A More Rigorous Test of Latinx Spatial Assimilation Using Discrete Choice Models

Pat Rubio Goldsmith, Texas A&M

Martín Puga, Texas A&M

Abstract

There is increasing concern that Latinx-white segregation is now being driven more by racialization than by spatial assimilation. Nevertheless, most studies of spatial assimilation use statistical models that cannot account for the multiple dimensions of residential attainment. In this paper, we test predictions of the spatial assimilation model using data from the National Educational Longitudinal Study on the residential attainment of 800 Latinx who have left their parental homes using discrete choice analyses. These models allow us to control for many other dimensions of neighborhoods related to residential attainment. We find limited support for spatial assimilation net of these other neighborhood dimensions. Net of other factors, all but the most highly educated Latinx move to neighborhoods with high percentages of co-ethnics, suggesting more evidence of racialization than spatial assimilation.

Racial and ethnic residential segregation reduces interracial contact and unequally distributes resources, producing racial and ethnic gaps in important life outcomes such as health and education. Now that Latinx are the largest subordinated racial and ethnic group in the United States, there is rising concern about Latinx-white residential segregation. Researchers find that Latinx-white segregation is not as not as high as black-white segregation, but black-white segregation has slightly declined and Latinx-white segregation has slightly risen, especially where the Latinx population grown (Logan 2013; Massey and Tannen 2018).

Sociologists consider racial and ethnic differences in migration to be one of the central causes of residential segregation. To understand Latinx segregation from whites, many researchers have used the spatial assimilation model. This model may be particularly apt for the study of Latinx's residential attainment because many Latinx are first or second generation immigrants and many have low socioeconomic status, two key explanatory factors in the spatial assimilation model, thus providing an explanation for rising levels of Latinx-white segregation. As applied to Latinx, the spatial assimilation model predicts that those Latinx that are more culturally and socioeconomically assimilated are 1) less likely to move to predominately Latinx neighborhoods and 2) more likely to move to predominantly white neighborhoods.

In this particular study, we test these two predictions. While many studies have found support for one or both of them (Iceland and Wilkes 2006; Lichter et al. 2010; Massey 1985; Pais, South, and Crowder 2012; South, Crowder, and Chavez 2005), there are numerous causes of neighborhood selection and many studies account for only a portion of them. We contribute to the literature by testing for spatial assimilation among Latinx with discrete choice analyses (DCA). These models are becoming increasingly popular in the study of migration patterns because they allow researchers to consider the influence of multiple dimensions of neighborhoods rather than just one, which has been the dominant practice in residential attainment for thirty years. We use DCA to examine whether Latinx's levels of assimilation relate to their migration patterns *holding constant other determinants of residential attainment*.

We begin by explaining the basic tenets of the spatial assimilation model. Next, we explain the advantages of the multidimensional approach provided by DCA. Afterwards, we review other theories of residential attainment, including place stratification, preferences, distance, housing prices, economic segregation and perpetuation theory. We use these theories to operationalize additional characteristics of individuals and neighborhoods to control for in DCA.

For our empirical test, we examine the residential attainment of almost 800 Latinx from the National Education Longitudinal Study 1988-2000. We examine the data with mixed-logit models, a form of DCA that is relatively assumption free. We find, as the spatial assimilation theory predicts, less culturally and socioeconomically assimilated Latinx move to neighborhoods with relatively fewer whites and more Latinx. But after we control for other dimensions of neighborhood selection, most of the differences between more and less assimilated Latinx disappear, leading us to question the contribution of the theory. Except for Latinx who are highly educated, Latinx become more likely to move to a neighborhood as its percentage Latinx rises.

Spatial Assimilation Theory

The spatial assimilation model (Massey 1985) has roots in what is now called straight-line assimilation theory. Straight-line assimilation theory contends that immigrants, through processes of chain migration and hostility from the native born, initially settle in ethnic enclaves to ease their transition to the United States. Over generations, most of the differences between the immigrating ethnic group and whites disappear. This occurs, first, because immigrants strive to assimilate. They try to learn English, adopt American customs, and move up the socioeconomic ladder. Second, it occurs because the boundary between the ethnic group and whites shifts or changes so that the new ethnic group becomes white.

The disappearance of ethnicity is believed to occur over three or more generations. The first generation, which is exemplified by immigrants that arrive as adults, may remain culturally distinguishable over their lifetime. Immigrants that arrive as young children (the 1.5 generation) and children born in the US to immigrant parents (the second generation), are often upwardly mobile and are either bilingual or English dominant. Members of the third generation are usually monolingual English speakers with knowledge of only bits and pieces of their grandparent's culture.

Spatial assimilation is believed to occur alongside an individual's assimilation. As members of the ethnic group culturally, economically and socially assimilate, they migrate into neighborhoods with relatively fewer coethnics and relatively more whites. In some formulations of the theory, the spatial assimilation model has been extended to predict that more assimilated individuals will move to higher income neighborhoods than their counterparts (Sampson and Sharkey 2008; South and Pais 2008). In this paper, we follow the work of Quillian (2014) and use DCA to distinguish between migration patterns related to neighborhood's racial as opposed to income composition. In this study, we examine the predictions of the spatial assimilation models as they pertain specifically to the racial and ethnic composition of destination neighborhoods.

The spatial assimilation theory has been investigated at macro and micro levels. Iceland and Wilkes (2006), for example, examine levels of Latinx-white segregation in metropolitan areas using data on tracts from the 2000 Census. Consistent with the theory, they find that among Latinx age 25 or older, the dissimilarity index measuring segregation from whites averages 0.62 and 0.36 across metropolitan areas for those without a high school diploma and those with a bachelor's degree or higher, respectively. This is a substantial difference given that the index represents the proportion of Latinx that would need to move to eliminate residential segregation from whites. The implication, they point out, is that if Latinx education rose, levels of Latinx-white segregation would decline. They also find, consistent with other researchers (Darden 1987; Clark and Ware 1997), that education is more important than other measures of SES in shaping patterns of spatial assimilation.

Research on the spatial assimilation model at the micro-level usually examines the spatial assimilation model by testing whether or not individual level measures of assimilation (e.g., language, nativity, education, and income) can predict the racial composition of movers' destination neighborhoods. For example, South, Crowder and Chavez (2005) regressed neighborhood percent white onto various measures of assimilation. They find that for every year of education, Latinx move to neighborhoods where the percent white is 0.86 percentage points higher other things equal. They also find that income and English fluency positively associate with the percent white in the destination neighborhood.

A new form of research on spatial assimilation combines these approaches by examining how microlevel determinants of residential attainment contribute to metropolitan area segregation (Fox and Fossett 2017). Similar to the residential attainment research, they find that more assimilated Latinx reside in neighborhoods with relatively more whites. However, they conclude that more assimilation will have modest effects on Latinx-white segregation because Latinx cannot convert items like education and income into residential contact with whites as readily as whites can.

Although the contribution of spatial assimilation to metropolitan segregation has been questioned in this most recent study, studies consistently find that spatial assimilation helps explain Latinx residential attainment. Tienda and Fuentes state that there is "extensive evidence from the residential segregation literature supporting the premises of spatial assimilation for Latinos (415)," but recent trends suggest a weakening of spatial assimilation and a strengthening of racialization (2014). Based on the theory, we expect that as income, education, English ability, social ties with whites, and generation increase, mobile Latinx will move to neighborhoods a lower percentage of Latinx and a higher percentage of whites. Next, we discuss how discrete choice analyses (DCA) may improve our understanding of Latinx migration and the spatial assimilation model.

Uni- and Multi-dimensional models of residential attainment

Over the last thirty years, research on residential segregation examining individual residential attainment has used what we will call a unidimensional model. By unidimensional model, we mean linear regression models that use one dimension of destination neighborhoods (e.g., percent white) as the dependent variable. Independent variables in these models include individual, origin neighborhood, and metropolitan area characteristics. I contrast this approach to the multidimensional approach that can be used in DCA. Figure 1 provides a visual depiction of the difference.

We call attention to four advantages of DCA. In DCA, each individual has a set of neighborhoods they are at risk of moving to, and the dependent variable is a dichotomous indicator of whether they moved to a neighborhood or not. The independent variables include neighborhood characteristics (either independently or in conjunction with individual characteristics). Since neighborhood characteristics are the independent variables, the first advantage is that numerous neighborhood characteristics can be used to model residential attainment and the model is multidimensional. This difference is depicted visually in Figure 1. The figure illustrates the unidimensional approach as only capturing neighborhood percent Latinx. In the multidimensional approach, researchers can simultaneously examine the importance of many characteristics. As Quillian (2015) explains, neighborhoods have "bundles" of characteristics, such as the poverty rate, percent white, percent Latinx, median rent and so on. Bruch and Mare (2012) argue that more than one dimension should be used because, "Any single dimension (of neighborhoods), when considered by itself, may be confounded with other distinct but correlated dimensions (109)."

Second, unidimensional models cannot well account for the neighborhood options available to individuals, which Quillian refers to as the "ecological dependence problem (2014:243)." This problem is particularly acute when the data include individuals living in different metropolitan areas because some metropolitan areas have relatively more predominantly Latinx (or predominantly white) neighborhoods than others. In DCA, the model accounts for how individuals in different metropolitan areas have different neighborhood options by including information on all neighborhoods in their risk set. For example, the model examines whether or not Latinx move to neighborhoods with relatively more Latinx than the other neighborhoods in their metropolitan area. Since neighborhood selection is relative to the available options, the models inherently control for differences across metropolitan areas in a manner that is similar to using fixed effects for metropolitan areas (Goldsmith, Pylman and Veléz 2017).

Third, the multidimensional models allow researchers to account for the location of neighborhoods in space. In this particular study, we examine neighborhood distance from the origin as a spatial dimension. Finally, the unidimensional approach has difficulty modelling curvilinear relationships of neighborhood dimensions. Some theories (e.g., those about preferences of neighborhood racial compositions) suggest that neighborhood percent Latinx will have an inverted U shaped relationship to selection. In DCA, a curvilinear relationship can be modeled with a linear and a quadratic term for percent Latinx because these are independent rather than dependent variables.

Researchers using unidimensional models are aware of the importance of multiple dimensions, differences across metropolitan areas, space, and curvilinear relationships. For example, a solution to the bundling problem has been to use nominal dependent variables that include more than one dimension. For example, this approach might categorize neighborhoods as 1) middle class white, 2) working class white, 3) middle class Latinx, 4) working class Latinx, and 5) other. This approach has the advantage of including two dimensions instead of one, but the number of dimensions is still limited. In addition, there might be large racial/ethnic differences within categories. For example, the middle class white neighborhoods that whites move to may have a much higher percentage of whites than the ones that Latinx move to. Researchers often include variables about the origin neighborhood and interpret them as partially capturing the composition of nearby neighborhoods (a spatial dimension). In the unidimensional approach, metropolitan area differences can be controlled with variables about aggregate differences between metropolitan areas (Pais, South and Crowder 2012). Nevertheless, controlling for aggregate characteristics of metropolitan areas will not completely capture the full distribution of neighborhood options that are available to individuals.

Of course, there are also disadvantages of the DCA approach. Beyond having to meet the assumptions of the model, which we discuss below, it is more difficult to substantively interpret the coefficients, which are estimated as log odds ratios. They also require more data preparation and computing time.[1] To take advantage of DCA in our study of spatial assimilation, we now examine other theories of residential attainment.

The place stratification model and preferences

The place stratification theory argues that whites will use a range of discriminatory tactics to limit the residential integration of Latinos into "white" neighborhoods. These tactics include discriminatory behavior from real estate agents, mortgage lenders, landlords and banks (Pais, South, and Crowder 2012) as well as intimidation from police and vigilantes (Herman

[1] The models we present take about 20 minutes each to converge on an average desktop computer.

2005). This theory deemphasizes assimilation and emphasizes racial processes of whites treating Latinx as a monolithic group. As such, it predicts that all Latinx, not just those that are less assimilated, will move to neighborhoods with relatively few whites and many Latinx.

Some theories claim that racial and ethnic differences in preferences for neighborhood racial compositions play an important role in creating residential segregation in metropolitan areas (Fossett 2006; Fossett and Waren 2005). This research suggests that Latinos generally prefer neighborhoods that are approximately 50 percent Latino and 50 percent white. These preferences imply an inverted U relationship where Latinos will become more and then less likely to move to a neighborhood as it's percent Latino increases, with the peak likelihood occurring when neighborhoods are 50 percent Latino. They also imply that Latinos' likelihood of moving to a neighborhood will rise and then decline as its percent white increases, with the peak likelihood occurring when the neighborhoods are 50 percent white.

Distance

Many residential moves cover short distances (Long 1988). The distance of a neighborhood from a mover's previous residence is among the best predictors of movers' destination neighborhood (Quillian 2014; Goldsmith et al. 2017). In part, the relationship may occur because people tend to move to neighborhoods that they have spent time in or where they knew people, which will largely consist of neighborhoods nearby where they grew up (Krysan and Crowder). There may also be an intergenerational inheritance of place (Sharkey 2013), which implies that young adults will often move to the same or to a very nearby neighborhood as the one they grew up in. The farther away the neighborhood from their original location, the less likely an individual is to move to it.

If distance is not controlled, then neighborhood dimensions that are correlated with distance will appear more strongly related to selection than they really are. In particular, neighborhoods that are nearby each other, especially if they are abutting, will tend to have similar racial and ethnic compositions. Demographers refer to the tendency of racially similar neighborhoods to band together as a type of residential segregation known as clustering (Massey and Denton 1988). Since many moves cover short distance and nearby neighborhoods tend to be similar, many residential moves will be from and to racially similar neighborhoods. If more assimilated Latinx tend to grow up in and nearby neighborhoods with relatively few Latinx and relatively many whites, then they will often move to these neighborhoods because they are nearby. If assimilation matters, we should observe its effects net of distance.

Housing Price and Income Segregation

The percent Latinx or percent white of a neighborhood is likely to be associated with neighborhood housing prices and neighborhood income levels. In general, it is likely that housing prices are lower in predominantly Latinx neighborhoods and higher in predominantly white neighborhoods (Cutler, Gleaser and Vigdor 1999, but see Krivo 1995). Many Latinx may be moving to predominantly Latinx neighborhoods because of their lower housing prices, especially those with low incomes, rather than because of their Latinx or white composition.

Income segregation is an uneven geographic distribution of income groups within a metropolitan area (Reardon and Bischoff 2011). It is created, in part, by people moving to neighborhoods where the current residents have similar income. In addition, there is likely to be a general aversion to high poverty neighborhoods and a general preference (when not stymied by discrimination) for selecting neighborhoods with greater affluence. Thus, low-income (and thus less assimilated Latinx) may select different neighborhoods from high-income ones for reasons related to both the racial/ethnic compositions of neighborhoods and the economic characteristics of neighborhoods in terms of housing prices, household income, and poverty.

Perpetuation Theory

Perpetuation theory maintains that individuals tend to be in similar racial contexts across institutions and over the life course (Braddock 1980). The theory originated from research on the long-term consequences school desegregation. Since then, researchers have shown that the racial compositions that youth experience in their neighborhoods and schools appear to effect children in ways that result in them being in similar racial compositions in their adult workplaces and residential neighborhoods (Goldsmith 2016; Goldsmith et al. 2017; Gamoran et al. 2016; Hearns 2010). Unlike the spatial assimilation model, it considers the context people are from rather than their individual level of assimilation as the important factor in determining residential attainment. We use the theory to predict that young adults will move to neighborhoods that have a similar percentage of whites as the neighborhoods and schools that they grew up in.

METHODS

Data

Data for this study comes from the National Educational Longitudinal Study (NELS) and file 3B of the 1990 and 2000 decennial Census. The NELS contains longitudinal data on adolescents who were 8th graders in 1988 with follow-ups in 1990, 1992, 1994, and 2000. We use the sample of respondents who participated in all panels, which the NCES constructed to be representative of the original sample frame. The benefits of these data are an over-sampling of Latinx and high rates of residential mobility from many sample members leaving their parental homes. We omit the 14 percent of the respondents still live with their parents. Respondents are about 26 years old in the last panel.

The NELS data are linked to the census using respondent's residential, five-digit ZIP-code numbers. The 1990 Census provides contextual data on respondent's ZCTAs (ZIP-code tabulation areas) for 1988, 1990, and 1992. The 2000 Census provides them in 2000. We also omit respondents who do not live in the same MSA in the twelfth grade panel and in the final panel.[2] We only include respondents who identify as Latinx and with at least one ZCTA in their MSA that is at least 40 percent Latinx. We used multiple imputations to impute missing data (1 imputation).[3] For each individual, there is a neighborhood risk set defined as the ZCTAs in their metropolitan area. The data include 798 individuals in 57 metropolitan areas selecting from 119,270 neighborhoods. Over a third of the individuals are in New York, Houston, Chicago and Los Angeles.

Discrete Choice Analysis (DCA)

Discrete choice analyses (Train 2003) is a family of models that estimate the probability of picking one outcome from a set of mutually exclusive, exhaustive and finite set of options. Like others, we estimate the probability of individuals moving to each of the neighborhoods in their metropolitan area given characteristics of the individuals and neighborhoods (Goldsmith et al. 2017; Bruch and Mare 2012; Quillian 2015).

We follow Train's (2003) description of these models. Let n = 1,…N Latinx young adults who can move to $j = 1,\ldots J$ potential neighborhoods in their current MSA. Assume that Latinx, given their structural constraints, attempt maximize utility (U) in their choice of neighborhoods. If so, then $U_{\mathrm{nj}} = \beta X_{nj} + \varepsilon_{\mathrm{nj}}$, where X_{nj} and $\varepsilon_{\mathrm{nj}}$ are observed and unobserved factors affecting utility, respectively. This model can be estimated as a conditional logit, which assumes that $\varepsilon_{\mathrm{nj}}$ is independent and identically distributed (iid) extreme value. Setting $y_{nj} = 1$ if individual *n* moves

[2] Investigating Latinx who are inter-metropolitan movers is difficult because our sample is small.
[3] Two variables, parent's nativity and respondent's income at age 26, result in the loss of about 15 percent of the sample. We imputed scores for them following (Allison xxx). We did not create multiple imputations because the mixed-logit models we estimate are time intensive.

to neighborhood *j* and = 0 otherwise, the conditional logit is

$$Pr\ (y_{nj} = 1) = \frac{e^{\beta' Xni}}{\sum_j e^{\beta' Xnj}}.$$

However, the conditional logit requires two assumptions that may not fit our data. According to Train (2003), the iid assumption requires that the unobserved factors affecting one alternative be independent of the unobserved factors affecting another alternative. This may be false in our data. For example, discrimination (which is unmeasured) may affect moving into predominantly white neighborhoods and into high income neighborhoods. Second, Train (2003) also explains that the conditional logit model assumes the much discussed Independence from Irrelevant Alternatives (IIA). The IIA helps researchers reduce computing time by using a sample rather than the population of the options/choices when estimating the conditional logit model. However, the assumption requires particular substitution patterns among the probabilities that may not fit the data. According to Allison (1999), the IIA assumption is more likely to be violated when the options vary across individuals. In these data, individuals in different metropolitan areas have different options, so it is plausible that the IIA assumption is violated.

The mixed-logit model does not require these assumptions. The mixed-logit model uses random coefficients to estimate β_n, a vector of parameters for each of the *n* adults selecting neighborhoods. We specify that these parameters be distributed normally, allowing us to interpret the means and standard deviations of the coefficients. In this formulation, mixed-logit probabilities are the integrals of a weighted average of the logit probabilities evaluated at values of β_n,

$$\Pr\ (y_{nj} = 1) = \int \frac{e^{\beta' nXni}}{\sum_j e^{\beta' nXnj}} \emptyset(\beta | b,\ w) d\beta,$$

with the weights given by the normal density $\emptyset(\beta | b,\ w)$ with mean b and covariance *w*. We report the means and standard deviations describing the distribution of parameters, as well as their statistical significance. The mean (or another value in the distribution) can be interpreted as a log-odds ratio because,

$$\text{Log}\ [\Pr(y_{nj} = 1) / \Pr(yn_{ni} = 1)] = \beta\ (x_{nj} - x_{ni}).$$

And the coefficients can be converted into odds ratios by exponentiating them (Allison 1999). Because the distributions are normal, 68 and 95 percent of the coefficients fall within plus or minus one and two standard deviations of the mean, respectively. For example, if the distribution of coefficients has a mean of 0.05 with a standard deviation of 0.02, then 95 percent of the respondents have coefficients between .01 and .09. The probabilities are estimated in the SAS procedure mdc (multinomial discrete choice) using Monte Carlo simulation with Halton quasi-random sequences.[4]

We report models that use a combination of random effects and fixed effects for our independent variables. We use fixed effects for variables that never had a statistically significant standard deviation in preliminary models. This resulted in estimating fixed effects for all variables except distance, which has a significant standard deviation. The standard deviations for the variables measuring neighborhoods' proportion Latinx and proportion white were extremely small relative to their standard errors (that is, a ratio of about 1/50). By using fixed effects for these proportions, more of the variance in their effects can be used to test for differences in the coefficients between assimilated and unassimilated Latinx, which is the central task of the study.

Measurement

[4] SAS cannot estimate mixed-logit models and simultaneously account for the complex survey design of data like the NELS, so these analyses are not weighted or adjusted for clustering in primary sampling units.

The dependent variable equals one if the person moved to the neighborhood (ZCTA) and zero otherwise. In DCA, individual characteristics (e.g., language, education) cannot be independent variables by themselves because they are constant with respect to the neighborhood options. Instead, there are three types of independent variables: 1) neighborhood characteristics (subscript nj), 2) interactions between neighborhood characteristics (nj) and individual characteristics (subscript n), and 3) similarities between neighborhood characteristics (nj) and individual characteristics (n).

Our two main independent variables are neighborhood characteristics, proportion Latinx (Hispanic of any race) and proportion white (non-Hispanic white). We also include their squares because they are significant in some models. We do not include cubed terms because they are never significant.

We use five measures of assimilation: income, education, language background, barrio background, and generation. Income is the respondent's individual income in 1999, as a natural log. Because the natural log of zero is undefined, we set individual income at $50 dollars if they report zero. Education is a dummy variable indicating if the respondent has a bachelor's degree or not; Language is a dummy variable indicating whether the respondent spoke English (= 1) or Spanish (= 0) in their home while growing up.

We created a dummy variable measuring whether or not the respondent grew up in a barrio or went to a predominantly Latinx school. To compute it, we averaged the percent Latinx in each respondent's 8^{th}, 10^{th}, and 12^{th} grade neighborhoods and schools. If a respondent was in the top quarter of the sample in either of these institutions, we coded them as one (1). Otherwise they were coded zero (0). While studies do not usually include barrio background as a measure of assimilation, we include it because the theory views social integration to be a predictor of spatial assimilation. Research shows that the racial and ethnic composition of youth's friendships and probably other types of ties are heavily constrained by the options available to them in their schools and neighborhoods (Mouw and Entwisle 2006).

For generation, we coded respondents as one if they have immigrant parents and zero if they do not. Since all respondents in the NELS were in the United States by 8th grade, the most recent arrivals are not the first but the 1.5 generation, so our measure compares the 1.5 and second generation to the 3rd plus generation.

Distance is the natural log of the miles from the center point of the respondent's twelfth-grade ZCTA and each ZCTA in the metropolitan area. To account for housing prices, we use ZCTA's median rent. Housing prices are also likely to sort individuals by their income, with higher income earners moving to neighborhoods with higher median rents and vice versa. To account for this sorting, we also include a measure of the similarity between individual income and the ZCTA's median rent. The formula for similarities is,

$-|m_n - r_{nj}|$,

Where m and r are variables describing individuals and neighborhoods, respectively. To capture sorting per housing prices, we use the similarity between individual income (m) and neighborhood median rent (r). Before taking the difference, we transformed them so that their mean equals zero and their standard deviation equals one. We take the absolute value of the difference because we are interested in how similar they are rather than which one is larger. The negative sign is used so that larger values indicate greater similarity. By transforming the two components into standard deviation units, the measure of similarity gets larger as an individual's income is about the same distance above or below the mean as is the neighborhoods median rent above or below its mean. To income segregation, we control the neighborhood poverty rate and median family income. We also create a measure of the similarity between individual income and median family income in the same way as the one discussed above.

To account for the predictions of perpetuation theory we use two similarities developed by Goldsmith and his colleagues (2017). One is the similarity between the average percent white in the schools they attended in 8^{th}, 10^{th}, 12^{th} grade and their first college (if they attended one) and the percent white in each of the neighborhoods in their MSA. The second one replaces the average percent white in their schools with the same thing in the neighborhoods they grew up in (averaged of 8^{th}, 10^{th} and 12^{th} grade). To account for housing availability, we include the number of houses in the neighborhood and the neighborhood vacancy rate.

RESULTS

Table 1 shows the means and standard deviations for the independent variables used in the models for the 798 neighborhoods that Latinx moved to and the 118,472 neighborhoods they did not move to but could have. Compared to the neighborhoods not moved to, Latinx tend to move to neighborhoods with a higher percentage of Latinx (40.8 vs 25.3) and a lower percentage of whites (41.7 vs 54.5). The measures suggested by perpetuation theory show that young adults tend to move to neighborhoods with more similarity in percent white (-14 vs -32 for percent white in schools and -14 vs -31 for percent white in youth neighborhoods). The similarities between individual income and rent and between individual income and median family income have similar means for the neighborhoods moved to and not moved to, but the standard deviations are smaller in the former, perhaps because Latinx rarely move to extremely high rent neighborhoods.

The neighborhoods Latinx move to are also nearer to where they grew up than the neighborhoods not moved to. Because distance is skewed, it is helpful to compare the distributions. The 25th, 50th and 75th percentiles of distance for the neighborhoods they moved to are 0.25, 1.61, and 6.21 miles. For the neighborhoods, they did not move to, these distances are 1.04, 1.78, and 29.21, respectively. The table also shows that Latinx move to neighborhoods with more housing units and a slightly lower vacancy rate. Latinx also move to neighborhoods with higher poverty rates but lower median family incomes and median rents.

Table 1 shows the variables measuring respondent's assimilation as well. Only 17.5 percent of the sample has a BA. The average of the natural log of income is 9.23, which is about $10,200. This average is about $2k above the poverty line for individuals in 1999. Seventy percent grew up in a Spanish speaking home, 36% grew up in a barrio, and 66 percent have immigrant parents.

Mixed Logit Models

The purpose of this study is to estimate the extent of spatial assimilation net of alternative explanations of residential attainment. To do this, we begin by estimating the extent of spatial assimilation in models that "limit" the controls to those about housing availability, which we consider to be exogenous. We show these limited models because many studies find support for spatial assimilation in methods that cannot control for other dimensions of neighborhoods related to residential attainment, and we expect to find that these results can be produced in DCA. Next, we estimate the extent of spatial assimilation in models that "fully" control for other explanations. We expect the full models will be able to explain some or all of the appearance of spatial assimilation observed in the limited models. We estimate limited and full models in relation to moving away from "Latinx" neighborhoods in Tables 2 and 3 and into "white" neighborhoods in Tables 4 and 5.

Assimilation and not moving to "Latinx" neighborhoods

Table 2 shows coefficients and standard errors from models estimating the extent of spatial assimilation out of Latinx neighborhoods in "limited" models. All of the models include proportion Latinx and its square plus three variables about housing availability (number of housing units, vacancy rate, and vacancy rate squared). Model 1 contains only these variables to estimate the "effect" of proportion Latinx for all Latinx individuals. The spatial assimilation model predicts that the "effect" of proportion Latinx will be smaller for more assimilated Latinx. In other words, more assimilated Latinx will be moving to neighborhoods where the percent Latinx is lower than it is for the less assimilated. We test for differences in the "effect" of percent Latinx with interaction between proportion Latinx and each of the measures of assimilation, which we test one at a time. For example, model 2 adds interactions between income (as a natural log) and proportion Latinx and its square.

To formally test for spatial assimilation, we use the change in -2 log-likelihoods between model 1 and each of the models with interactions (models 2-6). The change in -2LL between nested models is distributed as a chi-square statistic with degrees of freedom equal to the difference in the number of parameters ($df = 2$). A significant chi-square indicates that the two added variables improve the model fit. We use model fit tests because the standard errors for the interactions are inflated from the multicollinearity created by including four variables about proportion Latinx. Luckily, multicollinearity does not bias estimates of coefficients, so we can still interpret their magnitude.

As shown at the bottom of Table 2, these chi-square tests show that adding the interactions about education, language background, and barrio background are significant while those for income and generation are not. Null effects for income may result from the young age of the sample. At age 26, income inequality between more and less assimilated Latinx may be smaller than it would be at older ages. We did try operationalizing income in different ways (e.g., a dichotomous measure differentiating high income earners from the rest), but there does not appear to be any spatial assimilation associated with income in this sample. Generational differences may not be significant because all of these respondents went to school in the United States since they were in eighth grade, limiting the range of the variable. Still, the lack of support in even the limited models cast doubt on how much generation and income will affect spatial assimilation.

How large are the effects for education, language and barrio background? To understand their magnitude, we visually depict the logged odds ratios of moving to a neighborhood as its proportion Latinx rises. We show logged odds ratios rather than odds ratios because graphs of the scale of the latter makes positive effects look much more powerful than negative effects.

In model 1, (which applies to all Latinx), proportion Latinx has a positive linear term and negative squared term, which form an inverted U shaped curve. This curve is shown in Figure 2a with the line called "all Latinx." As seen there, the log odds ratios increase until proportion Latinx equals (-a /(2 * b) =) 0.82. This means that given the opportunities they have, they are most likely to pick neighborhoods that are 82 percent Latinx. At this point, Latinx's odds of moving to the neighborhood are (exp (b1*.82 + b2*.82*.82 = 2.68) =) 14.6 times greater than the odds of moving to a neighborhood with no Latinx. The figure also shows how the effect of proportion Latinx varies between those with and without a bachelor's degree. For those without a BA, there is an inverted U shaped curve that peaks when proportion Latinx equals 0.85 with an odds ratio of 20.5, both of which are slightly higher than for all Latinx. In contrast, the curve for those with a BA is an inverted U shape that peaks at 0.56 with an odds ratio of 4.27. Thus, Latinx with more education are moving to neighborhoods with lower proportions of Latinx than their less educated co-ethnics, as predicted by assimilation theory.

The curves for English vs Spanish background (estimated from model 4) are similar to the ones for education. For Spanish background Latinx, the curve peaks at 0.85 with an odds ratio of 25.2. For English speakers, these two estimates are 0.66 and 5.26 respectively. The curves for barrio backgrounds are different from those for education and language. For those with a barrio background, the curve rises rapidly and the peak of the curve is estimated to occur when proportion Latinx is greater than one, which is outside of the range of the data. When proportion Latinx reaches its maximum (one), the odds ratio is 168. For those not from barrios, the inverted U shaped curve is very peaked. It maxes out when proportion Latinx equals 0.52 and an odds ratio of 11.7, after which it declines rapidly. This means that those from and not from barrios have dramatically different odds of moving to predominantly Latinx neighborhoods. Thus, all the statistically significant interactions in the limited models suggest Latinx mobility is consistent with predictions from the spatial assimilation model.

We now turn to the full models. Before discussing the results pertaining to spatial assimilation, we will briefly discuss the coefficients from the added variables in model 1 of Table 3. We do not discuss them in the other models, except in one instance mentioned later, because their estimates are similar. First, notice that the -2LL has risen dramatically from about 800 to over 3300. Most of this increase is due to the inclusion of the natural log of distance. The effect of distance is estimated as a distribution of coefficients. The results show that the mean of the distribution is negative (-1.23), indicating that Latinx are less likely to move to a neighborhood the further away it is. It's standard deviation is also significant, and indicates that 95 percent of the respondents have a coefficient between (-1.23 +/- 2*0.51 =) -0.21 and -2.25.

These results indicate that distance is negative for nearly everyone, but more negative for some than for others. The coefficients for neighborhoods proportion white and its square are not significant, suggesting that other things equal, Latinx's residential attainment is not affected by the neighborhoods' proportion white. This finding is not consistent with the place stratification model, which predicts that Latinx would be less likely to move to a neighborhood as its percent white increases.

The only variable about housing prices or economic segregation which is significant is the one for the poverty rate. Although the dichotomous relationship indicates that Latinx move to neighborhoods with higher poverty rates (see Table 1), once other factors are controlled, Latinx are less likely to move to a neighborhood as its poverty rate rises, as seen by the negative coefficient for this variable. Most likely, the dichotomous relationship results from Latinx moving to neighborhoods with high proportions of Latinx, which tend to have high poverty rates. Since the models control for percent Latinx, the "effect" of the poverty rate becomes negative. Finally, the results show that Latinx are more likely to move to neighborhoods that have a proportion of whites that is similar to those of the schools they went to (1.51) and those of their neighborhoods in youth (1.01), which are consistent with perpetuation theory.

Once again, we test the hypotheses from the spatial assimilation model with the chi-square statistics at the bottom of the table after we add interactions in models 2-6. They show that none of the added interactions are significant except for the one about education. Thus, overall there is much less evidence for spatial assimilation in the full models. Figure 2b shows the effect of proportion Latinx for all Latinx and separately for those with and without a BA from the full models. As seen there, the relationship always follows an inverted U shaped curve. For all Latinx, it peaks when proportion Latinx equals 0.92—almost as high as possible—with an odds ratio of 5.9—recall that in the limited models the odds ratio peaked at 14.6. For those without a BA, the curve peaks at 0.92 with an odds ratio of 9.55—as opposed to 20.5 in the limited model. For those with a BA, the curve is very flat and never goes more than a standard error above or below zero. Thus, when we account for other factors, the effect of proportion Latinx is positive overall, positive for those without a BA, and nil for those with a BA. The effect of proportion Latinx does not vary by Latinx's income, language background, barrio background, or generation.

Assimilation and moving into "white" neighborhoods

The spatial assimilation model also predicts that as assimilation increases, Latinx increasingly move to "whiter" neighborhoods. Table 4 shows the "limited" models and Table 5 the "full" models.

As seen in model 1 of table 4, the coefficients for percent white and its square are positive and negative, producing an inverted U shaped relationship. It is shown in Figure 2c. The log odds of moving to a neighborhood rise as proportion white increases until the proportion becomes 0.13. When proportion white gets to 0.28, the effect becomes negative. When proportion white reaches one, Latinx's odds of moving to the neighborhood are one over 14.69 times as great as the odds of moving into a neighborhood with no whites. Thus, the effect is negative through most of the distribution of percent white.

Once again, the effects of spatial assimilation are tested by adding interactions and examining the chi-square statistics for improvement in model fit. These tests indicate that adding interactions for income and generation do not improve the model fit but that adding them for education, language background and barrio background do. Figure 2c shows the curves for Latinx with and without a BA. For the less educated, the "effect" peaks at 0.09, becomes negative at 0.18, and has an odds ratio of one over 19.91 when proportion white equals one. For those with a BA, there is more migration into “whiter” neighborhoods, as these estimates are 0.35, 0.70, and 4.45. We do not show the scatter plots for language background (model 3) or barrio background (model 4). The former estimates slopes for Spanish speakers and English speakers that are similar to those shown for Latinx without a BA and with a BA, respectively. In contrast, model 4 indicates that for Latinx from barrios, the effect of proportion white is negative through the whole range. Those not from a barrio have odds ratios that peak when proportion white equals 0.32, become negative at 0.65, and have an inverted odds ratio of 7.8 when proportion white equals one. Thus, Latinx from barrios are much less likely to move to predominantly white neighborhoods than Latinx not from barrios.

Table 5 shows the results from the full models. The coefficients from all of the control variables are similar to their coefficients in Table 3, which were discussed above. The one exception is that in Table 3 we controlled for neighborhood percent white and its square, which were both not significant, to account for discriminatory barriers to Latinx integration. In Table 5, since proportion white is our focus, we instead control for proportion Latinx. These models show positive linear effects, indicating that Latinx move to neighborhoods with more Latinx other things equal. This effect could be capturing the effects of own-group preferences, but it may also capture effects of homophilly beyond preferences since it is not an inverted U shaped relationship.

Model 1 of Table 5 shows that coefficients for proportion white are not significant in the “full” models when they are entered without any interactions. Figure 2d shows that the slope estimated by those coefficients stays close to zero over the range of proportion white. When interactions are added (models 2-6), only those with education, model 3, significantly improve the model fit. The interactions between proportion white and income, language, barrio, and generation are not significant, which is not consistent with spatial assimilation models. The estimated slopes for Latinx without a BA show that the effect stays close to zero over the range of proportion white. For those with a BA, the log odds ratio rises until proportion white reaches 0.67 with an odds ratio of 5.09 and they never become negative. When proportion white equals 1, Latinx's odds of moving to the neighborhood are 3.5 times greater than their odds of moving to a neighborhood with no whites. Thus, we find support for spatial assimilation in regards to Latinx education but for other forms of assimilation.

What creates the appearance of spatial assimilation

The limited models show that Latinx's mobility patterns are consistent with spatial assimilation, but the full models show that most of these mobility patterns are explained by other factors and not an individual's assimilation. In this section, we examine which of the other factors "explain" what looks like spatial assimilation. To do this, we estimate models that add independent variables to the baseline model (Table 2, model 1) one type of explanation at a time and then check whether or not adding the assimilation-by-group proportion interactions improve the model fit. For example, the row labeled LD tests whether adding these interactions improves the model fit with distance already in the model. By comparing the chi-square in the row labeled LD to the chi-square above it, we can estimate how much of the effect of spatial assimilation is explained by the addition of distance. The five models at the top and bottom of the table focus on assimilation and moving into "Latinx" and out of "white" neighborhoods, respectively.

We consider the explanatory impact of four sets of independent variables in this order: distance; either proportion white or proportion Latinx, whichever is the opposite of the main focus of the model; housing pricing and economic segregation; and the similarities predicted by perpetuation theory.

The findings show that distance explains little of the spatial assimilation that results from increased education, as seen by the small changes in chi-square when it is added to the limited model at the top (23.9 to 20.7) and the bottom (16.1 to 12.5). However, distance explains most of the contributions of language background, as seen by the changes to chi-square (from 27.3 to 6.2 and 25.9 to 8.1). It also explains most of the contribution of barrio background (from 136.2 to 12.4 and 88.7 to 14.0). This finding reveals that much of what appears to be spatial assimilation is Latinx frequently moving to nearby neighborhoods. Once we hold constant neighborhood distance, these individual background differences create much less spatial assimilation. Nevertheless, there models indicate some spatial assimilation net of distance.

The contribution of the interactions to model fit are relatively unchanged when the variables about proportion white/Latinx, housing pricing, and income segregation are added to the models. When the similarities suggested by perpetuation theory are added, the contributions of the interactions with language and barrio background are not significant, suggesting that this theory also helps explain the appearance of spatial assimilation in the limited models. The contribution of spatial assimilation from education remains significant and is only modestly reduced by the inclusion of all of the control variables.

DISCUSSION

In this paper, we test predictions from the spatial assimilation model using data from the NELS and the decennial Censuses of 1990 and 2000 on young adults who have left their parent's home and established an independent residence. We use mixed-logit models, a form of discrete choice analyses, to predict Latinx's destination neighborhood from the set of all neighborhoods in their metropolitan area. This study improves our understanding of spatial assimilation by testing predictions from it while controlling for other explanations of residential attainment. This is an important contribution because past attempts to test for spatial assimilation have held constant other characteristics of individuals, origin tracts, and metropolitan areas but not other characteristics of neighborhood options. They have also ignored spatial dimensions of neighborhoods, variation in neighborhood options available to individuals, and curvilinear effects of group proportions. Following the logic of spatial assimilation, we tested whether more assimilated Latinx move to “whiter” and “less Latinx” neighborhoods than less assimilated Latinx. We find some evidence consistent with the theory. When the controls are limited to those for housing availability, individual level assimilation in terms of education, language and barrio background result in more assimilated Latinx moving to Neighborhoods with relatively more whites and fewer Latinx. These findings are thus consistent with prior research that shows support for spatial assimilation. However, we do not find evidence of spatial assimilation resulting from income and generation. More importantly, when we control all of the other determinants of residential attainment, we do not find any evidence of spatial assimilation from language or barrio background, and that part resulting from education is reduced. The results of these tests lead us to question the viability of spatial assimilation to explain Latinx residential attainment.

Before any further discussion, it is important to address this study’s limitations. Our analysis improves our understanding by using additional controls, but it is still a descriptive study which is not capable of pinning down causation with confidence. The analysis also tests for spatial assimilation among young adults who have lived in the United States at least since 8th grade. More evidence of spatial assimilation might be observed between immigrants that arrived as adults and those who have been in the United States for multiple generations. That said, the theory nevertheless predicts that residential attainment should differ between the second and later generations. It is also possible that more evidence of spatial assimilation would be observed if we used smaller units to operationalize neighborhoods. We used ZCTAs. It is common for the magnitude of contextual effects to increase when the contexts are measured in smaller and hence more precise units (Wong 2009). While this is true, it is worth noting that using smaller units would be likely to increase the magnitude of all coefficients, and the relative contribution of spatial assimilation would likely remain similar.

Theoretical Implications

In a climate of rising levels of Latinx residential segregation, we find little evidence that that raising the incomes or waiting for more generations to be born will decrease Latinx residential segregation from whites. This study finds that these factors are unrelated to the relative presence of Latinx or whites in their destination neighborhoods.

We do find that Latinx with Spanish or barrio backgrounds generally move to neighborhoods with relatively more Latinx and relatively fewer whites than their English and non-barrio background co-ethnics. However, these differences in residential attainment may not be the result of individuals assimilating. Instead, we find that the distance people move largely explains what would commonly be viewed as spatial assimilation. When Latinx move, they usually move to the same or to a nearby neighborhood. If distance is not controlled, any characteristic that is common in the nearby neighborhoods can appear to influence residential mobility. In this case, Latinx from Spanish language backgrounds, compared to those from English language backgrounds, tend to grow up nearby neighborhoods with relatively more Latinx and fewer whites. Since so many people move a short distance, it creates a spurious relationship between language and the racial composition of the destination neighborhood. The spatial assimilation seemingly stemming from barrio/non-barrio backgrounds is also mostly a spurious relationship explained by distance.

Even after distance is held constant, we still observe some spatial assimilation from language and barrio background. That part of spatial assimilation is explained away by perpetuation theory. This theory argues that the racial context that people grow up in influences their psychology about interracial interaction, their knowledge and skills for how to live in different racial contexts, and the racial and ethnic diversity of their social ties. The net effect of these factors is that individuals perpetually inhabit the same racial contexts across institutions and overtime. Consistent with the theory, we find that Latinx are more likely to move to neighborhoods as its percentage of whites becomes more similar to the same thing in the neighborhoods of their youth and of the schools they attended.

It is not completely surprising that perpetuation theory explains some of the effects of spatial assimilation because the theories, at least on their face, contain overlap. Perpetuation theory focusses on the consequences of growing up in a neighborhood or school with a particular racial composition for an individual, while the spatial assimilation theory focusses on the consequences of individuals having a certain level of assimilation. The ways that contexts affect individuals (in perpetuation theory) have overlap with the way that assimilated and unassimilated individuals differ from each other. That is, it might be reasonable to view assimilation as psychological adaptation to a “white” context, as learning knowledge and skills for interacting with whites, and as developing social ties with whites.

While the theories seem to contain overlap, it is the variables from perpetuation theory that remain significant when the variables from both theories are included together in the model.

The difference may be that treating context as a continuous variable as percent white explains more of the variation in individual backgrounds than the dichotomous measures of assimilation. It may also mean that experiences in a context capture more of the important differences between individuals than does their own individual level characteristics (like language). It clearly seems to matter much more than their generational status and income.

Finally, we find that when assimilation is measured with education, we find robust effects of spatial assimilation net of other factors. We find no evidence that distance, housing prices, economic segregation, place stratification, preferences, or perpetuation theory can explain why more educated Latinx, compared to less educated Latinx, move to neighborhoods with higher percentages of whites and lower percentages of Latinx relative to the other neighborhoods in their metropolitan areas.

This finding could be interpreted as support for spatial assimilation model. However, it is worth considering why education leads to spatial assimilation while income, generation, language and barrio background do not. Spatial assimilation is usually understood as part of a "striving" to become white which is pursued within an unwelcoming context. Without being able to exist on the "white" side of the barrier, minority groups seek out co-ethnics for economic and social assistance. It may be that education enables minority group members to gain acceptance and assistance from whites, but it isn't clear why education allows this but income and language, for example, do not. It may be that education alters Latinx's migration in other ways. For example, it may be that highly educated Latinx take jobs further away from where they grew up and often move to neighborhoods near their jobs. In support of this idea, we find that Latinx with a BA move about two miles further than Latinx without a BA.

Except for highly educated Latinx, we find that even after controls for all other explanations, Latinx move to neighborhoods with relatively more Latinx than the other neighborhoods they could have moved to. In fact, they are most likely to move to neighborhoods with very high percentage of Latinx (92 percent). Thus, for most of the Latinx population, their reaction to the housing market is not one of more and less assimilated Latinx moving to different kinds of neighborhoods, but of the large majority of Latinx showing mobility into more "Latinx" neighborhoods. Other factors matter a great deal, especially distance and prior exposure to whites, but a migration towards Latinx neighborhoods looks more like a racialized minority group than an assimilating ethnic group.

Policy Implications

Residential segregation has negative effects on Latinx in important outcomes like adult health (Nelson 2013), educational attainment and occupational success (Steil, De La Roca, and Ellen 2015), and exposure to violence (Feldmeyer 2010). Finding ways to reduce residential segregation is likely to improve Latinx's quality of life. This particular study focusses solely on Latinx, so we are only prepared to make recommendations on their contributions to residential segregation. This study suggests that policies that would improve Latinx education would be likely to reduce their segregation from whites. It is well known that Latinx levels of educational attainment lag far behind those of whites (and blacks), and there have been important calls for improving Latinx education (Telles and Ortiz 2009). We echo these calls.

REFERENCES

Bischoff, Kendra and Sean F. Reardon. 2013. "Residential Segregation by Income, 1970-2009." Pp. 1–43 in *Diversity and Disparities: America Enters a New Century*, edited by J. Logan. New York: The Russel Sage Foundation

Braddock II, Jomills Henry. 1980. “The Perpetuation of Segregation across Levels of Education: A Behavioral Assessment of the Contact-Hypothesis.” *Sociology of Education* 53(3):178–86.

Clark, William A. V. and Julian Ware. 1997. “Trends in Residential Integration by Socioeconomic Status in Southern California.” *Urban Affairs Review* 32:825-43.

Crowell, Amber R., and Mark Fossett. 2017. "White and Latino Locational Attainments: Assessing the Role of Race and Resources in US Metropolitan Residential Segregation." *Sociology of Race and Ethnicity*.

Cutler, David M., Edward L. Glaeser, and Jacob L. Vigdor. 1999. “The Rise and Decline of the American Ghetto.” *Journal of Political Economy* 107:455–506.

Darden, Joe T. 1987. “Socioeconomic Status and Racial Residential Segregation: Blacks and Hispanics in Chicago.” *International Journal of Comparative Sociology* 28:1-13.

Dawkins, Casey J. 2005. “Evidence on the Intergenerational Persistence of Residential Segregation by Race.” *Urban Studies* 42(3):545–55.

Feldmeyer, Ben. 2010. “The Effects Of Racial/Ethnic Segregation On Latino And Black Homicide.” *The Sociological Quarterly* 51:600–623.

Fossett, Mark. 2006. “Ethnic Preferences, Social Distance Dynamics, and Residential Segregation: Theoretical Explorations Using Simulation Analysis*.” *Journal of Mathematical Sociology* 30(3–4):185–274.

Fossett, Mark and Warren Waren. 2005. “Overlooked Implications of Ethnic Preferences for Residential Segregation in Agent-Based Models.” *Urban Studies* 42(11):1893–1917.

Frank, Reanne and Ilana Redstone Akresh. 2016. “New Faces in New Spaces in New Places: Residential Attainment among Newly Legalized Immigrants in Established, New, and

Minor Destinations." *Social Science Research* 57:195–210.

Goldsmith, Pat Rubio, Maureen Pylman and William Veléz. 2017. "Are there Neighborhood Effects on Young Adult Neighborhood Attainment? Evidence from Mixed Logit Models." *Social Science Research* 64:25-42.

Hall, Matthew and Jonathan Stringfield. 2014. "Undocumented Migration and the Residential Segregation of Mexicans in New Destinations." *Social Science Research* 47:61–78.

Herman, Max. 2005. *Fighting in the Streets: Ethnic Succession and Urban Unrest in Twentieth-Century America. New York: Peter Lang*

Iceland, John, and Rima Wilkes. 2006. "Does socioeconomic status matter? Race, class, and residential segregation." *Social Problems* 53(2): 248-273.

Lichter, Daniel T., Domenico Parisi, Michael C. Taquino, and Steven Michael Grice. 2010. "Residential Segregation in New Hispanic Destinations: Cities, Suburbs, and Rural Communities Compared." *Social Science Research* 39:215–30.

Logan, John R. 2013. "The Persistence of Segregation in the 21st Century Metropolis." *City and Community* 12(2):160–68.

Massey, Douglas S. 1985. "Ethnic Residential Segregation: A Theoretical Synthesis and Empirical Review." *Sociology & Social Research* 69:315–50.

Massey, Douglas S., and Nancy A. Denton. 1988. "The dimensions of residential segregation." *Social forces* 67: 281-315.

Massey, Douglas S. and Jonathan Tannen. 2018. "Suburbanization and Segregation in the United States: 1970–2010." *Ethnic and Racial Studies* 41(9):1594–1611.

Mouw, Ted and Barbara Entwisle. 2006. "Residential Segregation and Interracial Friendship in Schools." American Journal of Sociology 112:394–441.

Nelson, Kyle Anne. 2013. “Does Residential Segregation Help or Hurt? Exploring Differences in the Relationship between Segregation and Health among U.S. Hispanics by Nativity and Ethnic Subgroup.” *Social Science Journal* 50(4):646–57.

Pais, Jeremy, Scott J. South, and Kyle Crowder. 2012. “Metropolitan Heterogeneity and Minority Neighborhood Attainment: Spatial Assimilation or Place Stratification.” *NIH Public Access* 59(2):258–81.

Sampson, Robert J. and Patrick Sharkey. 2008. “Neighborhood Selection and the Social Reproduction of Concentrated Racial Inequality.” *Demography* 45(1):1–29.

Sharkey, Patrick. 2013. *Stuck in Place: Urban Neighborhoods and the End of Progress toward Racial Inequality*. University of Chicago Press.

South, Scott J. and Jeremy Pais. 2008. “Inter-Neighborhood Migration and Spatial Assimilation in a Multi-Ethnic World: Comparing Latinos, Blacks, and Anglos.” *Social Forces* 87(1):415–43.

South, Scott J., Kyle Crowder, and Erick Chavez. 2005. "Migration and spatial assimilation among US Latinos: Classical versus segmented trajectories." *Demography* 42(3):497-521.

Steil, Justin, Jorge De La Roca, and Ingrid Gould Ellen. 2015. “Desvinculado y Desigual: Is Segregation Harmful to Latinos?” *Annals of the American Academy of Political and Social Science* 660:57–76.

Swisher, Raymond R., Danielle C. Kuhl, and Jorge M. Chavez. 2017. “Racial and Ethnic Differences in Neighborhood Attainments in the Transition to Adulthood.” *Social Forces* 91(4):1399–1428.

Telles, Edward M., and Vilma Ortiz. 2008. *Generations of exclusion: Mexican-Americans,* *assimilation and race.* Russel Sage Foundation.

Tienda, Marta and Norma Fuentes. 2014. "Hispanics in Metropolitan America: New Realities and Old Debates." *Annual Review of Sociology* 40:499–520.

Wong, David. 2009. "The Modifiable Areal Unit Problem (MAUP)." Pp. 105–23 in *The Sage Handbook of Spatial Analysis,* edited by A. S. Fotheringham and P. A. Rogerson. Los Angeles: Sage.

Table 1. Means and standard deviations comparing the neighborhoods that Latinx move to and not move within their metropolitan area.

	Moved to		Not moved to	
Individual characteristics	Mean	St. dev.	mean	St. dev.
Attained a bachelor's degree (1 = yes)	17.5%			
Individual income in 1999 (natural log)	9.23	2.53		
From a Spanish speaking home (1 = yes)	70.4%			
Grew up in a barrio (1 = yes)	36.3%			
Immigrant parents (1 = yes)	65.8%			
Neighborhood characteristics				
Proportion Latinx$_{nj}$	0.48	0.28	0.27	0.25
Proportion white$_{nj}$	0.34	0.25	0.52	0.31
Poverty rate$_{nj}$	0.18	0.11	0.14	0.11
Controls				
Median family income$_{nj}$ /10,000	4.51	1.74	5.90	2.91
Median rent$_{nj}$/100	5.91	2.02	6.80	2.73
Number of housing units$_{nj}$ /10,000	1.55	0.82	1.05	0.08
Vacancy rate$_{nj}$	0.13	0.04	0.14	0.08
Distance from origin$_{nj}$ (nl of miles)	0.25	1.88	2.81	16.95
25th percentile (miles)	0.25		1.04	
Median (miles)	1.61		1.78	
75th percentile (miles)	6.21		29.21	
Similarities				
Median rent$_{nj}$ to income$_{n}$	-0.95	0.83	-0.98	0.99
Median family income$_{nj}$ to income $_{n}$	-0.98	0.75	-1.02	0.96
Proportion white neighborhoods$_{nj}$ and schools$_{n}$	-0.14	0.14	-0.32	0.23
Proportion white youth$_{n}$ and adult$_{nj}$ neighborhoods	-0.14	0.13	-0.31	0.22
Housing availability				
Number of housing units$_{nj}$ /10,000	1.55	0.82	1.05	0.08
Vacancy rate$_{nj}$	0.13	0.04	0.14	0.08
N	798		118472	

Note: subscript *nj* indicates all of the neighborhood options available to person *n*.

Table 2. Coefficients from mixed-logit regression models predicting residential attainment.

	1		2		3		4		5		6	
Proportion Latinx	6.57	0.61***	3.13	2.25	7.15	0.69***	7.58	0.77***	9.02	1.41***	6.99	0.74***
Proportion Latinx^2	-4.02	0.59***	0.07	2.15	-4.23	0.66***	-4.45	0.72***	-3.90	1.16***	-4.19	0.72***
Proportion Latinx * income			0.37	0.23								
Proportion Latinx^2 * income			-0.44	0.22*								
Proportion Latinx * BA					-2.00	1.49						
Proportion Latinx^2 * BA					-0.33	1.58						
Proportion Latinx * English home							-2.52	1.27*				
Proportion Latinx^2 * English home							0.59	1.29				
Proportion Latinx * Not barrio home									0.45	1.62		
Proportion Latinx^2 * Not barrio home									-5.21	1.49***		
Proportion Latinx * 3rd+ generation											-1.43	1.27
Proportion Latinx^2 * 3rd + generation											0.65	1.25
Number of housing units	0.78	0.05***	0.78	0.05***	0.78	0.05***	0.78	0.05***	0.78	0.05***	0.78	0.05***
Vacancy rate	8.84	2.63***	8.85	2.63***	8.70	2.64***	8.97	2.63***	8.89	2.64***	9.03	2.63***
Vacancy rate^2	-23.9	6.56***	-24.0	6.56***	-23.6	6.58***	-24.2	6.55***	-24.3	6.55***	-24.4	6.55***
-2 log liklihood	796.1		800.7		820.0		823.4		932.3		801.3	
Chi-square vs model 1			4.6		23.9***		27.3***		136.2***		5.21	

Note: ***, **, * indicate $p < 0.001$, .01, and .05 on two-tailed tests, respectively.

Table 3. Coefficients from mixed-logit regression models predicting residential attainment.

	1		2		3		4		5		6	
Proportion Latinx	3.94	1.25**	0.89	4.15	4.90	1.31***	4.57	1.36***	4.67	1.92*	4.02	1.37**
Proportion Latinx^2	-2.20	1.17	1.08	3.60	-2.66	1.21*	-2.59	1.27*	-2.69	1.64	-2.43	1.30
Proportion Latinx * income			0.33	0.42								
Proportion Latinx^2 * income			-0.35	0.37								
Proportion Latinx * BA					-3.84	2.52						
Proportion Latinx^2 * BA					0.80	2.77						
Proportion Latinx * English home							-1.81	1.86				
Proportion Latinx^2 * English home							1.00	1.89				
Proportion Latinx * Not barrio home									-0.67	2.09		
Proportion Latinx^2 * Not barrio home									0.26	1.93		
Proportion Latinx * 3rd+ generation											0.06	1.84
Proportion Latinx^2 * 3rd + generation											0.49	1.77
Proportion white	1.29	1.15	1.38	1.16	1.18	1.17	1.28	1.15	1.17	1.17	1.21	1.15
Proportion white^2	-1.47	1.22	-1.56	1.24	-1.41	1.24	-1.50	1.23	-1.37	1.25	-1.34	1.23
Distance (natural log of miles) $\bar{X}$	-1.23	0.04***	-1.23	0.04***	-1.24	0.04***	-1.23	0.04***	-1.23	0.04***	-1.23	0.04***
Distance (natural log of miles) S	0.51	0.08***	0.51	0.08***	0.55	0.08***	0.51	0.08***	0.51	0.08***	0.51	0.08***
Median family income	-0.06	0.08	-0.06	0.08	-0.08	0.08	-0.06	0.08	-0.06	0.08	-0.07	0.08
Median rent	0.05	0.07	0.05	0.07	0.05	0.07	0.05	0.07	0.05	0.07	0.05	0.07
Poverty rate	-2.80	1.17*	-2.75	1.22*	-3.17	1.20**	-2.81	1.18*	-2.87	1.18**	-2.90	1.17**
Number of housing units	0.65	0.07***	0.65	0.07***	0.65	0.07***	0.65	0.07***	0.65	0.07***	0.65	0.07***
Vacancy rate	0.33	3.56	0.18	3.57	0.56	3.58	0.44	3.57	0.57	3.57	0.40	3.57
Vacancy rate^2	-0.66	8.58	-0.56	8.58	-1.49	8.61	-0.87	8.58	-1.16	8.59	-0.78	8.60
Similarities												
Income to median rent	0.21	0.18	0.20	0.18	0.24	0.18	0.21	0.18	0.20	0.18	0.22	0.18
Income to median family income	0.27	0.18	0.28	0.19	0.24	0.18	0.28	0.18	0.27	0.18	0.26	0.18
School to neighborhood whiteness	1.51	0.46***	1.50	0.46***	1.32	0.46**	1.49	0.46***	1.48	0.46***	1.57	0.46***
Youth-adult neighborhood whiteness	1.01	0.46*	1.01	0.46*	1.14	0.47**	0.95	0.46*	0.94	0.48*	1.00	0.46*
-2 log liklihood	3386		3388		3406		3389		3387		3387	
Chi-square vs model 1			1.6		19.5***		2.8		0.5		0.9	

Note: ***, **, * indicate $p < 0.001$, .01, and .05 on two-tailed tests, respectively.

Table 4. Coefficients from mixed-logit regression models predicting residential attainment.

	1		2		3		4		5		6	
Proportion White	0.99	0.56	-2.84	1.96	0.63	0.61	0.69	0.67	-0.60	1.10	0.69	0.66
Proportion White^2	-3.68	0.63***	-0.04	2.31	-3.63	0.70***	-4.03	0.79***	-5.75	1.58***	-3.56	0.77***
Proportion White * income			0.41	0.21*								
Proportion White^2 * income			-0.39	0.24								
Proportion White * BA					2.73	1.48						
Proportion White^2 * BA					-1.23	1.58						
Proportion White * English home							2.03	1.26				
Proportion White^2 * English home							-0.23	1.34				
Proportion White * Not barrio home									4.31	1.31***		
Proportion White^2 * Not barrio home									0.00	1.75		
Proportion White * 3rd+ generation											1.09	1.21
Proportion White^2 * 3rd + generation											-0.55	1.33
Number of housing units	0.80	0.05***	0.80	0.05***	0.80	0.05***	0.80	0.05***	0.80	0.05***	0.80	0.05***
Vacancy rate	9.55	2.64***	9.52	2.64***	9.35	2.65***	9.71	2.63***	8.91	2.65***	9.73	2.65***
Vacancy rate^2	-24.2	6.57***	-24.2	6.57***	-23.8	6.62***	-24.6	6.57***	-23.3	6.59***	-24.6	6.61***
-2 log liklihood	703		707		719		729		792		706	
Chi-square vs model 1			4.3		16.1***		25.8***		88.8***		3.3	

Note: ***, **, * indicate $p < 0.001$, .01, and .05 on two-tailed tests, respectively.

Table 4. Coefficients from mixed-logit regression models predicting residential attainment.

	1		2		3		4		5		6	
Proportion White	1.29	1.15	0.28	3.62	0.58	1.26	0.87	1.31	2.46	2.10	1.25	1.23
Proportion White^2	-1.47	1.22	0.62	3.93	-1.21	1.38	-1.37	1.45	-3.25	2.45	-1.05	1.34
Proportion White * income			0.13	0.37								
Proportion White^2 * income			-0.24	0.40								
Proportion White * BA					4.25	2.44						
Proportion White^2 * BA					-2.37	2.43						
Proportion White * English home							1.79	1.81				
Proportion White^2 * English home							-0.82	1.92				
Proportion White * Not barrio home									-1.20	2.03		
Proportion White^2 * Not barrio home									1.84	2.40		
Proportion White * 3rd+ generation											-0.23	1.82
Proportion White^2 * 3rd + generation											-0.90	1.96
Proportion Latinx	3.94	1.25**	3.87	1.25**	3.89	1.28**	4.02	1.27**	3.68	1.31**	3.95	1.25**
Proportion Latinx^2	-2.20	1.17	-2.10	1.17	-2.18	1.20	-2.26	1.18	-1.92	1.25	-2.24	1.17
Distance (natural log of miles) $\bar{X}$	-1.23	0.04***	-1.23	0.04***	-1.24	0.04***	-1.23	0.04***	-1.23	0.04***	-1.23	0.04***
Distance (natural log of miles) S	0.51	0.08***	0.51	0.08***	0.53	0.08***	0.51	0.08***	0.51	0.08***	0.51	0.08***
Median family income	-0.06	0.08	-0.05	0.08	-0.08	0.08	-0.06	0.08	-0.06	0.08	-0.07	0.08
Median rent	0.05	0.07	0.05	0.07	0.05	0.07	0.05	0.07	0.05	0.07	0.05	0.07
Poverty rate	-2.80	1.17*	-2.55	1.24*	-3.22	1.20**	-2.81	1.18*	-2.68	1.18*	-2.95	1.17**
Number of housing units	0.65	0.07***	0.65	0.07***	0.65	0.07***	0.65	0.07***	0.64	0.07***	0.65	0.07***
Vacancy rate	0.33	3.56	0.20	3.56	0.58	3.57	0.44	3.56	0.85	3.56	0.15	3.57
Vacancy rate^2	-0.66	8.58	-0.50	8.56	-1.50	8.60	-0.81	8.57	-2.33	8.56	-0.53	8.57
Similarities												
Income to median rent	0.21	0.18	0.21	0.18	0.22	0.18	0.21	0.18	0.21	0.18	0.20	0.18
Income to median family income	0.27	0.18	0.32	0.20	0.24	0.18	0.28	0.18	0.27	0.18	0.27	0.18
School to neighborhood whiteness	1.51	0.46***	1.49	0.46***	1.30	0.46**	1.44	0.46**	1.49	0.46***	1.64	0.46***
Youth-adult neighborhood whiteness	1.01	0.46*	1.03	0.46*	1.13	0.47*	0.97	0.46*	0.98	0.48*	1.02	0.46*
-2 log liklihood	3386		3388		3396		3390		3387		3390	
Chi-square vs model 1			1.4		9.9**		3.6		0.6		3.3	

Note: ***, **, * indicate $p < 0.001$, .01, and .05 on two-tailed tests, respectively.

Table 6. The contribution of spatial assimilation to model fit with the addition of controls.

	Proportion Latinx and its square interacted with		
Variables in the model	Education	Language	Barrio
L	23.9***	27.32***	136.21***
LD	20.72***	6.15*	12.38***
LDW	19.95***	6.64*	12.41***
LDW$	23.08***	6.99*	11.85***
LDW$P	19.50***	2.77	0.45
	Proportion white and its square interacted with		
	Education	Language	Barrio
L	16.05***	25.85***	88.71***
LD	12.45**	8.12*	19.38***
LDH	11.47**	8.73*	14.78***
LDW$	14.30***	9.66**	14.04***
LDW$P	9.86**	3.56	0.63

L = limited model which controls for housing availability
D = natural log of distance (as a distribution)
W = proportion white and its square
H = proportion Latinx and its square
$ = variables about housing prices and income segregation
P = similarities predicted by perpetuation theory

Figure 1. Unidemensional and multidimensional approaches to modelling residential attainment.

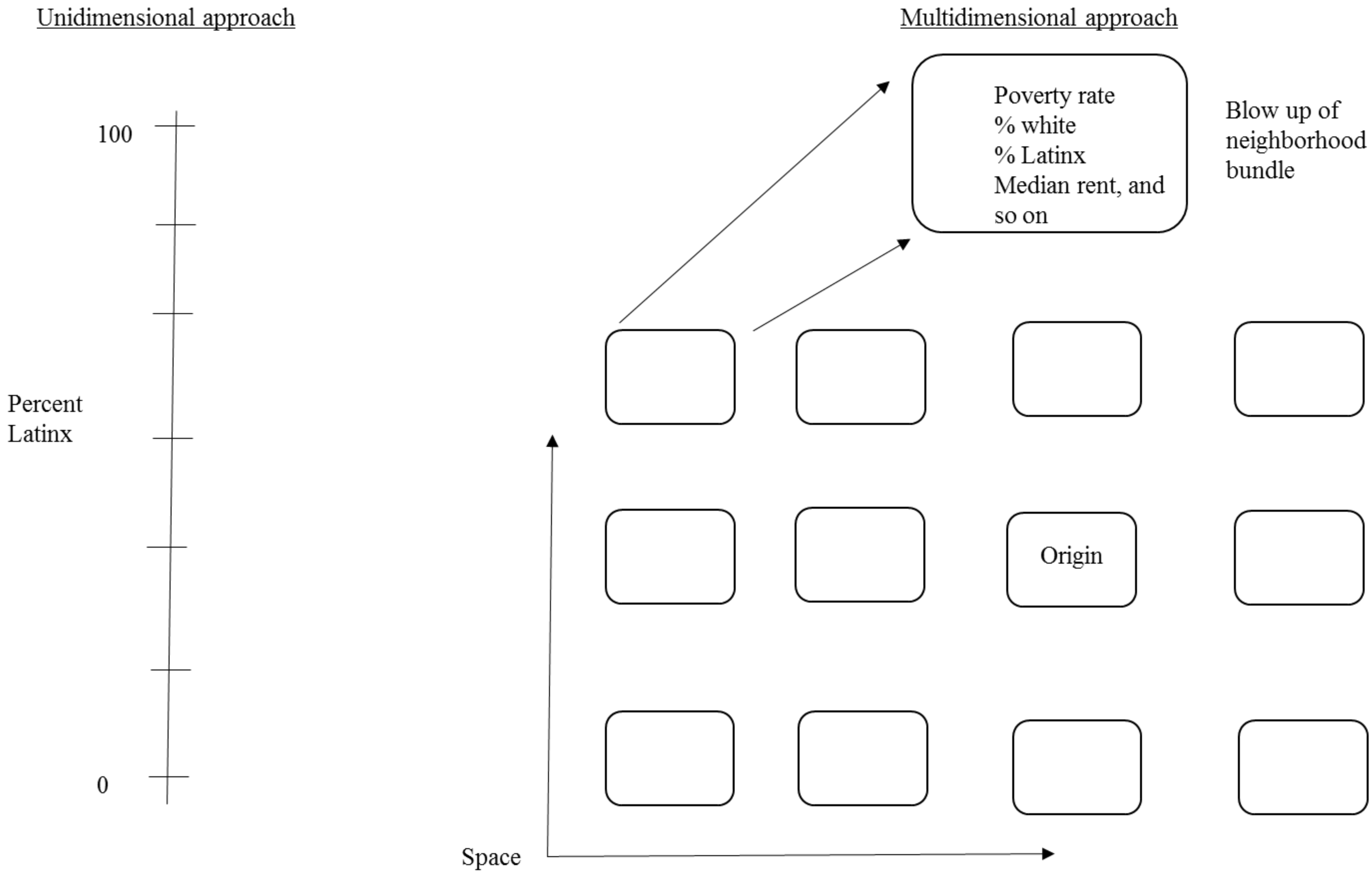
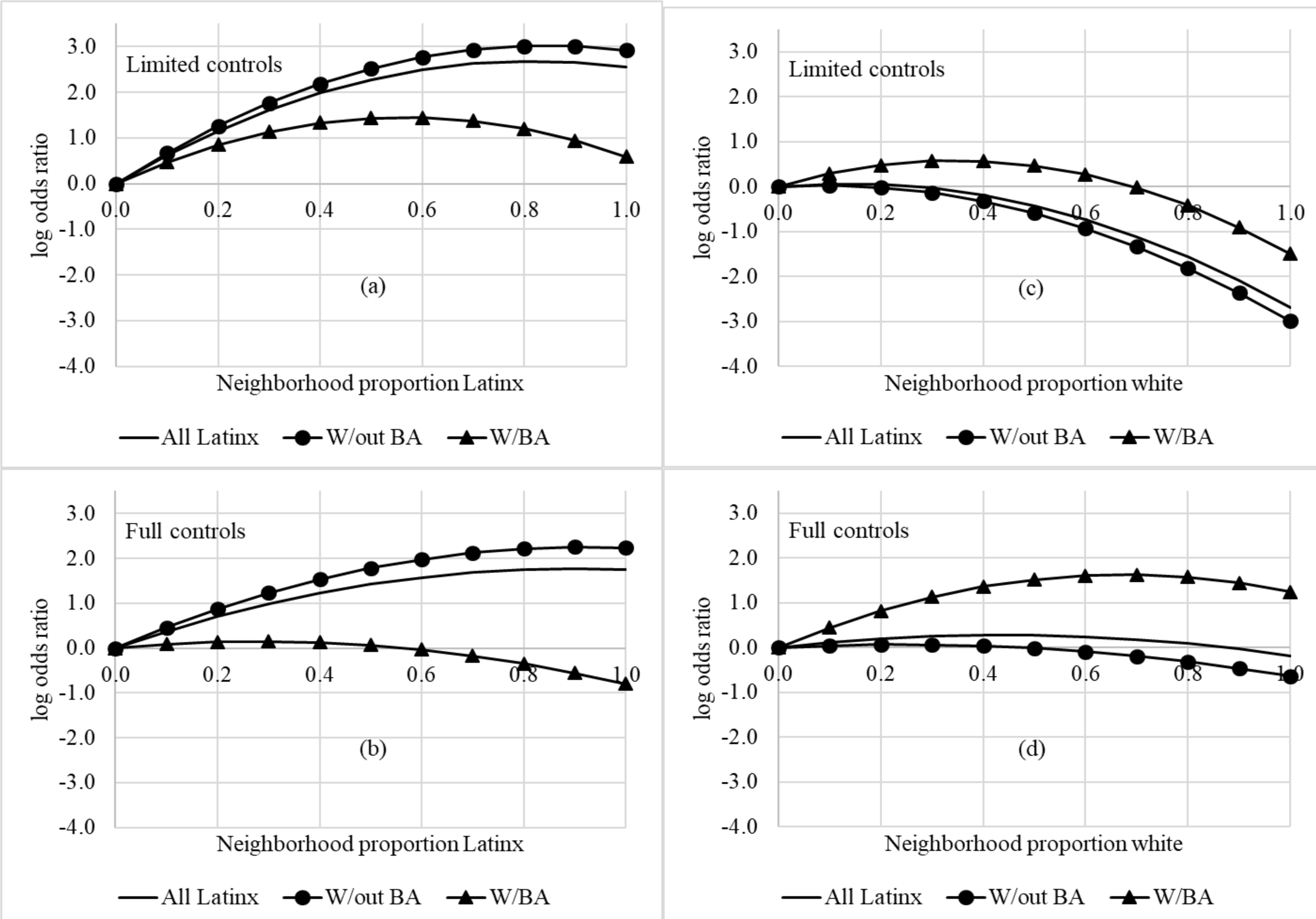


Figure 2. Latinx's relative odds of moving to a neighborhood.



Note: predicted values = $b_1 * L + b_2 * L * L$, where L = proportion Latinx or proportion white in neighborhood.