborhoods that have any visible black presence (Krysan and Farley 2002). A strong role for preferences, in which most blacks move to black neighborhoods because they prefer them, seems inconsistent with this evidence. Further, studies using surveys to ascertain the extent to which a desire for own-group contact is a key factor driving neighborhood preferences (Bobo and Zubrinsky 1996) have found little evidence to support its importance.

The class explanation of black migration, suggested in an early form by Myrdal (1996[1944]), is that segregation results from a combination of racial gaps in income combined with neighborhood differences in housing prices. Many scholars have examined this idea by contrasting the neighborhoods of whites and blacks with similar levels of income. Some studies have investigated this idea under the theoretical perspective of "spatial assimilation", suggesting that white and black households should tend

[4] Krysan et al. (2009), however, find that black households evaluate mixed and black neighborhoods as equally desirable.

to live in similar neighborhoods if they live in similar neighborhoods. These studies typically use locational attainment methods, regressing measures of racial composition on individual characteristics (e.g., Alba and Logan 1993; Alba, Logan, and Stults 2000a). Other studies calculate indexes of racial segregation separately for households in different income ranges (Sharp and Iceland 2013, Iceland and Wilkes 2006, Massey and Fischer 1999). These studies find that income differences explain less than half of white-Hispanic segregation, and less than one fifth of white-black segregation; the ultimate conclusion is that these income differences are unimportant.

Yet these studies also face a problem resulting from their defining the neighborhood outcome based on share black only, and omitting housing prices. Implicitly, these studies tend to assume that housing prices in otherwise comparable black and white neighborhoods tend to be about the same. Yet some evidence indicates that disproportionate demand relative to supply of white neighborhoods may cause housing prices to be higher in white neighborhoods than comparable black ones (Cutler, Glaeser, and Vigdor 1999). Black families might then choose black neighborhoods in part because housing prices are lower, even in the absence of other barriers to the entry of white neighborhoods. Income differences by race further accentuate the effect of these differences on segregation, but this explanation fundamentally emphasizes neighborhood price differences related to racial composition rather than group income differences. To better test this explanation, we need methods that allow us to simultaneously examine individual income, neighborhood housing price, and neighborhood racial composition.

The discrimination explanation of black migration emphasizes discrimination by housing market agents like owners and real-estate agents that denies blacks entry to white neighborhoods or steers them toward black neighborhood destinations. Often this interpretation is offered to account for residual race differences in mobility or locational attainment between whites and blacks after income and other controls. More direct evidence is available from housing audits, which have found substantial evidence of housing discrimination against black renters and owners (Turner et al. 2002). But it is difficult to draw conclusions about how much segregation is the product of housing market discrimination based on audits. The one study that related rates of entry of black households to white neighborhoods with metropolitan measures of racial discrimination found no association (South and Crowder 1998).

Beyond Neighborhood Race and Class: Locational Factors in Migration

The theoretical opposition of race and class factors is useful because these are distinct explanations that suggest different policy responses. Yet the race-class debate itself underspecifies the mechanisms that produce segregation. One of the most important omissions from these debates has been distance. Most studies of neighborhood migration treat neighborhoods as unrelated islands, ignoring the fact that neighborhoods are spatially located relative to migrating households and each other, and that distance is a basic factor that structures migration.

One of the earliest systematic statistical studies of migration, Ravenstein's (1888) "laws of migration," noted the fundamental role of distance in guiding migration: Ravenstein's first law of migration was that rates of migration between any two locations tend to be inversely related to distance. Subsequence studies continually reaffirm the basic role of distance (Cadwaller 1992).

While a few studies of the decision to move out have incorporated characteristics of nearby locations (e.g. Crowder and South 2008), geographic migration has not been incorporated into models of migration destinations. This reflects again the problem that the predominant methods of analyzing migration characterize destination neighborhoods by only one characteristic at a time.

Distance is likely to influence segregation because migration guided (inversely) by distance tends to increase the chance of moving to racially similar neighborhoods if racially similar neighborhoods are clustered together. Black-white segregation is especially characterized by strong clustering above the neighborhood level and with distinct black-white areas of cities, a pattern called "hypersegregation" by Massey and Denton (1988; see also Wilkes and Iceland 2004). Segregation at higher spatial levels may then play a role in maintaining segregation at the neighborhood level, because distance-guided migration will tend to lead back to racially similar areas.

Moreover, just as physical distance may structure the distance between origin and destination neighborhoods, social distances from origins are also likely predictive of destinations. There is a high degree of continuity over time in the racial composition and economic level of individuals' neighborhoods (Sampson and Sharkey 2008; Sharkey 2008). This suggests that characteristics of the neighborhood of origin will predict neighborhood of destination net of individual characteristics and available opportunities.

Sorting on origin neighborhood social characteristics is suggested by the fact that residents have familiarity and comfort with the type of neighborhood they already live in, which probably makes them more likely to choose a similar neighborhood. South and Crowder (1998) find households living in a black neighborhood at origin are more likely to move to a black neighborhood of destination, net of many individual characteristics. Similar sorting may also occur on other characteristics of neighborhoods such as level of income.

Theory suggests distance from origin residential neighborhood, both spatially and socially, is likely to be important in producing segregated migration. Further, these forms of distance may combine complexly with race and class factors in the production of segregated migration streams. In order to consider these possibilities, we need a model of migration that allows us to examine how multiple types of neighborhood attributes, including race, class, but also geographic location, and social distance from origin neighborhood, influence the neighborhood of outcome.

LOCATIONAL ATTAINMENT AS A MULTIDIMENSIONAL PROCESS

A number of theories have been developed about the role of race and class at the individual and neighborhood level in producing segregated migration. Yet examination of these theories has been hampered because the main approaches to modeling migration in sociology cannot incorporate multiple attributes of places simultaneously in understanding the factors guiding migration.

The predominate approach to modeling migration and residential location in sociology has been the "locational attainment" model. Locational attainment views residential location as the outcome of an individual-level attainment process, similar to the way occupational status has been viewed in the status attainment tradition (Alba and Logan 1993, Logan and Alba 1993). In locational attainment models, the outcome is a measure of racial composition or affluence of the neighborhood of residence or destination, most commonly percentage white or median household income. This locational attribute is regressed on individual and household characteristics, most importantly measures of individual or family socioeconomic status.

The locational attainment approach has also been widely applied with panel data and in studies of migration (e.g. South and Crowder 1998; Ellen 2000; Rosenbaum and Friedman 2001; Woldoff and Ovadia 2009; Crowder, Pais, and South 2012; Pais, South, and Crowder 2012). In migration studies, the dependent variable is often defined categorically as neighborhood type (e.g. 0-30% black, 30-60% black, more than 60% black) and modeled as a function of independent characteristics with multinomial or binary logistic or probit regression. The categories usually represent a single dimension of place, but it is also possible to create categories of neighborhoods that cross-classify neighborhoods by race and class level (for instance white poor neighborhoods, black poor neighborhoods, white nonpoor neighborhoods, etc.). This approach, however, becomes unworkable in analysis with more than a small number of neighborhood categories. Likewise, some studies calculate transition matrices that represent rates of mobility across neighborhood types (e.g. Massey, Gross, and Shibuya 1994; Quillian 2002), but these too can only accommodate a fairly small number of neighborhood categories.

Neighborhoods in these approaches are represented by a single characteristic, most often percentage white or median income, or by a few characteristics combined to form a small number of categories. What this omits is the fact that locations are actually bundles of several characteristics that are important for household relocation decisions. Households care simultaneously about race of neighbors, price, neighborhood income level, geographic location, and other characteristics in choosing where to live. Further, multiple characteristics of place are associated with housing market processes that match individuals with destinations, such as neighborhood familiarity and housing discrimination.

That multiple neighborhood characteristics are important to households is well known to anyone who has looked for a place to live and is affirmed by research on housing search. Studies of neighborhood satisfaction and likelihood of buying or renting, for instance, find these to be influenced by many neighborhood attributes simultaneously (Emerson, Yancey, and Chai 2001; Swaroop and Krysan 2011). Households typically must make tradeoffs between desired characteristics because optimal choices on all dimensions are almost never available. Rosenblatt and Deluca (2012), for example, find that low-income households often selected poorer neighborhoods because large dwellings were available for lower prices there.

Current approaches have considered more than one characteristic of place as outcomes—for example, measures of racial composition, income of neighborhood residents, or housing price—but studies have done so examining these features separately and one at a time rather than simultaneously. This makes it impossible to distinguish whether associations of an individual characteristic to the outcome, say percentage white, are actually responding to percentage white or other related attributes, like the neighborhood income level. Furthermore, when multiple attributes govern mobility, and destinations are limited, these attributes may combine in interactive, complex ways. Bruch (forthcoming), for instance, shows that if both neighborhood racial composition and income govern neighborhood choice, decisions grounded in tradeoffs between correlated dimensions can produce effective interactions between these factors that are different than their additive effects.

A Multidimensional Approach to Locational Attainment

What we need is a model similar to locational attainment—allowing for flexible and complex inclusion of individual and household characteristics--but that also allows attainment to occur simultaneously among multiple neighborhood attributes simultaneously. This would allow us to examine empirically how these attributes in combination with individual attributes are linked to the outcome of migration destination.

Such a multidimensional model of locational attainment can be derived using models for discrete choice (McFadden 1973).[5] This follows a longstanding suggestion by McFadden (1978) that these models be applied to residential location, which has recently been recommended as an approach to modeling migration by Bruce and Mare (2012). These approaches are distinguished from the approach of traditional locational attainment models in that it asks which of a discrete (but potentially large) set of possible neighborhoods an individual moves to and models the factors guiding that choice,

[5] A related alternative that might be applied are models from the social network literature applied to dyads, including P* or exponential random graph (ERG) models used for analysis of social networks (Wasserman and Pattison 1996; Snijders et al. 2006).

rather than modeling the numeric value of a selected characteristic of the destination neighborhood (or the probability of a neighborhood within a category). The destination neighborhood is the outcome of sorting between individual characteristics and destination neighborhood characteristics, with multiple individual characteristics (e.g., race, income, spatial location of current residence) and neighborhood characteristics (e.g., race, price, income, spatial location) potentially having importance in determining the neighborhood of destination. The empirical questions then become: Which neighborhood characteristics guide migration? How do the effects of these neighborhood characteristics differ across groups? And how do multiple attributes of neighborhoods combine to generate aggregate patterns of residential mobility?

Models of discrete choice have a significant history of use in the literature on transportation economics and inter-regional migration (e.g., Ben-Akiva and Lerman 1985; Davies, Greenwood, and Li 2001). Only a few of these studies have focused on neighborhood migration or issues related to segregation. Sermons (2000) and Bayer, Ferreira, and MacMillan (2007) apply a discrete choice model (combined with a hedonic price model for Bayer et al.) to estimate household preferences driving neighborhood sorting using cross-sectional data on residential location in San Francisco. Mare and Bruch (2003) and Bruch (forthcoming) use conditional logit analyses of panel data as the bases for agent behavior in agent-based simulation models of neighborhood dynamics. Relatedly, Sampson (2012, chapter 13) applies a network-based approach to migration flows among Chicago neighborhoods using aggregate data on migration flows and linear regression to analyze these flows. None of these analyses, however, employ these models as alternatives to consider questions traditionally considered through locational attainment models.

METHODS

The discrete choice approach asks which of a discrete (but large) set of possible neighborhoods an individual moves to and analyzes the household and neighborhood characteristics associated with the destination. The list of places that a household might move to is the "destination set" or "choice set" of possible destination neighborhoods. In this application, I define the "destination set" as all census tracts in a household's metropolitan area (discussed under "data" below).

In one form, the model is a binary outcome model. The observations represent combinations of each household in the years they move from their origin tract to a different destination tract (as discussed below, only mover household-years are used) and each neighborhood in their destination set; a dummy variable indicates the household's destination tract from the destination set and is the outcome of the model. The independent variables are characteristics of the household, the potential destinations, and interactions of the two. Estimation employs a conditional logit model, which is a simple discrete choice model closely related to a binary logistic regression model with a household fixed effect.

To describe the model more formally, denote households in the data with i; the potential neighborhoods they could move to with j; and time points (discrete) with t. Let p_{ijt} denote the probability that the ith household moves to the jth neighborhood at time t: this is the outcome. Note that p is the probability of moving to a single neighborhood (j) in the household's destination set, not the probability of moving to a type of neighborhood as has commonly been used in multinomial locational attainment models. For each household, summing probabilities over their destination set (summing over j) will sum to one because everyone moves to one of the possible destination neighborhoods.

Denote by U_{ijt} the attractiveness of the *j*th neighborhood to the *i*th household at time *t*. I broadly define "attractiveness" as capturing whatever forces guide the ith household toward the jth destination, including preferences for neighborhood characteristics, but also limits to information about certain types of neighborhoods, discriminatory processes in markets to specific types of destinations, etc. The attractiveness of a neighborhood for a household depends on characteristics of individuals and households. We denote the mth characteristic for the ith individual at time with X_{mit} and the kth neighborhood characteristic with Z_{kjt}. Let η_{jt} denote unobserved features of neighborhood *j* that affect desirability, which are common to all individuals; and ε_{it} denote a household-specific unobserved component. Then the attractiveness of the jth neighborhood to the ith household is:

$$U_{ijt} = F(Z_{kit}, X_{mit}, \eta_{jt}, \varepsilon_{it})$$

If *F* is a linear function, and allowing individual characteristics (X) to change responses to neighborhood characteristics (Z) then the basic model is:

$$U_{ijt} = \sum_k \beta_k Z_{kit} + \sum_m \gamma_m X_{mit} + \sum_k \sum_m \delta_{km} Z_{kit} X_{mit} + \eta_{jt} + \varepsilon_{it} + \alpha_k Z_{jt} \varepsilon_{it} + \theta_k X_{kit} \eta_{jt}$$

Where $\beta_k, \gamma_m, \delta_{km}, \alpha_k, \theta_k$ are parameters. Some of these parameters will be estimated; others will fall out of the final model. Especially important are the coefficients δ_{km}, which gives how the estimated effect of the kth neighborhood characteristic (Z_k) is altered by the mth household characteristic (X_m) in determining movement to a destination.

When individuals choose where to live they implicitly compare neighborhoods in their destination set. Neighborhoods are chosen on the basis of differences in their relative attractiveness, which takes into account both measured and unmeasured neighborhood characteristics. Given data on the characteristics of individuals and neighborhoods, the neighborhoods moved to by individuals and neighborhoods, and an assumed probability distribution of the unobserved characteristics of individuals and neighborhoods, one can estimate the parameters of a choice model. If the errors follow an extreme value distribution, we obtain the discrete choice conditional logit model (see McFadden 1973, Train 2009):

$$p_{ijt}(Z_{kjt}, X_{mit}, C_{(i)}) = \frac{\exp(\sum_k \beta_k Z_{kjt} + \sum_m \sum_k \delta_{km} Z_{kjt} X_{mit} - q_{ijt})}{\sum_{w=1}^{C_{(i)}} \exp(\sum_k \beta_k Z_{kwt} + \sum_m \sum_k \delta_{km} Z_{kwt} X_{mit} - q_{iwt})} \qquad (1)$$

where $C_{(i)}$ denotes the set of neighborhoods available ("destination set") for the ith household, and w is an index used to sum over elements of this set. In this model, β_k is an estimated coefficient indicating the attractiveness of the kth neighborhood characteristic (Z_{kjt}). Positive coefficients indicate positive sorting (migration attraction) toward a neighborhood with that attribute; negative coefficients indicate negative sorting (migration aversion). The coefficient δ_{km} gives how the estimated effect of the kth neighborhood characteristic (Z_k) is altered by the mth household characteristic (X_m). The model shown in (1) allows for all household and neighborhood characteristics to interact, but in practice I will constrain some of the household and neighborhood characteristics to not interact (setting $\delta_{km} = 0$ for some combinations of k and m). The term q_{ijt} represents an offset used to represent sampling from the destination set to reduce computation, as discussed further under "data" below. The coefficients are estimated by maximum likelihood. For further technical details, see Bruch and Mare (2012) and citations therein.

In equation (4), sorting of a household characteristic with a neighborhood characteristic is specified through a multiplicative interaction between a neighborhood characteristic and an individual characteristic ($Z_{kwt}X_{mit}$). For instance, a dummy variable indicating the respondent is black and neighborhood share black might be interacted to allow for difference responses to share black for black and nonblack respondents, capturing the likely positive race sorting (attraction) with share black for blacks and negative race sorting (aversion) with share black for whites. Although not shown in (1), I can also specify sorting through other variables that relate a household and neighborhood characteristic, such as ratios between a household and neighborhood characteristic or the differences between household and neighborhood characteristics. For instance, I use ratios of household income to price to represent affordability, and I use absolute differences between income of households (an X) and income of neighbors (a Z) to represent strength of sorting of household income with neighborhood income.

Note that individual characteristics (the X_{mit}s) do not influence the probability of destinations except as they interact with neighborhood characteristics. The models are equivalent to a logistic fixed effect model; effects of individual characteristics alone are not estimated.

Given that most metro areas have a relatively large number of potential destinations—larger metropolitan areas include hundreds or a few thousand census tracts--the number of combinations of household mover years and potential destinations is large. To analyze the data efficiently, I estimate the model using a sample of neighborhoods from each destination set. I randomly sample 100% of origin and destination tracts and 5% of other tracts as destinations. I then employ weights to represent this sampling, weighting sampled cases 20 to 1 for non-sampled cases. The offset term in equation (1), *q*, is the weight employed to represent this sampling. Standard errors are adjusted for clustering on the basis of household.

The conditional logit model implies a type of proportional substitution across alternatives as the choice set is altered, an assumption often called the independent of irrelevant alternatives (or IIA see Train 2009, chapter 3). The assumption is that the odds ratios between any two destinations will be unchanged when a third alternative is removed from the destination set. (The widely-used multinomial logit models also make this assumption.) While a series of empirical tests of this property in any sample has been proposed, simulations studies have indicated serious problems with these tests (Cheng and Long 2007). As a result, current best advice suggests that outcomes be defined in a way as to be distinct from each other. In experimenting with alternative outcomes definitions, I redefined the neighborhoods to fall into categorical types based on neighborhood covariate categories and estimated the model in this fashion, which resulted in a generally similar pattern of results to those reported here.

Given the problems in testing the IIA assumption, and the likelihood that it likely does not hold perfectly, it is worthwhile to consider the consequences of IIA not holding. Studies suggest that if the coefficients are regarded as population averages (of preferences, or in our application attractiveness), then coefficients from a conditional logit model when IIA does not hold will still tend to be accurate. The main consequence of violating IIA is that predictions made in situations in which the choice set is altered will tend to be inaccurate (Cushing and Cushing 2007). Correspondingly, studies that have compared these estimators in real and simulated situations suggest they lead to broadly identical conclusions with the exception for predictions with modified choice sets (Dahlberg and Matias Eklof 2003, Cushing and Cushing 2007). The lessons of this seems to be that coefficients are likely reliable, and predictions with the original choice sets ("destination sets" in my application) can be used, but these predictions cannot be safely extended to alternative choice sets.

Interpreting the Model Parameters

Applications of discrete choice models in economics are generally based in a random utility model of choice. Individuals select the choice that provides them greatest utility, with “randomness” resulting because of unobserved factors of the alternatives that influence choice. If individuals are familiar with the alternatives, choice is unconstrained (or constraints are accounted for in the model), and the model is correctly specified, then the coefficients may be interpreted as preferences (see Train 2009, chapter 3).[6]

The conditions required to strictly interpret conditional logit parameters as preferences are difficult to defend except under fairly specific conditions, most often found in survey or laboratory choice experiments. In my application, I cannot separate preferences as a source guiding mobility from market discrimination, information constraints (lack of knowledge about some alternatives), or effects of specific housing search methods.

I instead apply a more descriptive interpretation of the coefficients: the parameters represent the importance of the neighborhood factors (Xs) or the combination of individual and neighborhood characteristics (ZXs) in sorting households to destinations. These parameters are in part capturing preferences, but they are also capturing social and contextual influences on housing, such as discrimination in housing markets, knowledge of local areas, and neighborhood perceptions (correct and incorrect).

For numeric interpretation of the coefficients, I employ methods often used for standard logistic regression. The model implies that the odds of an individual selecting one destination, f, versus a second

[6] Some sociological accounts also discuss the model coefficients as revealed preferences under correct conditions. For instance, see Zeng and Xie (2008) or Bruch and Mare (2012).

destination, g, are a function of the characteristics of these two destinations (the characteristics are indexed below by k), individual characteristics (indexed below by m), and the estimated parameters:

$$p_{ift} / p_{igt} = \exp(\sum_k \beta_k (Z_{kft} - Z_{kgt}) + \sum_m \sum_k \delta_{mk} X_{mit} (Z_{kft} - Z_{kgt})) \quad (2)$$

This implies I can insert a value for a variable into the model and apply the exponential operator to give the odds ratio of moving into a neighborhood with that characteristic relative to a base category. In the results sections below, I use this approach to create graphs of how the odds of moving into a neighborhood change as values of the Zs change for a household with fixed X values, relative to the odds for when Z=0.

DATA

I estimate the model using data from the Panel Study of Income Dynamics (PSID), a large nationally representative panel longitudinal study of families that began in 1968. To capture recent mobility, I use data on households in the PSID from the year 1997 to 2009 matched to data on census tracts from the 2000 census.[7] During this time, the PSID conducted interviews every other year, giving us up to seven

[7] Because of high sampling error in tract-level estimates using American Community Survey data, the only source of tract-level information available for recent years, we decided it was preferable to use the more accurate estimates from the 2000 Census to characterize tracts for all years. In addition, at present, 2000 is the most recent year PSID geocodes are available for tracts based on 2000 census boundaries.

years of observations per household. I use households as the units because movements among members of the same household are interdependent.[8]

Like many PSID analyses, I include households with only black and white heads. There are too few Latino households in the PSID during this time period to generate separate high-quality estimates for Latinos, although I examine how whites and blacks respond to neighborhood percentage Hispanic.

The models require an explicit definition of the universe of potential destinations for each household. I use only within-metropolitan area moves, taking the destination set for each individual as all neighborhoods (census tracts) in their metro area. Most household moves by metropolitan residents observed at the end of the two-year window—about 83% in the PSID—are within the same metropolitan area. Many studies using the multinomial logistic and other approaches have employed this same simplifying limitation to within-metropolitan moves (e.g., South and Crowder 1998).

I study destinations of moves, limiting the analysis to person-years in which people changed census tracts. It is possible to build a model that incorporates mover and destinations and stayers in one model (see Bruch and Mare 2012), but the main advantage of this approach is how destinations are represented. I found that the mover parameter estimates from a model with movers and stayers together were similar to those from the mover-only model presented here.

Variables

I employ a simple set of the individual characteristics (Xs): race, family income in the origin year (in constant 2000 dollars), and housing tenure status (own/rent). For family income, I use a moving average

[8] I define households by household composition at the destination year. In cases where households split from a common origin household, such as a child moving out of a family home, the two households in the destination year are treated as separate households with the same origin characteristics.

of the five preceding years of income reports to the survey year (using as many of the previous five years as observed, which is at most three years because of the every-other-year interview schedule), in thousands of year 2000 dollars, and centered at the overall mean of income. Sampson and Sharkey (2008) report that neighborhood mobility trajectories are overwhelmingly guided by socioeconomic status and race, suggesting the most important individual characteristics are in the models.

I characterize tracts along four main dimensions of investigation: race and ethnic composition, income level, price, and location. These dimensions and sorting of these dimensions with individual characteristics are represented in the model through several variables:

1. Race and Ethnic composition: Race and ethnic composition are represented with percentage of the tract black and the percentage of the tract Hispanic. I enter these as continuous predictors with a third-order polynomial specification. The model includes percentage black, percentage black to the second power, and percentage black to the third power. Percentage Hispanic is represented similarly. The models are estimated consistently separately by race.
2. Neighborhood income level: Neighborhood income is represented by tract median income. A second variable captures income sorting through the absolute difference between household median income of a moving household and tract median income of destinations. Squared versions of both variables are also included to allow non-linearity.[9]
3. Housing price: I use a measure of median housing cost as a percentage of annual income for each household's potential destinations to represent housing price. This is entered as four dummy variables representing quintiles of annual housing costs as a percentage of annual income: Below 13%; 13% to 20%; 20% to 31%; 31% to 52%, and above 52%. These indicate the percentage of a household's income it would take to pay the median housing cost in the

[9] Cubed neighborhood income and housing price variables were consistently nonsignificant for both blacks and whites.

destination tract. Housing costs used to create this variable depend on the renter or owner status at destination of the household: tract housing cost is defined by median rental payment multiplied by 12 for renters and median monthly mortgage payment (for households with a mortgage) multiplied by 12 for owners, with renter or owner status defined by the household's market status at the destination time.

4. Locational sorting: I examine location sorting through two sets of the variables. One variable is distance, which is the distance of the centroid of each potential destination tract from the household's origin tract. A second group of variables are differences between origin tract characteristics and potential destination tract characteristics. I create measures of the absolute difference between origin tract and potential destination tracts in percent black, percent Hispanic, median income, and price (percentage of the household's income required to pay for a dwelling at the median price of the destination tract).

Descriptive statistics for these variables are shown in table 1a for white households and 1b for black households. Averages and standard deviations are shown for each variable at the level of each household by potential destination year (after sampling) and for each household year at their origin tract location. Variables representing differences of tract-of-origin and tract-of-destination are necessarily zero for the results tabulated at origin, shown in the right column.

RESULTS

Why do whites move to mostly white destinations, and blacks to mostly black destinations? To investigate the factors driving segregated mobility, I first estimate a model to capture the total extent of individual and neighborhood race sorting without other controls. I then add other neighborhood characteristics (based on income, price, distance, and origin tract characteristics) and their interactions (or differences) with individual characteristics to the model to examine how these factors weaken (or fail to weaken) race sorting.

The models are estimated separately for whites and for blacks. Many of the model parameters are not interpretable in raw form because of the use of second and third order polynomial terms to allow for non-linear forms for many variables, and because of the logged form of the ratio of probabilities that is the outcome. To understand the results, I graph the odds ratios (applying the relation in equation [2]) based on the model coefficients.

Determinants of White Mobility

Sorting between household and neighborhood race for whites is estimated by including tract percentage black, and squared and cubed forms of tract percentage black, to predict destinations. The squared and cubed terms allow for nonlinearity. The coefficients are shown in the first three rows of table 2A. The share black coefficients are strongly significant evaluated jointly (shown as a row below the third order term in table 2A), although not each of the three polynomial terms is individually significant. The three polynomial terms are retained because they are significant in the model for black movers, and I wish to maintain a uniform specification across racial groups.

Interpretation is provided by graphs. Figure 1 shows the race-sorting effects for whites, graphing the multiplicative change in the odds (the odds ratio) of moving into a white tract as its share black increases. An effect of one is no change on the odds (multiplication by 1), while effects greater than one indicate greater odds of moving to a destination than a zero percentage black destination, and an effect below one indicate odds are below a zero percentage black destination.[10]

The first model gauges the total extent of race-sorting by including only the percentage black and percentage Hispanic variables and a tract population control. The ratio of white odds of moving into a tract as percentage black changes in this model are shown as a solid line (first line in the legend, corresponding to model m1 in table 2). The downward slope indicates that as share black increases, the odds a white household enters the tract decreases. The odds are about half as great that a white family will move to a 50% black tract as an otherwise similar census tract that has no black residents.[11]

The second model (m3 in Table 2A) adds median tract income, the difference between household income with median tract income, and affordability measures (capturing ratios of household income to tract median housing cost). The second line in the legend of figure 1 shows the extent of race sorting after these controls. Race sorting effects become weaker, especially in low percentage black destinations, but only slightly. For whites, little of the migration tendency to avoid black neighborhoods reflects household income sorting or income-price sorting.

The third model adds linear distance from origin to each destination (m7). Distance causes some change in shape when it is accounted for, producing a more direct drop in probability of destination with increasing percentage black rather than a small increase before a dive. The fourth model adds characteristics of the origin tract as predictors, which does little to further alter percentage black effects.

[10] There are some dangers in comparing odds ratios across logistic regression results for different groups and across models arising from how unmeasured heterogeneity affects coefficients in these models (see Allison 1999; Norton 2012). In the case of conditional logit, Norton (2012) concludes that odds ratios remain one of the best ways to understand the model. In addition, the conclusions are verified by probability simulations from the model discussed in the last part of the results.

[11] This is the odds of moving into a single 50% black tract relative to a single 0% black tract. Because there are many fewer 50% black tracts than 0% black tracts in the destination sets of most households, the probability that a move will end in any 50% black tract relative to any 0% black tract is significantly lower.

The results in Figure 1 suggest that little migration of white households toward white destinations can be accounted for by tract household income, housing price, or tract geographic distance. In debates about the effects of neighborhood class and neighborhood race on white avoidance of black neighbors, these results are more consistent with the "pure-race" interpretation, because incorporating neighborhood class and geographic distance weakens white avoidance only slightly.

In Figure 2, the characteristic examined is tract percentage Hispanic. The figure shows that whites are quite unlikely to move into tracts with high share Hispanic; in fact, the avoidance of percentage Hispanic is nearly as strong as percentage black.[12] The first model includes only racial composition and population, and the subsequent three models add neighborhood median income and housing price, distance from origin, and origin tract characteristics. These controls make little difference in the extent of white avoidance of Hispanic neighbors.

Is the unimportance of neighborhood class in explaining white avoidance of black and Hispanic neighbors because neighborhood income is not important? Figure 3 graphs the odds of moving to a destination as a function of the difference between household income and the median income of the destination neighborhood. Sorting on income is quite important—odds of moving in decline sharply with difference between household and tract income--and little of its effect is accounted for by other forms of sorting. Sorting of higher income neighborhoods with more expensive neighborhoods (not graphed), by contrast, is in general less important than sorting on neighborhood income. [13] But despite its importance, household income sorting accounts for little race sorting.

Figure 4 presents the effects of income level on destinations for whites. In addition to income sorting, the models allow income effects on destination; because the models are estimated by race, this

[12] The PSID sample from 1968 includes few "white Hispanics" as a result of how it was drawn, which may result in low rates of white movement into Hispanic tracts relative to samples with more white Hispanics.
[13] This might be because median income of residents better captures housing price constraints than monthly housing cost reports from the census.

effectively is race sorting with income level of destination. Figure 4 shows that, in the model with no controls, white families are more likely to enter high median income tracts, holding constant other model parameters (including income sorting). Yet, after introducing controls for race sorting (m3), this effect disappears: white families then seem to be equally likely to move into neighborhoods, regardless of neighborhood income. Adding controls for other forms of sorting does not further alter this result. White households are likely to move to higher-income tracts (controlling their own income) because they move to white tracts, which are on average higher in income.

Distance sorting is graphed in Figure 5. The graphs show a very sharp drop in odds of moving to a neighborhood with distance from the origin tract: a five mile distance produces an 80% decline in the odds of moving to a destination. From table 2a, the Bayesian Information Criterion (a fit statistic that penalizes for model complexity, see Raftery 1995) shows a major improvement in fit when distance is added. This is a far greater improvement than any of other model variables (except for tract population): distance is the best predictor of destination in the model.

Determinants of Black Mobility

Estimates of the models are shown for black households in table 2B. The specifications parallel the white models.

The neighborhood percentage black coefficients for black movers are displayed in Figure 6. The first model captures total neighborhood race effects; tract population and percentage Hispanic are the only other controls. The odds of moving into a tract for a black household increase greatly as the percentage black increases. There is strong sorting of black households to high percentage black tracts.

This sorting is increased in apparent magnitude by the fact that predominately black tracts are a small share of most metropolitan areas, thus increasing the apparent odds ratios.

In contrast to whites, when sorting between household income and neighborhood income and housing price are added, the odds of moving toward a black tract are reduced (second line in legend, m6). This indicates that part of the reason that black households have high rates of mobility to black neighborhoods are income sorting and lower average housing prices in black neighborhoods.

The third line of Figure 6 shows sorting with tract percentage black after accounting for distance. After this control, the percentage black line is yet flatter, indicating that part of the reason black households tend to move to high percentage black tracts is because these are the tracts that are on average geographically closest. Adding tract of origin characteristics accounts for little additional race sorting.

For black households, a significant part of movement toward black destinations can be accounted for by sorting household with neighborhood income, affordability, and (inversely) with distance. Yet a significant degree of sorting of black households with black destinations remains after these forms of sorting are accounted for. The residual could reflect discrimination or steering in housing markets, or preferences for living with black neighbors, or lack of knowledge about housing or neighborhoods away from black neighborhoods.

The estimated effects of neighborhood percentage Hispanic on odds of black mobility to a destination tract are shown in Figure 7. In the first model without other forms of sorting, black households seem attracted to moderately Hispanic tracts: odds of moving in are higher for moderately Hispanic destinations than for zero percent Hispanic destinations. When the model includes neighborhood income level, affordability, and interactions with household income, however, this apparent attraction disappears, indicating that black households tend to move to moderately Hispanic destinations in part because these locations are less expensive and have neighbors with income similar to their own. When I further account for distance, the odds of moving to Hispanic neighborhoods further decreases, and net of these factors, there is evidence of weak avoidance of high percentage Hispanic destinations.

Income sorting for black households is graphed in Figure 8. Income sorting is strong, in fact somewhat stronger than it is for white households, and similar to whites, it is not much altered in strength by other forms of sorting. Similar to white households, affordability (in table 2b, not graphed) is a significantly weaker predictor of destinations than household income sorting.

The effects of neighborhood income level on destinations for black households, holding constant income sorting, are shown in Figure 9. This shows an effect of race on income level of destination, holding constant the income level of the moving household. Without race sorting accounted for, in the first model shown in the figure, black mobility is systematically slanted toward lower income neighborhoods. When race sorting is included, the tendency to move into lower income neighborhoods disappears. Adding other forms of sorting makes little additional difference. Black households move to less affluent tracts net of their own income because they tend to move to black destinations, and on average black tracts are poorer than white tracts.

Finally, Figure 10 shows that distance effects are powerful for black households as they were for white households. Similar to white households, distance is the best single predictor of destination neighborhood. Tract of origin characteristics are statistically significant in predicting destinations, but are relatively weak.

Overall, black households are much more likely to move to highly black neighborhoods, but a substantial part of this reflects income sorting, housing affordability, and distance. Blacks have a weak aversion for share Hispanic after these other factors are accounted for. Income and distance sorting are important and similar to whites.

Segregation in Migration Destinations

To understand the implications of these factors for racial segregation in migration destinations, I take the fullest model (m8) and generate destination probabilities for all PSID households. These probabilities are summed across households and destination tracts, giving us the number of households expected to move to each tract by the model (almost always a fractional number). For all metropolitan areas with at least one black and white PSID household, I then calculate the index of dissimilarity between the black and white expected counts of households by destinations.[14] Finally, I compute an average of these MSA-level segregation indexes weighted to represent the number of white and black PSID cases in the metropolitan area. The results of this procedure are shown in the top line of Table 3. The MSA-average dissimilarity of expected white/black destinations from the fullest model with all variables at their origin values is .65.

I then impose counterfactual conditions in the predictions that include eliminating (zeroing out) the role of several bases of sorting, effectively imposing indifference to that characteristic. I compute expected number of households moving to each destination and, from these expected counts, indexes of segregation between the expected migration destinations of white and black households under each counterfactual. By considering changes in the index of dissimilarity relative to baseline, I am able to examine the effects of imposing indifference to each characteristic on segregation in migration destinations. The results are shown in the top panel of Table 3.

[14] I use the full data on neighborhoods to make these predictions rather than the sampled (5% of non-destinations) that were used to create the estimates. This is expected destinations of mobility one year from the baseline.

As Table 3 shows, the biggest drop in black-white migration segregation comes when I take out the direct race sorting effect. The level of dissimilarity in migration destinations drops to .42. The other major drop comes from zeroing out the influence of distance, which drops dissimilarity to .53. Other factors have only minor effects on migration segregation, dropping the level of segregation by .02 or less.

Given the strong effects of neighborhood racial composition for white and black mobility, why is there not a greater decline in segregation in migration when direct race effects are eliminated from the model? The reason is because the different bases of sorting overlap. White census tracts tend to be more affluent, more expensive, and geographically close to white areas; black tracts tend to be less affluent, less expensive, and geographically close to black areas. These characteristics imply disproportionate mobility to racially similar tracts, even in the absence of direct neighborhood race effects.

To examine this further, in Table 4, indexes of segregation are calculated for counterfactuals incorporating multiple changes to migration simultaneously: indifference to characteristics in Table 4 is cumulative rather than one-at-a-time. The results show much larger reductions in segregation in mobility when multiple criteria of indifference are incorporated together. Furthermore, declines in segregation from the imposition of indifference to a condition have greater effects when other bases of sorting contributing to segregation have already been eliminated. The estimated "effects" on segregation are greater relative to the effect in Table 3 the further a condition is down the list.[15] When a single basis of sorting is eliminated while others continue to operate, the others tend to partially reproduce segregated migration patterns. The system that produces racially segregated migration is partially over-determined by multiple form of sorting.

[15] Varying the order in which indifference conditions are imposed (not shown) verifies this.

DISCUSSION

Race, Class, and Location in the Production of Segregated Migration

What accounts for persistent segregation in migration? I find that race sorting is most important, location sorting second most important, and class sorting least important. Yet I also find these dimensions combine complexly so that the system functions as more than just a sum of these effects.

The contrast of racial factors and class factors has animated recent theoretical discussions of the cause of segregated migration in sociology. The results here indicate that direct race effects trump class effects in the production of racially segregated migration. White avoidance of black neighborhoods is hardly weakened when we account for sorting on income, housing price, geographic distance, and origin tract characteristics. Black mobility toward black destinations is partially driven by income sorting and geographic distance, but overall little dissimilarity in white and black destinations of mobility can be accounted for by income or price factors. While the black mobility results are partly consistent with Cutler, Glaeser, and Vigdor's (1997) price-based explanation of segregation, the dissimilarity calculations under the counterfactual of no price effects suggest this mechanism has little influence on segregation overall.

The stability of white avoidance despite accounting for sorting on other bases suggests directly racial factors drive white avoidance of black neighborhoods, such as prejudices, stereotypes, or racial discrimination in the housing market. White households are quite unlikely to move to a majority black tract, even if this tract has median income equal to their own income, is affordable, and is geographically close to where they live. These results are more consistent with the "pure-race" hypothesis than the "racial-proxy" hypothesis regarding white mobility, because white response to neighborhood racial composition cannot be accounted for by correlated neighborhood income conditions.

The models also demonstrate that racial segregation combined with race-correlated neighborhood income differences are responsible for consistent, and large, racial gaps in the income level of neighborhoods of destinations. Past studies have shown that black households have more difficulty translating individual income to neighborhood income than white households (Alba, Logan, and Stults 2000b). The process that could produce this outcome was unclear, and could reflect difficulties in affording or obtaining financing, difference in wealth of black and white households, or differences in the typical income levels of black neighborhoods relative to white neighborhoods as destinations. I find that this reflects the latter: neighborhood race is the strongest factor guiding households to destinations, and racial gaps in income of destinations occur as a product of neighborhood race sorting because on black destinations tend to be less affluent than white destinations. This is consistent with Massey and Denton's (1993, chapter 5) model of racial segregation and poverty concentration; we find no residual to be explained by factors like wealth differences or racial credit market constraints in separately playing a large role in the mobility of black households to poorer tracts. Otherwise, we find little racial difference in the sorting process of income of household and income and destination.

Location matters (a lot): distance from origin is the best overall predictor of tract of destination. This might be expected from the migration literature. Less expected is the significant role of this in contributing to segregation. Because black and white tracts tend to be close to each other, distance plays a significant role in upholding segregation among neighborhoods. Segregation at multiple levels of geography tends to reinforce each other in the production of segregation at other levels. The fact that black residential patterns are "hypersegregated"(Massey and Denton 1993; Wilkes and Iceland 2004) —

or are segregated on multiple scales and geographic dimensions—is one factor that makes segregation more resilient, because segregation at higher scales, combined with distance influence on migration, helps to produce segregated migration flows among neighborhoods.

When the system of these forms of sorting are considered together, they over-determine the outcome of segregation in migration. Race, class, and geographic factors are somewhat redundant in producing segregated mobility dynamics: white neighborhoods tend to be affluent, expensive, and geographically proximate to other white neighborhoods; black neighborhoods tend to be less affluent, inexpensive, and geographically proximate to other black neighborhoods. When direct race sorting is eliminated, segregation in mobility diminishes, but less than might be expected because class and location factors still result in a largely segregated pattern of mobility dynamics. To undercut racially segregated patterns of mobility rapidly, several of these conditions need to be changed simultaneously. The overlap in these factors helps to illustrate how multiple dimensions of factors guiding mobility produce a durable structure of segregation that is resistant to rapid change.

Discrete Choice Models as a New Approach for Locational Attainment

A discrete choice approach provides a method that can complement, extend, and in some cases replace the longstanding use of traditional locational attainment models of migration. The empirical questions this model can then address are the importance of various dimensions of sorting in driving migration and the extent to which total sorting on some dimension, such as race, actually reflects sorting on other neighborhood and individual attributes.

The analysis here only begins to exploit the potential of discrete choice models applied to this problem. We have focused on only three broad dimensions (albeit important ones in past theory): race, class, and location. But a discrete-choice approach is well suited to incorporating a richer set of place characteristics as factors guiding mobility and interacting with household race and class, such as school quality, area crime rates, proximity to workplaces, etc., to determine how these interact with individual characteristics in affecting mobility decisions. The main challenges in extending this approach to more dimensions are the availability of data on the characteristics and the complexity inherent in a model with many factors and a large number of interacting variables.

The approach of traditional locational attainment models using regression of single characteristics, or techniques that define neighborhoods in a few categories, will continue to be useful for some applications. In particular, these models will likely remain useful when it is desired to know how individual characteristics relate to overall racial or economic composition of neighborhoods. The discrete choice approach, however, provides greater realism about migration processes and an ability to address many questions inaccessible from the traditional locational attainment approach. In applications seeking to understand the many social factors responsible for migration that generates segregation, multi-dimensional approaches will often be superior. The cost is a more complex model, with the attendant difficulties of managing that complexity, but this largely reflects the actual complexity of the migration process.

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Table 1A: Descriptive Statistics, PSID White Households, Mover-Years 1997-2009

Variable	Mover Household Years by Potential Destinations: Mean	Std. Dev.	Mover Household Years at Origin: Mean	Std. Dev.
Racial Composition				
Tract Percentage Black	17.44	27.56	8.76	14.75
Tract Percentage Hispanic	14.49	20.74	8.80	13.44
Income Matching				
Absolute Difference, Income and Tract Median Income	40.68	48.87	31.13	41.96
Tract Median Income	49.50	23.14	48.71	19.10
Housing Cost Quintile (Dummies)				
1st: Income/(Median Cost) Below .13	0.31		0.25	
2nd: Income/(Median Cost) in .13 to .20	0.24		0.28	
3rd: Income/(Median Cost) in .20 to .31	0.19		0.22	
4th: Income/(Median Cost) in .31 to .52	0.16		0.17	
5th: Income/(Median Cost) above .52	0.10		0.09	
Distance in miles from origin	20.13	15.27	0.00	0.00
Origin Tract Characteristics				
Absolute difference in % Black, origin-destination	17.34	25.69	0.00	0.00
Absolute difference in % Hispanic, origin-destination	12.13	17.53	0.00	0.00
Absolute difference in median income, origin-destination	21.90	20.61	0.00	0.00
Absolute difference in cost ratio, origin-destination	0.09	0.26	0.00	0.00
Log of population of destination tract	8.24	0.64	8.47	0.47

N = 2836 Households, 4437 Household Years, 114552 Household Years by Destinations

Table 1B: Descriptive Statistics, PSID Black Households, Mover-Years 1997-2009

Variable	Mover Household Years by Potential Destinations: Mean	Mover Household Years by Potential Destinations: Std. Dev.	Mover Household Years at Origin: Mean	Mover Household Years at Origin: Std. Dev.
Racial Composition				
Tract Percentage Black	26.37	33.27	58.71	33.06
Tract Percentage Hispanic	12.65	20.54	8.86	15.32
Income Matching				
Absolute Difference, Income and Tract Median Income	28.57	23.64	17.27	15.13
Tract Median Income	48.75	24.06	33.11	13.40
Housing Cost Quintile (Dummies)				
1st: Income/(Median Cost) Below .13	0.12	0.32	0.14	0.34
2nd: Income/(Median Cost) in .13 to .20	0.17	0.38	0.22	0.42
3rd: Income/(Median Cost) in .20 to .31	0.20	0.40	0.23	0.42
4th: Income/(Median Cost) in .31 to .52	0.22	0.42	0.21	0.41
5th: Income/(Median Cost) above .52	0.28	0.45	0.20	0.40
Distance in miles from origin	18.43	14.48	0.00	0.00
Origin Tract Characteristics				
Absolute difference in % Black, origin-destination	45.78	33.88	0.00	0.00
Absolute difference in % Hispanic, origin-destination	11.23	16.77	0.00	0.00
Absolute difference in median income, origin-destination	22.70	21.30	0.00	0.00
Absolute difference in cost ratio, origin-destination	0.18	0.47	0.00	0.00
Log of population of destination tract	8.25	0.65	8.35	0.54

N = 2375 Households, 4506 Household Years, 149352 Households Years by Destinations

Table 2A: Conditional Logit Models of Destinations on Tract and Household Characteristics, Whites

Variable	m1		m2		m3		m6		m7		m8	
Tract Percentage Black	0.0088				0.0077		0.0074		-0.0161	*	-0.0145	
	(0.0077)				(0.0078)		(0.0078)		(0.0081)		(0.0081)	
Percentage Black Squared	-0.0004				-0.0004		-0.0004		0.0003		0.0004	
	(0.0003)				(0.0003)		(0.0003)		(0.0003)		(0.0003)	
Percentage Black Cubed (coef. x 1000)	0.0009				0.0006		0.0006		-0.0043		-0.0048	*
	(0.0021)				(0.0021)		(0.0021)		(0.0022)		(0.0022)	
Joint significance, Tract % Black	***				***		***		***		***	
Tract Percentage Hispanic	0.0181				0.0111		0.0108		-0.0149		-0.0137	
	(0.0092)				(0.0098)		(0.0098)		(0.0103)		(0.0103)	
Percentage Hispanic Squared	-0.0012	***			-0.0010	**	-0.0010	**	-0.0003		-0.0002	
	(0.0003)				(0.0003)		(0.0003)		(0.0003)		(0.0003)	
Percentage Hispanic Cubed (coef. X 1000)	0.0086	***			0.0074	**	0.0073	**	0.0020		0.0014	
	(0.0024)				(0.0024)		(0.0024)		(0.0026)		(0.0027)	
Joint significance, Tract % Hispanic	***				***		***		***		***	
Tract Population (Logged)	0.9682	***	0.9766	***	0.9696	***	0.9667	***	1.0603	***	1.0494	***
	(0.0479)		(0.0479)		(0.0487)		(0.0487)		(0.0501)		(0.0503)	
Absolute Difference, Income			-0.0176	***	-0.0176	***	-0.0166	***	-0.0151	***	-0.0150	***
and Tract Median Income			(0.0021)		(0.0023)		(0.0026)		(0.0022)		(0.0021)	
Absolute Difference, Income			0.0000		0.0000		0.0000		0.0000		0.0000	
and Tract Median Income Squared			(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Tract Median Household Income			0.0283	***	0.0031		0.0011		0.0090		0.0116	*
			(0.0046)		(0.0044)		(0.0045)		(0.0048)		(0.0051)	
Tract Median Household Income Squared			-0.0002	***	-0.0001		0.0000		-0.0001	**	-0.0001	**
			(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	

Models: m1, m2, m3, m6, m7, m8

(table 2a continues)

Table 2A Continued:

Variable	m1	m2	m3	m6		m7		m8	
Quintile of Housing Cost, Dummy Variables									
1st: Income/(Median Cost) Below .13				-0.2690	*	-0.0104		0.0005	
				(0.1058)		(0.1123)		(0.1128)	
2nd: Income/(Median Cost) in .13 to .20				-0.1809	**	-0.0921		-0.0859	
				(0.0697)		(0.0726)		(0.0726)	
3rd: Income/(Median Cost) in .20 to .31				(reference)		(reference)		(reference)	
4th: Income/(Median Cost) in .31 to .52				0.0777		-0.0414		-0.0491	
				(0.0813)		(0.0874)		(0.0877)	
5th: Income/(Med. Cost) above .52				-0.0757		-0.2765		-0.2571	
				(0.1429)		(0.1511)		(0.1519)	
Distance in Miles from Centroid of Origin Tract						-0.2348	***	-0.2281	***
						(0.0074)		(0.0079)	
Distance Squared						0.0031	***	0.0030	***
						(0.0003)		(0.0003)	
Distance Cubed (Coef. X 1000)						-0.0137	***	-0.0125	***
						(0.0020)		(0.0020)	
Absolute Difference in Percentage Black, Origin-Destination								-0.0120	***
								(0.0026)	
Absolute Difference in Percentage Hispanic, Origin-Destination								-0.0102	***
								(0.0030)	
Absolute Difference in Median Income, Origin-Destination								0.0061	**
								(0.0020)	
Absolute Difference in Cost Ratio, Origin-Destination								-0.3564	
								(0.2018)	
N	114552	114552	114552	114552		114552		114552	
Bayesian Information Criterion (BIC)	47098	47100	46800	46833		41124		41103	

Notes: * = p < .05; ** = p< .01; *** = p< .001, two-tailed tests. Standard errors adjusted for clustering by household in parentheses.

Table 2B: Conditional Logit Models of Destinations on Tract and Household Characteristics, Blacks

	Models											
Variable	m1		m2		m3		m6		m7		m8	
Tract Percentage Black	0.1532	***			0.1379	***	0.1376	***	0.1073	***	0.1075	***
	(0.0067)				(0.0069)		(0.0069)		(0.0071)		(0.0072)	
Percentage Black Squared	-0.0023	***			-0.0020	***	-0.0020	***	-0.0016	***	-0.0016	***
	(0.0002)				(0.0002)		(0.0002)		(0.0002)		(0.0002)	
Percentage Black Cubed (coef. X 1000)	0.0116	***			0.0102	***	0.0102	***	0.0080	***	0.0080	***
	(0.0010)				(0.0010)		(0.0010)		(0.0010)		(0.0010)	
Joint significance, Tract % Black	***				***		***		***		***	
Tract Percentage Hispanic	0.0102				-0.0062		-0.0071		-0.0084		-0.0053	
	(0.0094)				(0.0095)		(0.0095)		(0.0099)		(0.0100)	
Percentage Hispanic Squared	0.0000				0.0003		0.0003		0.0002		0.0001	
	(0.0003)				(0.0003)		(0.0003)		(0.0003)		(0.0003)	
Percentage Hispanic Cubed (coef. X 1000)	-0.0019				-0.0037		-0.0039		-0.0031		-0.0026	
	(0.0025)				(0.0025)		(0.0025)		(0.0026)		(0.0026)	
Joint significance, Tract % Hispanic	***				***		***		***		***	
Tract Population (Logged)	0.9825	***	0.9786	***	1.0667	***	1.0651	***	1.1931	***	1.1895	***
	(0.0443)		(0.0354)		(0.0472)		(0.0472)		(0.0487)		(0.0494)	
Absolute Difference, Income and Tract Median Income			-0.0223	***	-0.0224	***	-0.0206	***	-0.0212	***	-0.0212	***
			(0.0030)		(0.0035)		(0.0036)		(0.0039)		(0.0039)	
Difference Income and Tract Median Income Squared			-0.0001	**	-0.0001	*	-0.0001	*	-0.0001		-0.0001	
			(0.0000)		(0.0001)		(0.0001)		(0.0001)		(0.0001)	
Tract Median Household Income			-0.0656	***	-0.0051		-0.0089		0.0006		-0.0001	
			(0.0042)		(0.0052)		(0.0053)		(0.0053)		(0.0054)	
Tract Median Household Income Squared			0.0002	***	0.0000		0.0000		-0.0001		0.0000	
			(0.0000)		(0.0001)		(0.0001)		(0.0001)		(0.0001)	

(table 2b continues)

Table 2B Continued:

Variable	m1		m2		m3		m6		m7		m8	
Quintile of Housing Cost, Dummy Variables												
1st (Income/Median Cost Below 13%)							-0.2770	*	0.0089		0.0149	
							(0.1185)		(0.1220)		(0.1221)	
2nd (Income/Median Cost 13% to 20%)							-0.1279		-0.0334		-0.0310	
							(0.0765)		(0.0801)		(0.0801)	
3rd (Income/Median Cost 20% to 31%)							(reference)		(reference)		(reference)	
4th (Income/Median Cost 31% to 52%)							0.1800	*	0.1231		0.1206	
							(0.0805)		(0.0846)		(0.0844)	
5th (Income/Median Cost above 52%)							0.0458		-0.0169		-0.0183	
							(0.1374)		(0.1404)		(0.1403)	
Distance in Miles from Centroid of Origin Tract									-0.2458	***	-0.2435	***
									(0.0097)		(0.0104)	
Distance Squared									0.0030	***	0.0029	***
									(0.0004)		(0.0004)	
Distance Cubed (coef. X 1000)									-0.0113	**	-0.0106	**
									(0.0035)		(0.0033)	
Absolute Difference in Percentage Black, Origin-Destination											0.0013	
											(0.0010)	
Absolute Difference in Percentage Hispanic, Origin-Destination											-0.0061	*
											(0.0027)	
Absolute Difference in Median Income, Origin-Destination											-0.0012	
											(0.0027)	
Absolute Difference in Cost Ratio, Origin-Destination											-0.1162	
											(0.0954)	
N	149352		149352		149352		149352		149352		149352	
Bayesian Information Criterion (BIC)	48055.86		50354.4		47590.46		47619.7		42761.5		42798.8	

Notes: * = p < .05; ** = p< .01; *** = p< .001, two-tailed tests. Standard errors adjusted for clustering by household in parentheses.

Table 3: Black-White Dissimilarity in Destinations, Predictions with Single Counterfactuals

Model Counterfactual	Average MSA Black-White Dissimilarity (D) in Destinations
Baseline Model (no altered variables)	0.65
Neighborhood % Black Indifference	0.42
Neighborhood % Hispanic Indifference	0.63
No Income-of-Neighbor Matching	0.63
No Price Differences	0.65
No Distance Effects	0.53
No Race-of-Tract-of-Origin Effects	0.63

Notes: MSA average weighted by $1/(n_w+n_b)$, where n_w and n_b are the number of white and black PSID mover household years in each MSA. For each counterfactual, other variables are set at original values.

Table 4: Black-White Dissimilarity in Destinations, Predictions with Cumulative Counterfactuals

Model Counterfactual (Cumulative)	Average MSA Black-White Dissimilarity (D) in Destinations
Baseline Model (no altered variables)	0.65
Neighborhood % Black Indifference	0.42
Neighborhood % Hispanic Indifference	0.40
No Income-of-Neighbor Matching	0.36
No Price Differences	0.36
No Distance Effects	0.08
No Race-of-Tract-of-Origin Effects	0.04

Note: MSA average weighted by $1/(n_w+n_b)$, where n_w and n_b are the number of white and black PSID household mover years in each MSA. Counterfactuals above stated counterfactual are retained, other variables at original values.

Figure 1: White Destination Odds and Tract Percentage Black

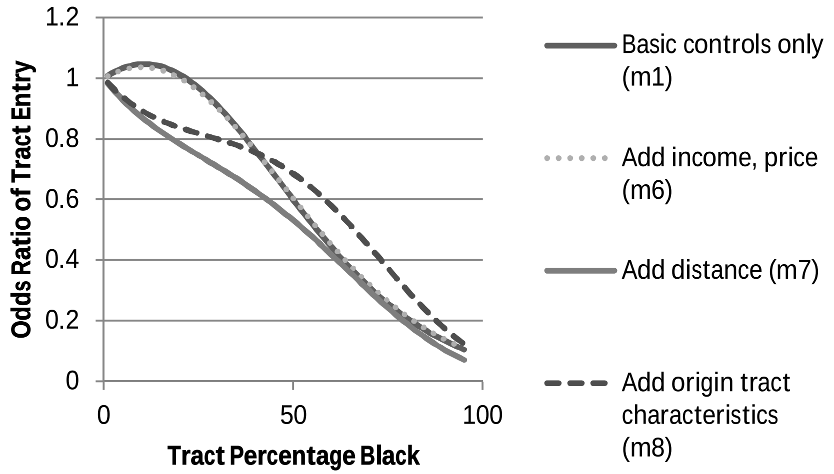

Figure 2: White Destination Odds and Tract Percentage Hispanic

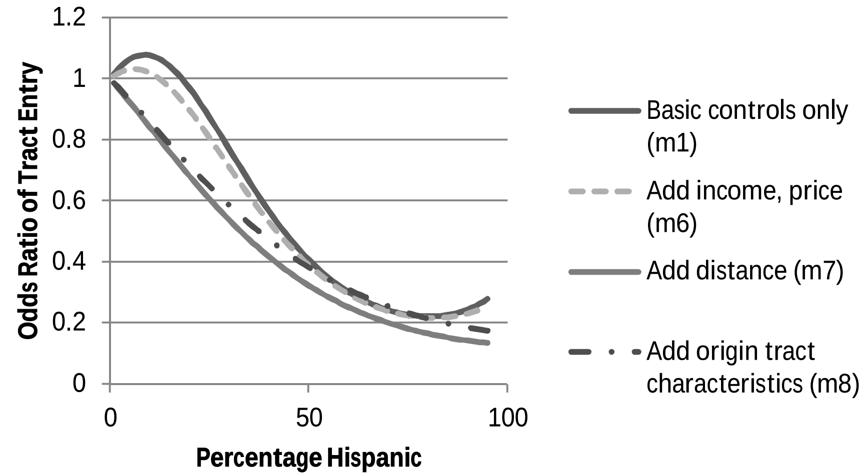

Figure 3: White Income Matching

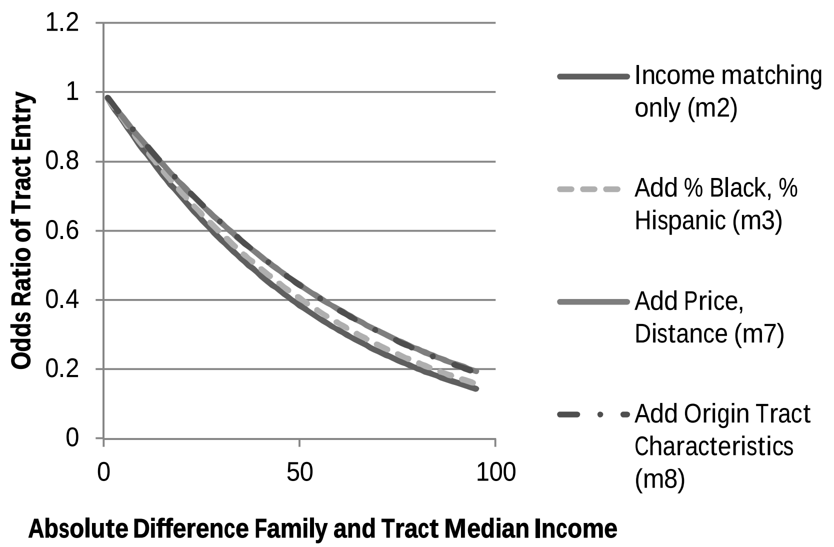

Figure 4: White Destination Odds and Tract Median Income

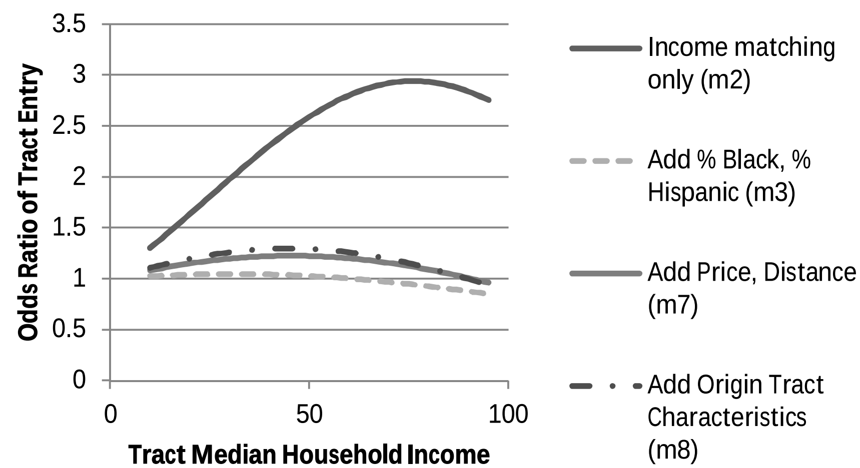

Figure 5: White Odds of Tract Entry and Distance

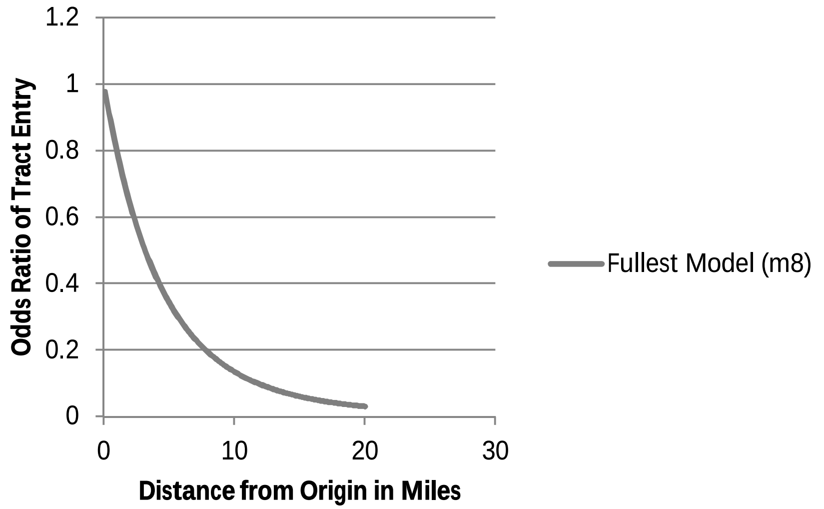

Figure 6: Black Destination Odds and Tract Percentage Black

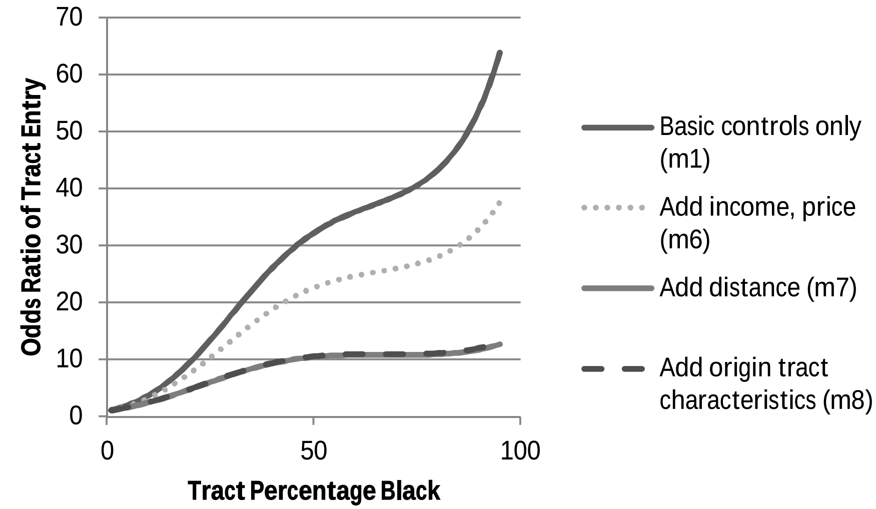

Figure 7: Black Destination Odds and Tract Percentage Hispanic

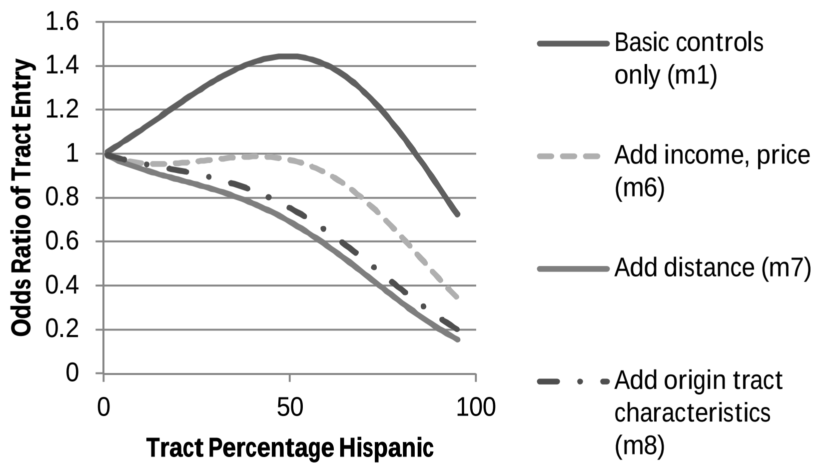

Figure 8: Black Income Matching

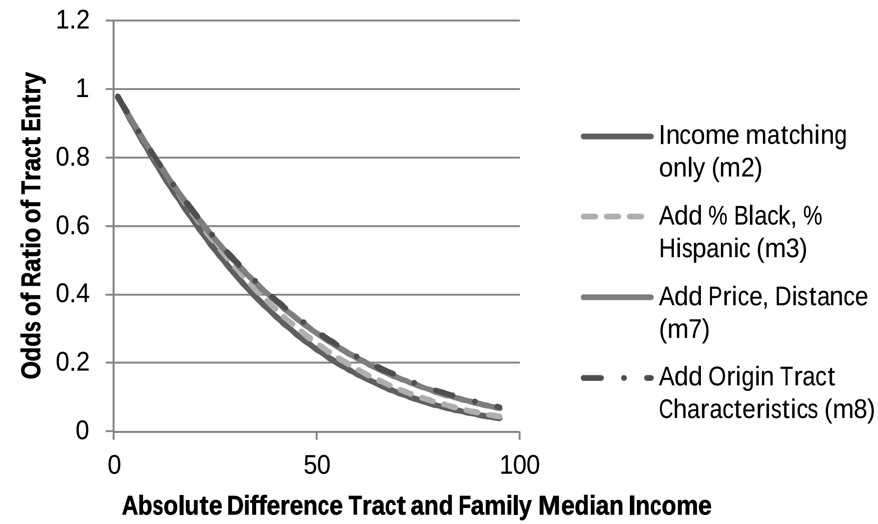

Figure 9: Black Destination Odds and Tract Median Income

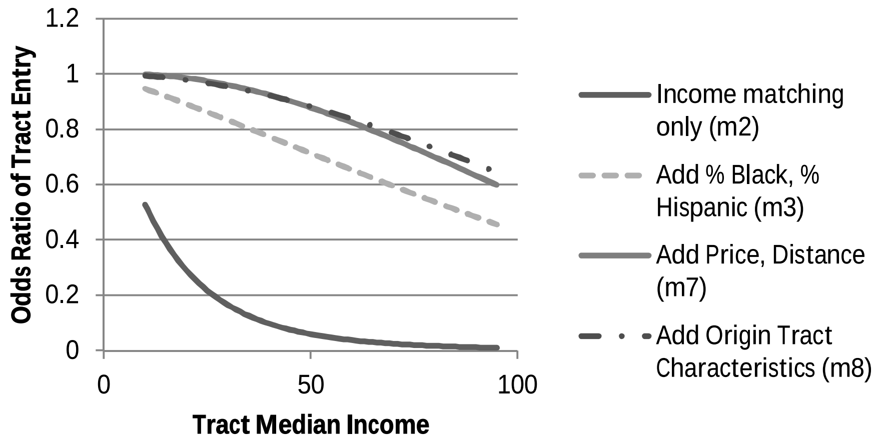

Figure 10: Black Odds of Tract Entry and Distance