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Skill-Based Contextual Sorting: How Parental Cognition and Residential Mobility Produce Unequal Environments for Children

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Abstract

Highly skilled parents deploy distinct strategies to cultivate their children's development, but little is known about how parental cognitive skills interact with metropolitan opportunity structures and residential mobility to shape a major domain of inequality in children's lives—the neighborhood. We integrate multiple literatures to develop hypotheses on parental skill-based sorting by neighborhood income and school quality, which are then tested by analyzing an original follow-up of the Los Angeles Family and Neighborhood Survey. These data include over a decade's worth of residential histories for households with children that are linked to census, geographic information system, and educational measures. We construct a discrete choice model of neighborhood selection that accounts for heterogeneity among household types, incorporates the unique spatial structure of Los Angeles County, and includes a wide range of neighborhood factors. Our results show that parents' cognitive skills interact with neighborhood affluence to predict neighborhood selection after accounting for, and confirming, the expected influence of race, income, education, housing market conditions, and spatial proximity. Moreover, among middle and upper-class parents, cognitive skills predict sorting on K-12 school quality, specifically, rather than neighborhood status generally. We thus reveal skill-based contextual sorting as an overlooked driver of urban stratification.

Influential scholarship on socioeconomic stratification has increasingly emphasized the role of individual "skills" in shaping one's life chances. Cognitive skills, in particular, have been linked to income levels, education, occupational attainment, and criminal behavior, net of race and class background (Duncan and Magnuson 2011; Farkas 2003; Heckman and Mosso 2014; Heckman, Stixrud, and Urzua 2006; Jencks 1979). Combined with strong parent-child skill correlations (Anger and Heineck 2010; Sastry and Pebley 2010), this body of research has solidified cognitive skills as a key mechanism linking parents' and children's circumstances and fueled a burgeoning economic literature on the intergenerational process of skill development (Heckman 2006). Important sociological research has further illuminated this mechanism, documenting how highly-skilled parents' deployment of particular parenting tactics and investments enhance children's cognitive skill development, a process that has been characterized as "concerted cultivation" (Bianchi, Robinson, and Milke 2006; Lareau 2011; McLanahan 2004; Schneider, Hastings, and LaBriola 2018).

Parenting tactics constitute only one part of the intergenerational transmission of skills, however. The quality of children's environmental conditions—childcare, schools, and neighborhoods—is arguably just as important. Yet in contrast to parenting tactics, the link between parental skills and environmental selection is often treated as a background factor to be controlled, rather than as a sorting process worthy of direct examination. Existing studies on neighborhood and school sorting, for example, implicate parents' race and class characteristics and rarely disentangle the role of parents' cognitive skills from these correlated factors. But just as cognitively skilled parents more frequently engage their children in enrichment activities, we argue that cognitively skilled parents disproportionately sort their children into neighborhood, school, and child care environments with perceived skill-promoting features and higher status. Concretely, we propose that in an era of changing housing market and school enrollment dynamics, parents with higher cognitive skill levels are more likely to sort into the most desirable or high-status neighborhoods, even after accounting for the wide range of individual-level, household-level, and neighborhood-level characteristics emphasized in prior studies. Further, among middle/upper class parents, the highly skilled are more likely to sort not on neighborhood affluence, specifically, but on a correlated neighborhood amenity believed to shape children's skill development: K-12 school quality.

We test these ideas by linking a dozen years of residential histories from an original third-wave follow-up of the Los Angeles Family and Neighborhood Survey (L.A.FANS). Combined with census, geographic information system (GIS), and educational administrative data, we construct a discrete choice model of neighborhood selection that accounts for heterogeneity among household types, incorporates Los Angeles County's unique spatial structure, and includes a wide range of neighborhood factors, beyond race and class composition, notably K-12 school quality. We find that cognitive skills shape neighborhood selection within the context of a vast, complex, and rapidly evolving urban housing market. Analogous to the way that the concerted cultivation paradigm illuminates how parents' skills shape parenting tactics conducive to children's skill development, our model reveals how parental cognitive skills interact with opportunity structures to determine the quality of their children's residential environments and, in turn, their children's skill and socioeconomic trajectories. By linking research on demography, education, and neighborhood stratification processes, our study reveals *skill-based contextual sorting* as an overlooked driver of urban inequality and, in turn, the intergenerational transmission of status.

PARENTS' COGNITIVE SKILLS AND CHILDREN'S ENVIRONMENTS

Over the past two decades, scholarship on the mechanisms driving socioeconomic stratification has taken an analytic turn toward the intergenerational transmission of skill development. Skills encompass "capacities to act… [shaping] expectations, constraints, and information" (Heckman and Mosso 2014:691). The conceptual model connecting skills to socioeconomic inequality suggests:

cognitive, linguistic, social, and emotional skills shape individuals' socioeconomic outcomes; a dynamic interplay between genetic endowments, parenting tactics, and environmental conditions determines a child's degree of skill mastery; and skill acquisition occurs in a cumulative and complementary fashion, rendering early childhood experiences central to producing skill levels over the long term (Cunha and Heckman 2007; Heckman 2006). Studies have uncovered direct associations of cognitive skills – which can be conceived of as either "fluid intelligence" (i.e., individuals' rate of growth in learning) or "crystallized knowledge" (i.e., the amount of acquired knowledge, measured with standardized achievement tests) – with a growing set of social and economic outcomes, including income, educational attainment, teen pregnancy, smoking, and criminal behavior (Duncan and Magnuson 2011; Farkas 2003; Heckman et al. 2006; Kautz et al. 2014).

Combined with strong parent-child cognitive skill level correlations (Anger and Heineck 2010; Sastry and Pebley 2010), this body of research has identified cognitive skills as a key mechanism linking parents' and children's circumstances. Although controversial earlier studies implicated genetics in transmitting cognitive skills across generations (Herrnstein and Murray 1994), recent analyses suggest that two other channels play important roles: parents' (a) engagement in particular childrearing tactics and investments and (b) selection of environments (e.g., childcare, schools, neighborhoods) conducive to cognitive skill development. A rich body of work has probed channel (a), finding that more cognitively skilled parents tend to devote more time to child rearing, in general, and to child enrichment activities in particular. These activities, such as reading to and engaging in high-quality conversations with children, support learning and encourage exploration which in turn bolster their children's skill development—part of the process of concerted cultivation (Bianchi et al. 2006; Bornstein, Haynes, and Painter 1998; Lareau 2011; see also Heckman 2008; Heckman and Mosso 2014).

Scholars have much less frequently probed channel (b): whether and how parents' cognitive skills shape selection into various environmental contexts that influence children's skill development. Unlike parenting tactics, the environmental context input is often treated by skills scholars as "a statistical nuisance" (Sampson and Sharkey 2008: 1) to be controlled away, rather than as determined through a sociological sorting process worthy of direct examination. Recent analyses demonstrate the utility of using richer neighborhood selection models to clarify the size of and mechanisms underlying neighborhood effects on children's outcomes (e.g., van Ham, Boschman, and Vogel 2018). However, parents' cognitive skills and neighborhood features beyond their socio-demographics are not consistently incorporated in residential sorting analyses. As a result, our growing understanding of how parents' cognitive skills yield skills-promoting parenting tactics is not matched by a similarly deep knowledge of how parents' cognitive skills facilitate access to skills-promoting environments for children.

Skills and Neighborhood Attainment in an Evolving Housing Market

Although the connection between parents' cognitive skills and neighborhood sorting has received far less scrutiny among scholars than the link between cognitive skills and parenting tactics, demographic and urban sociological research has taken the neighborhood sorting process as its object of analysis and thus serves as a useful framework in illuminating the skills-neighborhood link. Just as the classic status attainment model predicts the payoffs and penalties of individuals' race, social origins, and lifecycle stage to their income or occupational prestige, neighborhood attainment models estimate the effects of similar individual- and household-level factors on neighborhood status, measured by race and/or class composition (e.g., Alba and Logan 1993; Logan and Alba 1993; Pais 2017; Sampson 2012; Sampson and Sharkey 2008; South et al. 2016; South, Crowder, and Pais 2011). These models' key assumptions are that all households aim to sort into the highest-status neighborhoods, typically perceived as the richest (e.g., Sampson and Sharkey 2008) and often whitest (e.g., South et al. 2011), they can and that their success in realizing this preference is contingent on the constraints imposed by their individual- and household-level characteristics and by the degree of race and class discrimination within the housing market (see Bruch and Mare 2012; Krysan and Crowder 2017; Quillian 2015).

This structural orientation has generated a vigorous debate on whether and why race- and class-based gaps in neighborhood socio-demographics remain after accounting for individuals' socioeconomic circumstances. Generally speaking, the spatial assimilation perspective attributes race and class disparities in neighborhood socio-demographics to group gaps in status attainment markers, such as wages, wealth, and educational attainment. Accounting for these individual- and household-level factors should substantially attenuate group differences in neighborhood socio-demographics (Massey and Denton 1985). The alternative perspective, place stratification, holds that sizable residual gaps in race and class groups' neighborhood socio-demographics will remain, net of the aforementioned factors. These residual gaps are commonly attributed to housing markets' discriminatory barriers manifested through real estate agent and broker steering, zoning regulations, or other institutional mechanisms (Logan and Molotch 1987; Trounstine 2018).

Cognitive skills rarely factor into empirical analyses informing this important debate. When they do, they tend to play a secondary role to race and class in explaining neighborhood outcomes. For example, the few neighborhood sorting studies that have incorporated measures of cognitive skills into their models (e.g., Sampson and Sharkey 2008; Sharkey 2008; South et al. 2016) typically treat skills as control variables that modestly diminish race- and class-based differences in neighborhood socio-demographic composition, and not as theoretically important predictors in their own right. This approach may reflect the assumption that the structural headwinds imposed by housing and labor markets render individuals' cognitive skills trivial factors in predicting neighborhood attainment outcomes; if they matter at all, it is likely indirectly, through income, education, and wealth effects.

However, the dynamics of skills in neighborhood sorting are largely unknown and the context of inequality is changing. Although persistently high levels of residential segregation underscore the enduring roles of race and class in stratifying housing markets, we argue that evolving opportunity structures amplify cognitive skills' role in leading individuals into the highest status neighborhoods they can afford. For example, large public housing developments that historically concentrated poor, minority households in the "inner city" have been demolished (Goetz 2011), and the ascendant federal housing strategy—Section 8 vouchers—theoretically empowers low-income households with more choices on where to live. Within the private sector, the real estate industry has shifted from predominately small-scale operations relying on word-of-mouth referrals and covering narrow submarkets—conditions that facilitated discrimination—to large agencies with broader market coverage that heavily utilize the internet for marketing and that increasingly partake in fair housing training and minority recruitment (Anderson, Lewis, and Springer 2000; Ross and Turner 2005).

There has been a simultaneous information explosion that has saturated urban housing markets and transformed how Americans navigate them (Zumpano, Johnson, and Anderson 2003). Cognitive processing is increasingly incentivized or rewarded, especially in sprawling and fragmented metropolises, a dynamic for which few neighborhood attainment studies have accounted. Given the advent of real-time, publicly available data on neighborhood quality and housing unit openings, the proliferation of digital tools facilitating connections with real estate brokers, financial institutions, and local authorities (e.g., public housing agencies), and the demonstrated link between cognitive skills and digital engagement (Tun and Lachman 2010), these skills arguably shape both the intensity of preferences for neighborhoods with "ideal" conditions and individuals' abilities to overcome myriad constraints to realize these preferences.

The information age not only expands the set of plausible neighborhood options available to city residents; it also renders the benefits of affluent neighborhoods more tangible by linking them to concrete environmental quality, school quality, crime, and housing value appreciation measures via websites like NeighborhoodScout and Redfin. Both of these dynamics are likely accentuated among those who more frequently, quickly, and efficiently process large amounts of often-complex information. Even if preferences for neighborhood affluence varied minimally by skill level, cognitive skills plausibly enable individuals to overcome constraints to accessing units within highly coveted communities. All else equal, higher-skilled individuals who consistently track housing market dynamics and housing unit availability may possess a more accurate and up-to-date understanding of neighborhood conditions, have less difficulty finding high-value deals, and enjoy a first-mover advantage in acquiring dwellings within higher-income neighborhoods – especially neighborhoods on the rise. They may also more deftly signal desirability as a potential tenant/buyer (e.g., through communication skills) and more efficiently navigate numerous institutional hurdles (e.g., filling out application forms, completing credit checks, acquiring references) (see also Özüekren and van Kempen 2002).

In short, we argue that while deeply stratified by race and class, contemporary housing markets increasingly reward information processing, amplifying the role of cognitive skills in shaping neighborhood attainment and reinforcing inequality. A concrete hypothesis follows:

Hypothesis 1: In contemporary housing markets, parents with higher levels of cognitive skills are more likely to sort into neighborhoods that are societally defined as desirable/affluent, even after accounting for parents' and neighborhoods' socio-demographic characteristics.

Social Class, Parents' Cognitive Skills, and the Quality of Children's Schools

By assuming a homogenous desire among households to optimize for neighborhood status, and by conceptualizing status primarily in socio-demographic terms, the traditional neighborhood attainment model does not distinguish whether cognitive skill effects reflect disproportionate sorting on the basis of (a) some vague notion of neighborhood desirability/quality, of (b) neighborhood race and/or class composition preferences specifically, or of (c) other correlated neighborhood amenities (e.g., school quality, crime levels, environmental quality) (Bruch and Mare 2012; Harris 1999; Quillian 2015). However, the literature on cognitive skills and parenting tactics has not only observed a correlation between the former and the latter; it has identified the particular cognitive skill types (e.g., verbal aptitude) associated with particular skills-promoting activities (e.g., high-quality conversational engagement) (e.g., Bornstein et al. 1998). Ideally, analyses of skills and neighborhoods would follow suit by identifying the particular neighborhood features upon which parents with high levels of certain skill types disproportionately sort.

Several scholars for example, have argued that a more realistic neighborhood choice framework would account for heterogeneity among various household types in their propensity to sort on neighborhood features, beyond race and class composition. While certain neighborhood features are likely valued among all households (e.g., aesthetic attractiveness, superior air quality, low crime), other amenities may be more salient to particular types of households than they are to others (e.g., school quality among parents with children or accessibility to employment hubs among working-age adults) (Goyette, Iceland, and Weininger 2014; Owens 2016; Rossi 1955). Even among households with similar sets of prioritized neighborhood amenities, the relative emphasis they place on each may meaningfully vary across subgroups. A more theoretically refined model of residential selection would account for this possibility by evaluating whether the observed sorting of certain types of households into higher (or lower) status neighborhoods may partially reflect differential tradeoffs made among neighborhood amenities that are correlated with, but conceptually distinct from, the community's socio-demographic composition.

In applying this framework to the cognitive skills-neighborhood connection, an important question emerges: which neighborhood amenities garner disproportionate priority by parental cognitive skill level? The concerted cultivation model of parenting might imply that middle/upper class parents optimize for neighborhood features they perceive to directly shape children's skill development. School quality, measured by school test scores, constitutes one such neighborhood feature. In fact, many studies suggest that highly-educated and middle/upper class parents use school test scores as proxies for neighborhoods' suitability for their children (e.g., Johnson 2006; Lareau and Goyette 2014). Further, the intensity of focus on school test scores likely varies within this group based on skills – a possibility not previously examined. We propose that among middle/upper class parents, more cognitively skilled parents calculate higher returns to investing in their children's developmental outcomes, particularly through residential access to high-quality schools. The most highly skilled within this group may also prioritize or give greater cultural weight to child-optimizing neighborhood amenities, such as schools, over other amenities that generate a lower long-term yield, such as housing stock characteristics. This orientation could reflect, in part, the understanding that higher levels of cognitive skill formation at earlier ages fosters an increased rate of growth in skills later on (Cunha, Heckman, and Schennach 2010).

Hypothesis 2: Among middle/upper class parents, those with higher cognitive skill levels are more likely to sort into neighborhoods with higher K-12 school test scores, even after accounting for parents' and neighborhoods' socio-demographic characteristics.

We test our theoretical framework by employing a novel dataset of Angelenos' residential histories spanning a dozen years. Los Angeles County is a theoretically important, but relatively underexplored, urban ecology that is spatially distinct from and more racially and ethnically diverse than geographies examined in prior residential mobility analyses (Sampson, Schachner, and Mare

2017). This race-ethnic diversity permits closer examination of neighborhood sorting patterns among two rapidly growing but less frequently studied groups: Latinos and Asians. We also take seriously L.A.'s unique spatial structure by incorporating a network-based measure of spatial proximity into our models and, following Bruch and Swait (2018), by constructing more realistic choice sets that oversample potential neighborhood options from meaningful sub regions.

Our individual-, household-, and neighborhood-level predictors, many of which are time-varying, are distinct relative to prior studies as well. This is one of the few neighborhood sorting studies that incorporates a well-validated measure of cognitive skills. Our neighborhood characteristics, drawn from census, GIS, and administrative sources, cover a wider range of features than most residential sorting analyses; beyond neighborhood socio-demographics, we include time-varying measures of housing market conditions and school quality. Lastly, our discrete choice framework is particularly well suited to capture heterogeneity in household subgroups' sorting patterns vis-a-vis multiple neighborhood features simultaneously and to incorporate information on realistic, rather than abstract, neighborhood options (Bruch and Mare 2012; Quillian 2015). In contrast to many similar studies, we model both movers and stayers in our discrete choice analyses, providing a more nuanced portrait of residential decisions (Bruch and Mare 2012; Sampson and Sharkey 2008). The timeframe of our data – 2001 through 2012 – provides further theoretical and analytic leverage, insofar as it captures an era of profound change in the region. Importantly, the data are captured directly before and directly after the exogenous shock of the Great Recession.

RESEARCH DESIGN AND MEASURES

This study is part of the Mixed Income Project (MIP)—a data collection effort aimed at examining neighborhood context, residential mobility, and income mixing in Los Angeles and Chicago. MIP evolved out of two anchor studies, L.A.FANS and the Project on Human Development in Chicago

Neighborhoods (PHDCN). L.A.FANS wave 1 data collection was conducted in 2000-2002, with a probability sample design that selected 65 Los Angeles County neighborhoods (census tracts). Within each tract, a sample of blocks was selected, and within selected blocks, a sample of households was selected. 3,085 households ultimately completed household rosters. Within each household, researchers attempted to interview one randomly selected adult (RSA) and, if present, one randomly selected child (RSC), the primary caregiver of the child (who could, or could not be, the RSA), and a randomly selected sibling of the RSC. In households with at least one child present, the RSC's mother was designated as the primary caregiver (PCG). If the RSC's mother did not reside within the household or could not answer questions about the child, the child's actual primary caregiver received the PCG designation. Ultimately, 1,957 PCGs completed a wave 1 interview, of whom 21 percent were white, 60 percent were Latino, 8 percent were black, and 7 percent were Asian American/Pacific Islander. The remainder were Native American or multiracial.

Follow-up interviews were conducted with wave 1 respondents between 2006 and 2008 (wave 2 response rate 63%) if they still resided within L.A. County, which constituted the clear majority of the sample (85%). Approximately 1,800 RSA and RSC respondents completed interviews during both waves of L.A.FANS, rendering them eligible for MIP between 2011-2013. After drawing a random probability sample from the eligible respondent list and excluding residents who left L.A. County, consistent with the LA.FANS design, or who were institutionalized, incapacitated, or deceased, 1,032 wave 3 interviews were completed for an overall response rate of 75 percent. Of this sample, 300 were PCGs at wave 1. Crucially, each wave of data collection not only updated a detailed battery of items from earlier waves but also tracked a continuous record of respondents' residential locations over the interim years, enabling residential histories spanning approximately 2000 through 2013. For more details on the L.A.FANS and integrated MIP—L.A.FANS designs, see Sampson et al. (2017) and (Sastry et al. 2006).

Because this study centers on skill-based residential sorting among parents, we examine neighborhood selection among respondents designated as PCGs (typically mothers) at wave 1, who were confirmed both to have completed a survey and to have resided within L.A. County at each of the three data collection efforts (i.e., 2000-2002, 2006-2008, and 2011-2013) and for whom cognitive skill measures and network distance calculations between their origin and potential destination neighborhoods were available. The specifications produce an analytic sample of 284 primary caregivers, most of whom have continuous census tract-coded residential history data (in 2000 boundaries) from 2001 through 2012. See Appendix – "Analytic Sample" for more details.

Neighborhood-level Measures

Our outcome of interest is a binary measure indicating whether a given census tract within a choice set of plausible options was selected by a given household in a given year (1 indicates the tract was selected, 0 indicates it was not). We predict this outcome as a function of neighborhood-level covariates and their interactions with both household- and individual-level characteristics. We include annual neighborhood-level measures of tract *median family income (logged)* and *racial composition* (% black, % Latino, % Asian), which are commonly employed by neighborhood attainment analyses as proxies for neighborhood status or desirability broadly defined.

To test our proposition regarding neighborhood sorting among middle/upper class parents, our other core neighborhood-level measure is an annual estimate of *K-12 school quality*. There is no straightforward, commonly accepted strategy for calculating neighborhood-level school quality estimates. Given our focus on how parental perceptions of neighborhoods shape their residential decisions, we start with the most widely publicized and parsimonious measure of school quality: average levels of achievement (i.e., test scores), which are publicly disclosed via the Internet and newspapers. We aggregate local schools' test scores up to the neighborhood level by overlaying county-provided school catchment boundaries from 2002 with 2000 census tract boundaries via a GIS spatial merge. We run this merge three times, for elementary, middle, and high school catchment boundaries separately, and then calculate a simple average of the three tract measures to create an aggregate neighborhood measure of school quality for each year between 2001 and 2012. Of course, some families opted to send their children to magnet, charter or private/parochial schools instead of the local public school within their catchment zone. However, approximately 90% of children included in the L.A.FANS panel sample attended traditional public schools at wave 1 or 2 of data collection, indicating that catchment school quality is directly salient to the vast majority of parent respondents.[1] See Appendix – "Operationalizing Neighborhood School Quality" for more details.

We employ several neighborhood-level controls. A binary variable indicates whether the selected tract in a given year is the same as the respondent's *origin tract*, i.e., the neighborhood of residence at t - 1 (1 indicates stayer in a given year, 0 indicates mover), enabling us to capture the residential decisions of both movers and stayers (see Bruch and Mare 2012). We interact this control with neighborhood school quality to test whether higher scores not only attract certain households to move in but dissuade certain households from moving out. We also track the *network distance* (i.e., road length in miles, rather than point-to-point distance) between neighborhood destination options and the origin tract using ArcGIS software, under the assumption that familiarity and networks shape residential choices (Krysan and Crowder 2017). Finally, we include more traditional neighborhood-level controls identified by prior residential mobility studies, including: *median housing value (logged)*, *owner occupancy rate (%)*, and *number of housing units (logged),* the latter of which proxies housing availability for potential movers (Bruch and Mare 2012; Spring et al. 2017). The

[1] Even among those parents who send their children to a non-public school, it is likely that school quality still matters through its impact on shared perceptions and reputations of neighborhood desirability, which influences housing price appreciation and sales potential.

neighborhood's share of adult residents with a *bachelor's degree or higher (%)* is included to account for the potential confounding effect of educational homophily on skill-based neighborhood sorting.[2],[3]

Parental Cognitive Skills and Individual/Household-level Measures

The primary individual-level characteristics of interest in this study are parents' cognitive skills, typically conceptualized in the skills and stratification literature as acquired knowledge (Heckman et al. 2006; Kautz et al. 2014). L.A.FANS collected skill measures only for PCGs and child respondents. We capture cognitive skills by using PCGs' wave 1 results from the Woodcock-Johnson *Passage Comprehension* assessment, conducted in either English or Spanish. The test captures individuals' ability to process written information, a theoretically important skill for evaluating neighborhood options. Test takers read short passages of increasing complexity and identify missing key words. Raw scores are converted into an age-based national percentile ranking. We convert these percentiles rankings into sample-based tercile rankings labeled "low", "medium," and "high", enabling nonlinear skill effects to be captured. We apply wave 1 data to all yearly estimates of PCGs' cognitive skill measures because the data are considerably more complete for this wave than others and because cognitive skills tend to stabilize in adulthood (Roberts, Walton, and Viechtbauer 2006;

[2] Yearly estimates for all ACS-derived tract-level variables are based on the middle year of each ACS timeframe (e.g., ACS 2005 – 2009 is used for 2007 estimates). To calculate these variables between 2001 and 2006, we linearly interpolate values from decennial census 2000 and ACS 2005-2009 data, given the gap in tract-level data availability between the two. Yearly estimates of median family income and median housing values are standardized to year 1999 dollars and then logged.

[3] Missing data rates for all yearly estimates of tract-level variables are trivial, except for network distance between origin and potential destination tracts (~1%), median housing value (log) (~2%), and school quality score (~7%). The latter two variables' missing values are imputed for each missing tract-year combination based on predicted values from a linear regression that includes tracts' housing, socioeconomic, and racial/ethnic characteristics. Core model results are robust to excluding imputed values.

Rönnlund, Sundström, and Nilsson 2015). It is important to note that passage comprehension scores are highly correlated with scores on Woodcock-Johnson tests of other cognitive skill types.[4]

We also include a time-varying dummy variable indicating whether the respondent has acquired a *bachelor's degree* or higher. In our pooled sample analyses testing Hypothesis #1, this control is interacted with tract educational attainment and tract income to determine whether these interactions confound skill-based sorting patterns. To test our argument linking skills to neighborhood school quality among middle/upper class parents, we stratify the sample by this time-varying educational attainment variable. The bifurcated sample enables us to compare skill-based heterogeneity in sorting patterns vis-à-vis particular neighborhood amenities (e.g., K-12 school quality) within and between middle/upper class and less advantaged parents (Hypothesis #2).[5]

We supplement these predictors of neighborhood sorting with commonly employed controls: *race-ethnicity* (i.e., a binary indicator for whether the respondent is white, black, Latino/Hispanic, or Asian/Pacific Islander) and *household income quintile*. The former is time-invariant, whereas the latter is annually interpolated based on estimates from each of the three data collection efforts, then standardized to year 1999 dollars and converted into a sample-based quintile ranking.

ANALYTIC STRATEGY

Our first research objective is to evaluate whether parents' cognitive skills interact with neighborhood contexts' desirability/status to produce neighborhood sorting outcomes. We then

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[4] Among L.A. FANS panel respondents who were children at wave 1 but aged into adulthood by wave 2 and retook Woodcock-Johnson tests at that time, passage comprehension percentile rankings correlate 0.8 with broad reasoning percentile; 0.7 with math reasoning and applied reasoning percentiles; and 0.6 with letter word identification percentile.

[5] Data are complete on all individual/household-level measures for the analytic sample except for household income (~15% is missing data for at least one of the three waves). We use the imputed wave 3 household income values calculated by Sampson et al. (2017), which employ a wide range of covariates, to estimate missing values. See the citation for additional detail.

examine an explanation of skill-based residential selection that links middle/upper class parents' skill levels to neighborhood school quality, specifically, rather than neighborhood status broadly. To these ends, we follow recent residential mobility analyses in employing discrete choice methods to model the neighborhood selection process (e.g., Bruch and Mare 2012; Bruch and Swait 2018; van Ham et al. 2018; Logan and Shin 2016; Quillian 2015; Spring et al. 2017). Discrete choice models conceptualize selection as a process in which individuals examine a specific set of available options and select one with characteristics that most closely match their preferences and constraints. Interactions between characteristics of the choosers and of the choice option reveal heterogeneity in preferences and/or constraints (a theoretically important distinction explored in more detail below) vis-à-vis particular item characteristics among subgroups.

The neighborhood choice or sorting outcome of interest here is the tract destination at time *t* – a binary outcome – which is modeled as a function of multiple neighborhood characteristics and the interaction of these neighborhood-level characteristics with individual-/household-level characteristics. The data structure consists of various person-period-tract options; tract options typically capture a sample of neighborhood choices the individual may have selected in a given period, including the tract actually chosen in that period, which is marked 1; all other choice set options are marked 0.

Consensus on two theoretically important features of the data structure remains elusive: (1) whether the choice set should include the tract chosen in the prior period (t-1) – i.e., the origin tract, or D_{ij} in Bruch and Mare (2012)'s parlance – and (2) how the neighborhood choice set should be conceptualized and constructed. Regarding (1), we include both stayers and movers in our analytic sample, using the binary origin tract indicator to indicate whether the household is mobile within a given year. As for (2), residential mobility studies typically conceptualize the choice set as every tract in a metropolitan area (Bruch and Mare 2012; van Ham et al. 2018; Quillian 2015; Spring et al. 2017), but due to computational intensity limitations, theoretical considerations, and empirical evidence, we opt for a different tack. We assign all county tracts to one of eight geographic regions – Central Los Angeles, San Fernando Valley, San Gabriel Valley, Gateway Cities, South Bay, Westside Cities, Santa Clarita Valley, and Antelope Valley – which, based on our analysis, tend to retain high proportions of residents over time (see Figure 1). We then use these regions to shape respondents' choice sets, a strategy similar to that employed by Bruch and Swait (2018) who examine "cognitively plausible" neighborhood choices among Angelenos. For each person-year combination we construct a circumscribed choice set of tract options, consisting of the tract selected; the person's tract of residence during the prior year (i.e., the origin tract, which may or may not be the same as the tract selected); and 49 to 50 randomly-sampled tracts, about half of which are drawn from the respondent's county region of residence in the prior year, and about half from the entire county as a whole. This sampling structure produces a choice set of 50 to 51 tracts for all 3,317 person-periods with valid residential mobility data among our analytic sample of 284 unique primary caregivers, yielding a core analytic sample of 168,692 person-period-tract alternatives. For further details on our procedures and underlying rationales, see Appendix – "Modeling the Choice Set."

Figure 1 about here

We follow Quillian (2015) in characterizing how this data structure translates into a formal discrete choice model of neighborhood selection, which consists of two core components. The first, Equation 1, estimates U_{ijt}, which represents neighborhood *j*'s attractiveness to individual *i*, in year *t*: If we consider just two household characteristics (X_{1}, X_2) and two neighborhood features (Z_1, Z_2), and assume a probability distribution of the unobserved neighborhood characteristics influencing attractiveness, then the neighborhood attractiveness model's nonrandom portion is represented by:

(1) $U_{ijt} = \beta_1 Z_{1it} + \beta_2 Z_{2it} + \delta_{11} Z_{1it} X_{1it} + \delta_{11} Z_{1it} X_{1it} + \delta_{21} Z_{2it} X_{1it} + \delta_{12} Z_{1it} X_{2it} + \delta_{22} Z_{2it},$

where β_k represents the attractiveness of neighborhood *j*'s characteristic *k* at time *t* (Z_{kjt}) and δ_{km} represents the interaction effect of neighborhood *j*'s characteristic *k* at time *t* and individual *i*'s characteristic *m* (X_{mit}) on neighborhood attractiveness at time *t*.[6] Note that individuals' characteristics only influence neighborhood attractiveness through their interactions with neighborhood features. Assuming the errors follow an extreme value (Gumbel) distribution, a discrete choice conditional logit model generates a predicted probability of individual *i* selecting neighborhood *j* at time *t* (Equation 2):

$$\textbf{(2)}\ \ p_{ijt}\left(Z_{kjt}\,, X_{mit}, C_{(i)}\right) = \frac{\exp(\widehat{U}_{ijt} - q_{ijt})}{\sum_{w=1}^{C(i)} \exp\,(\widehat{U}_{ijt} - q_{iwt})}$$

$C_{(i)}$ represents the neighborhood choice set for individual *i*, and w is an index used to sum over elements of this set for the *i*th individual. We follow prior analyses in incorporating an offset term, q_{ijt} , into our models in order to differentially weight tract options based on the probability of the tract entering the circumscribed choice set for a given person-year via the sampling procedures described above (see Appendix – "Modeling the Choice Set" for more detail).

The model applies maximum likelihood procedures to generate a predicted probability that each neighborhood within the individual's choice set will be selected based on a set of estimated coefficients (described in Equation 1) indicating neighborhood characteristics' positive or negative effects on a neighborhood's attractiveness (main effects) and whether these effects are strengthened or attenuated by the individual or household's characteristics (interaction effects). We convert these coefficients into odds ratios to facilitate interpretation. Odds ratios above 1 indicate the neighborhood characteristic increases the likelihood of residence either on its own or through an interaction with an individual/household characteristic; odds ratios below 1 indicate a depressive

[6] We use the term "effect" here and throughout to remain consistent with the language typically employed in the discrete choice literature, but we recognize the limitations of our data and empirical strategy in identifying causal parameters.

effect on this probability. We discuss a common concern regarding the accuracy and interpretation of conditional logit models' results in the Appendix – "The Independence of Irrelevant Alternatives."

DESCRIPIVE RESULTS

Table 1A, which presents descriptive statistics for all individual and household variables, reveals that whites and Latinos dominate our sample's race-ethnic distribution; the groups constitute 28 and 47 percent of the analytic sample, respectively, while Asians make up 13 percent and blacks are 9 percent of the sample. This variation provides sufficient coverage to examine sorting patterns among all four major race-ethnic groups, a key benefit compared to data sources used for prior neighborhood sorting analyses. The cognitive skills categorical classification indicates a low skew compared to the national distribution of passage comprehension scores: the sample's middle tercile spans national percentile ranks 10 – 30.

A simple correlation matrix (Table 1B) presents unconditional associations between primary caregivers' individual- and household-level attributes measured at baseline and operationalized in continuous, rather than categorical, terms for passage comprehension and household income to maximize specificity. One might expect classic indicators of adult socioeconomic attainment – household income and bachelor's degree – to strongly correlate with cognitive skill levels, indicating skill effects on neighborhood outcomes are likely absorbed by socioeconomic effects. In fact, this is not the case. Passage comprehension score (measured in continuous terms) is only correlated about 0.30 with household income (logged) and 0.38 with bachelor's degree attainment (all measured at baseline), suggesting that substantial variation in skill levels exists even among parents with similar educational attainment levels or household incomes.

Table 1 about here

Attributes of chosen and nonchosen tracts, presented in Table 2A, suggest that residential mobility is relatively rare in this sample. On average, 94 percent of the sample remained within their origin tract during a given year. Also note that chosen neighborhoods' race/ethnic distribution closely mirrors that of our primary caregiver analytic sample and confirms L.A. County's distinctiveness relative to the rest of the country. The high average share of Latino residents, which exceeds 50 percent, is striking. The Asian share is also elevated in L.A. compared to elsewhere, averaging about 13 percent. Whites and blacks constitute an average of about 28 and 7 percent of selected neighborhoods' residents, respectively.

Tables 2B and 2C present unconditional associations between individual/household- and chosen tract-level attributes, as well as chosen tract-level attributes associations with each other, providing preliminary clues about the skills-neighborhood link. Comparing the correlation between cognitive skills and *neighborhood*, rather than *household*, socioeconomic characteristics reveals the possibility that cognitive skills affect neighborhood outcomes directly and that these skills are even more salient to neighborhood attainment than they are to socioeconomic attainment, a previously unexamined possibility. Passage comprehension scores are correlated 0.43 with time-varying neighborhood income levels, but only 0.30 with baseline household income levels.

We might further expect, based on the neighborhood attainment literature, that chosen neighborhoods' income levels and other socio-demographic properties sufficiently capture the differential appeal of neighborhoods to households. Tract-level associations within our sample confirm that neighborhood socio-demographics are strongly related to neighborhood school quality, as we would expect (e.g., De la Roca et al. 2014). However, the correlations are not sufficiently high to preclude disentangling each factor's role in attracting households based on skills. For example, tract school quality is correlated 0.54 with tract median housing value (logged) and 0.62 with median family income (logged) when accounting for all selected neighborhoods and all years of data. Tract school quality is associated -0.57 with proportion Latino, 0.56 with proportion white, -0.29 with proportion black, and 0.33 with proportion Asian.

Table 2 about here

DISCRETE CHOICE MODELS

We begin our core analyses in Table 3 with baseline Model 1 that reflects a structural conceptualization of neighborhood selection congruent with previous neighborhood attainment studies (e.g., Bruch and Mare 2012; Quillian 2015; Spring et al. 2017). Our predictors of interest are interaction terms capturing racial homophily for all four major race/ethnic groups (e.g., tract % white and individual white dummy variable), educational homophily (tract % bachelor's degree or higher and individual bachelor-degree holder), and income-based sorting (tract median family income logged and household income quintile). We expect these interaction terms to be significant and substantively large. We also include neighborhood-level controls, including: the origin tract indicator; network-based spatial proximity between the origin tract and choice set options; housing availability and pricing; homeownership rate; racial composition; educational attainment; and median family income (logged).

As expected, households are far more likely than not to remain in place in a given year (OR = 14381.97 $p < .01$). When they do move, network distance is important; the further the neighborhood option is from the origin neighborhood, the less likely it is to be selected (OR = 0.80, $p < .01$). Also congruent with prior work, neighborhoods with more housing units increase the likelihood of selection (OR = 2.87, $p < .01$).

Table 3 about here

The odds ratios on individual/household-level and neighborhood-level interaction terms generated by this model also largely confirm prior neighborhood attainment analyses on a national scale (e.g., Quillian 2015) and of L.A. County during a shorter time period (Bruch and Mare 2012). In terms of class sorting patterns, the interactions of household income quintiles and neighborhood income (log) are all significant, and the odds ratios increase at higher quintiles. Educational homophily is also evident (OR = 1.02, $p < 0.05$). As for race-ethnic sorting, groups traditionally perceived as lower status show clearer patterns of racial homophily than do higher-status groups. Both black and Latino parents are more likely to sort into neighborhoods with higher proportions of own-race residents. Interestingly, white and Asian parents do not exhibit similarly significant race-ethnic homophily patterns within this sample. The surprising lack of evidence for white homophily may reflect both whites' reduced moving propensity compared to all other groups and the county's race-ethnic composition changes during the timeframe in question.[7]

Cognitive Skill Based Neighborhood Income Sorting

After accounting for structural sorting patterns, is there evidence that parents' cognitive skills also shape neighborhood attainment? Indeed there is, especially at the top end of the skills distribution. Model 2 in Table 3 preserves all covariates from Model 1 but adds interaction terms capturing heterogeneous sorting on neighborhood income (logged) by passage comprehension tercile and a control interacting neighborhood affluence and bachelor's degree attainment. Including these additional interactions leaves the significance and direction of Model 1's coefficients largely intact. Although the educational homophily interaction term becomes non-significant, its magnitude is consistent. Most importantly, the top tercile passage comprehension-tract affluence interaction term (OR = 3.04, $p < 0.01$) is strongly significant, net of race-, class-, and education-based sorting patterns. Also note that the household income and neighborhood income interaction terms barely

[7] Whites constituted 32 percent of census tract residents, on average, in 2001, but only 28 percent by 2012. Within the residential tracts of our analytic sample's white respondents, the drop was even more precipitous during the same period: from 53 to 43 percent.

change when compared to the previous model. To the extent that skills shape neighborhood income sorting, they operate largely independently of income-based sorting. This finding supports Hypothesis #1: parents' cognitive skills influence neighborhood attainment processes independent of race- and class-based sorting.

Hypothesis #1 is reinforced by falsification and robustness checks. Using an identical model specification to Model 2 in Table 3, the parental skills-neighborhood status link is *not* significant among parents who still reside with their own parents as of wave 1 data collection and among parents who no longer have children (i.e., residents under 18) in their household by wave 2. However, among parents whose households contain young children (i.e., under 10) in both waves 1 and 2, the skill-neighborhood income interactions are considerably higher in magnitude than they are for the overall analytic sample and significant for both middle and top skill terciles, indicating that neighborhood conditions may be particularly salient to highly skilled parents of *young* children (see Goyette et al. 2014). The top skill tercile interaction with neighborhood income is significant in a movers-only model, as well.[8]

We illustrate the magnitude of the effects of cognitive skills and neighborhood affluence for the core analytic sample (Model 2, Table 3) by stratifying top and bottom skill tercile parents and comparing each subgroup's (a) predicted conditional probability of residing within tracts at various points in the neighborhood affluence distribution to (b) the probability of selecting that tract randomly from their choice sets. Higher ratios indicate a disproportionate likelihood of selecting a certain tract type over other options (see Logan and Shin 2016 for more detail on this type of

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[8] Additional robustness check models included: interactions for individual race and tract income (logged) (see Quillian 2015), age and tract income (logged), origin tract and household income, and origin tract and skills; operationalizations of household income and parents' cognitive skill scores in continuous, rather than categorical, terms; and comparison of results before and after the Great Recession. Results for all models are not substantively changed compared to Model 2 (Table 3). Output for all falsification and robustness checks is available upon request.

simulation). Figure 2 reveals that this ratio varies markedly across neighborhood affluence quintiles based on the respondent's skill tercile. For top tercile respondents, the probability ratio is about 0.5 – 0.7 for the two lowest neighborhood affluence quintiles; high scorers are just over half as likely to select a lower-income tract as they are to select any given tract in their choice set, all else equal. This ratio approaches 1 when the middle affluence quintile is considered and then ascends toward 1.5 between the fourth and fifth quintiles, indicating this group is nearly 50 percent more likely to select a tract within the most affluent quintile as they are to select any given tract in their choice set. On the other hand, bottom-tercile parents are much more likely to select a neighborhood within the two lowest affluence quintiles and much less likely to select a neighborhood within the two highest affluence quintiles than they are to select a random tract within their choice set.[9]

Figure 2 about here

Skill-Based Preferences or Constraints?

We now evaluate our account of skills and neighborhood sorting, derived from a modified concerted cultivation model, suggesting that among middle/upper class parents, cognitive skills are associated with sorting on K-12 school quality, specifically, rather than neighborhood status generally. Model 1 in Table 4 employs the same model described in the previous paragraph but specifies the sample to only include bachelor-degree holders during the period in question and removes bachelor-degree interactions with neighborhood traits. We then interact neighborhood school quality with parents' cognitive skill tercile, as well as with household income quintile and

[9] Large relative differences in predicted versus random selection probabilities at various points in the neighborhood affluence distributions reflect small absolute differences in predicted probabilities of selecting a particular neighborhood from an individual's choice set. This pattern reflects the tendency of residents to remain in place—another dimension of how inequality is reproduced (Sampson and Sharkey 2008). Yet we know from simulation models that even small group-based divergences in propensities to move and in where to move to can generate major group-based disparities at the population level (Bruch and Mare 2006; Schelling 1971).

origin tract as controls. Based on the concerted cultivation literature we expect neighborhood school quality to shape residential decision-making within this advantaged group. Model 1 confirms this expectation. Not only is the interaction between origin tract and school quality positive and significant (OR = 1.01, $p < 0.05$), suggesting that middle/upper class parents are less likely to move out of a neighborhood if local test scores are higher. More central to Hypothesis #2, advantaged parents within both the top and middle cognitive skill terciles are more likely to sort into neighborhoods with higher-quality schools (ORs = 1.02, $p < 0.05$).[10] Significant skills-school quality interaction terms are replicated in a similar model specification that applies a broader definition of middle/upper class: whether the parent holds a bachelor degree *or* is part of a household at the top two quintiles of the income distribution.

As a falsification check, we confirm that the same patterns do not apply to less advantaged parents. Using an identical model specification as Model 1 in Table 4 but only including those *without* a bachelor's degree in a given time period, origin tract-neighborhood school quality and cognitive skill-neighborhood school quality sorting links are not significant, though the interaction between top skills tercile and neighborhood income is positive, significant, and similar in magnitude (Model 2, Table 4: OR = 2.92, $p < 0.01$), as it was for the full analytic sample.[11],[12]

Table 4 about here

[10] Parents plausibly use schools' socio-demographic properties, rather than standardized test scores, to infer school quality, given the well-established link between race, class, and achievement test scores (Rich 2018). Because we link school quality to neighborhoods and our models control for sorting on neighborhood racial and economic status, we partially account for this possibility, though future research probing this concern is necessary.

[11] Additional falsification checks leveraging differences *within* the advantaged parent group are precluded due to the small size of the bachelor's degree or higher subsample.

[12] Applying the same model specification to the full analytic sample confirms significant interactions between parents' cognitive skills and tract income but not between parents' cognitive skills and tract school quality. This is the expected result, given that only about a fifth of the pooled sample is a bachelor's degree holder within a given year. Model output is available upon request.

The aforementioned results obscure a theoretically important distinction. Does the observed skills-neighborhood school quality link among middle/upper class parents primarily reflect skill-based variation in *preferences* for neighborhoods with high-quality schools or skill-based variation in *constraints* to accessing these neighborhoods? As we alluded to above, the preferences account implies that more highly skilled middle/upper class parents prioritize or give greater cultural weight to child-optimizing neighborhood amenities, such as schools, compared to other neighborhood features than do the less cognitive skilled. In contrast, the constraints account suggests middle/upper class parents of all skill levels may exhibit comparable preferences for neighborhoods with high-quality schools, but the highly skilled are more adept at overcoming informational barriers to accessing them. Access requires determining elementary, middle, and high school catchment zones and identifying and interpreting informational resources that contain objective quality metrics, which are rarely constructed at the neighborhood level by educational authorities. Less-cognitively skilled middle/upper class parents may be more inclined to infer school quality from correlated proxies, such as neighborhood and school socio-demographic composition, or to rely on word-of-mouth (see Favero and Meier 2013; Lareau and Goyette 2014; Rich and Jennings 2015 for more in-depth discussions of how parents evaluate school quality).

Unfortunately, our discrete choice models cannot cleanly disentangle the relative roles played by differential prioritization of, versus accessibility constraints to, neighborhoods with high-quality schools on the basis of skills (see Quillian 2015 for a discussion of the preferences versus constraints concern as it applies to residential sorting). Although our read of the concerted cultivation literature leads us to believe that skill-based preferences rather than constraints predominate in neighborhood selection among middle/upper class parents, to our knowledge, no existing data provide a definitive resolution.

Thus, we opt to exploit descriptive data bearing on this question. Figure 3A reveals the proportion of a subsample of L.A.FANS panel primary caregivers (i.e., those who participated in waves 1 and 2 of data collection, regardless of MIP participation, and who moved residences within the prior five years) reporting in wave 1 that proximity to better schools was a driver of their neighborhood choice. Congruent with the concerted cultivation literature, middle/upper class parents are measurably more likely, overall, to report access to better schools for their kids as a mobility driver than are other parents. How do skills factor in? The cognitive-skill based gradient in these proportions is noticeably steeper among middle/upper class parents than it is among other parents. Top tercile parents with bachelor's degrees are about twice as likely to cite school quality as a mobility driver as bottom and middle tercile parents with bachelor's degree when pooled together; the analogous ratio is lower among less educated parents. This finding reinforces the discrete choice model results indicating the skills-neighborhood school quality link is significant among middle/upper class parents and not among other parents. We can tentatively infer that the link primarily reflects heterogeneity in neighborhood amenity preferences rather than constraints based on skills among advantaged parents. This intuition is strengthened by the finding that average school quality scores of the chosen tract at baseline are similarly high for parents who report better schools as a driver of residential mobility, *regardless of their class status*. If constraints, rather than preferences, differed based on skills, we would expect average scores to diverge along class lines – given class differences in skill levels – even among those with similar stated preferences. The results therefore suggest a preference-based interpretation.

DISCUSSION & CONCLUSION

The centrality of parental skills to recent socioeconomic stratification research has fueled a burgeoning literature on the intergenerational process of skill development. That literature highlights the role of parenting tactics but not contextual selection. Although a rich literature spanning demography and urban sociology takes contextual selection as its object of analysis, its structural orientation has deflected a deep examination of cognitive skills' role in shaping these processes. We believe cognitive processes meaningfully contribute to the intergenerational transmission of context. Neighborhoods shaped parents' skill development as children and these skill levels predict their own children's neighborhood conditions. Evolving housing market dynamics and school choice systems may amplify parental cognitive skills' roles in neighborhood sorting, rendering the connection between the two worthy of study.

To assess this framework, we compile over a decade's worth of data on Angelenos' socio-demographic characteristics, cognitive skills, residential histories, as well as census, GIS, and administrative data on L.A. County neighborhoods' spatial locations, housing markets, socio-demographics, and school quality. Applying discrete choice models to the neighborhood attainment framework, we first show that cognitive skills interact with evolving opportunity structures to independently shape neighborhood selection. Parents' passage comprehension scores interact with neighborhood affluence to positively predict neighborhood selection, even after accounting for, and confirming, the key roles played by race and class, educational background, housing market conditions, and spatial proximity. Among middle/upper class parents, the results show that cognitive skills are associated with sorting on K-12 school quality, specifically, rather than neighborhood status generally, net of interactions between skills and neighborhood affluence and a wide range of individual-, household- and neighborhood-level controls. Moreover, we have offered plausible evidence that differential preferences rather than constraints vis-à-vis neighborhood school quality by cognitive skills among middle/upper class parents drive this pattern.

Overall, then, the results suggest that neighborhood sorting occurs not only the basis of race and class but also on the basis of cognitive skills, a mechanism we call *skill-based contextual sorting*.

This model has important implications for the urban stratification and intergenerational transmission of skills literatures. As Krysan and Crowder (2017) argue, the urban stratification literature's structural orientation, which primarily implicates economic resources, racial residential preferences, and housing discrimination, may obscure key processes underlying the observed propensity of advantaged households to sort into advantaged neighborhoods. Race and class continue to profoundly shape housing markets, but their firm grip may be slowly weakening, and the roles played by information and networks are undoubtedly expanding; these dynamics could plausibly open the door to skill-based stratification. Moreover, the perceived neighborhood status hierarchy may no longer be determined solely based on race and class composition, particularly within multiethnic metropolises and among middle/upper class parents seeking to give their children a leg up in a competitive knowledge economy. It follows that salient institutional factors, such as perceived K-12 school quality and desirable childcare options, may supplement socio-demographic composition in shaping parents' neighborhood sorting patterns. Future urban stratification research should continue examining these possibilities.

The intergenerational transmission of skills literature, for its part, should supplement its focus on parenting tactics with a deeper analysis of how skills shape, and are shaped by, environmental conditions to which children are exposed. The neighborhood appears to be an important domain for skills development, but contextual sorting vis-à-vis other domains (e.g., childcare, K-12 schools) are also likely salient. Skills scholars should contemplate and examine what features of these other environmental domains interact with what parental skills to produce sorting.

We acknowledge the limitations of our study. While expansive, L.A.FANS encompasses a relatively small group of parents within one urban ecology during one temporal era. Broader generalizability will require replicating our analyses using a larger sample, encompassing more diverse household structures and lifecycle phases, a broader geographic area, and a longer time period. Exogenous shocks to neighborhood incomes and amenities and data on charter, magnet, and private school options could prove useful. Deeper theorizing is also required to determine what additional skills (e.g., noncognitive or socioemotional capacities) and neighborhood features (e.g., environmental toxicity, crime levels) should be incorporated into ever richer neighborhood sorting models. Continuous refinement of these sorting processes promises to improve non-experimental estimates of neighborhood effects on children's outcomes (van Ham et al. 2018) and clarify the mechanisms linking parents' and children's circumstances.

Another limitation is that our dataset and empirical strategy cannot definitively resolve whether sorting patterns reflect skill-based differences in preferences for and/or constraints to neighborhood characteristics. The challenge of disentangling preferences from constraints is endemic to all research on complex decision-making processes. However, analyses that stratify respondents based not only on race and class but also on skills and combine stated preferences (perhaps neighborhood vignettes) with revealed preferences (assessed in residential mobility histories) may provide leverage. Additional qualitative research that closely documents both how the contemporary residential search unfolds and how cognitive skills factor into the process is also necessary. Moreover, like Bruch and Swait (2018), we customize choice sets on the basis of their geographic region within L.A. County, but explicitly modeling *skill*-based differences in "cognitively plausible" neighborhood choice sets constitutes a promising avenue for future research, given that it is congruent with theories of how skills matter (Heckman and Mosso 2014) and is testable via the theoretical and empirical frameworks developed by Bruch and Swait (2018) in examining race and class differences in neighborhood choice sets.

Our results are nonetheless robust in identifying skill-based contextual sorting as an emerging axis along which urban inequality is unfolding. This development is important to explore, especially in an era of liberalized, choice-oriented urban policy marked by school choice regimes and housing voucher programs. Enabling individuals to make unconstrained residential and school-enrollment decisions in such an era, while intended to equalize contextual conditions and socioeconomic outcomes across race and class lines, could well amplify skill-based stratification instead.

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TABLE 1

Descriptive Statistics and Correlations:

LA FANS-MIP Longitudinal Study, Primary Caregivers (N = 284)

A. Person-level attributes (measured at baseline)

Variable	Mean	S.D.	Min	Max
Race/ethnicity				
White	0.28	0.45	0	1
Latino	0.47	0.50	0	1
African-American/Black	0.09	0.28	0	1
Asian/Pacific Islander	0.13	0.34	0	1
Other	0.03	0.18	0	1
Socioeconomic Status/Education				
Household income (1999 constant $)				
< $16,000	0.18	0.39	0	1
$16,000 – 27,999	0.21	0.41	0	1
$28,000 – 41,999	0.21	0.41	0	1
$42,000 – $65,999	0.20	0.40	0	1
$66,000+	0.20	0.40	0	1
Bachelor's degree or higher	0.19	0.39	0	1
Cognitive Skills				
W-J Passage Comp. national rank				
< 10 percentile	.34	0.47	0	1
10 – 30 percentile	.34	0.47	0	1
> 30 percentile	.32	0.47	0	1

B. Correlation matrix of person-level attributes (measured at baseline)

	Passage comprehension	Household income (log)	Bachelor's degree +
Passage comprehension	*	0.3032	0.3811
Household income (log)	0.3032	*	0.3788
Bachelor's degree +	0.3811	0.3788	*
White	0.3491	0.1769	0.1362
Latino	-0.2545	-0.3392	-0.3019
African-American/Black	-0.0098	0.0335	0.0020
Asian/Pacific Islander	-0.1388	0.2018	0.2479

Notes

[a] Means are weighted, reflective of all nonmissing observations, and measured at wave 1. Baseline values of bachelor's degree or higher and household income (log) represent educational attainment and estimated annual income for the earliest year available, usually 2000 or 2001. Age is calculated as of January 1, 2001 and ranges from 19 to 67 at baseline, with a mean of 35 years old.

[b] Correlation values capture weighted unconditional correlations based on continuous rather than categorical values of observations without missing data and/or with imputed data on the two variables in question. However, correlation values are similar when categorical values of passage comprehension and household income variables are applied (results available upon request).

TABLE 2

Descriptive Statistics and Correlations: Time-Varying Person and Tract Attributes

A. Person-year-tract attributes (time-varying)

	Chosen Tracts		Nonchosen Tracts	
Variable	Mean	S.D.	Mean	S.D.
Origin tract	0.94	0.24	0.001	0.04
Network distance from origin (mi)	0.41	2.60	19.19	16.60
# housing units (log)	7.55	0.39	7.27	0.61
Median family income (log)	10.69	0.45	10.73	0.50
Median housing value (log)	12.52	0.45	12.59	0.46
% Owner-occupied	52.02	24.06	51.06	26.51
% White (ref)	27.74	24.70	30.10	27.20
% Black	6.85	8.79	8.83	14.24
% Latino	50.12	28.04	45.99	29.28
% Asian	12.75	13.03	12.40	15.13
School quality score	701.39	89.13	699.13	94.35
% Bachelor's degree or higher	22.86	17.72	25.35	19.31
N (person-year-tracts)	3,317		165,645	

B. Correlation matrix of person, person-year, and chosen tract attributes, *N* = 3,317

Person and Person-Year Attributes	Tract Median Family Income (log)	Tract School Quality Score
Passage comprehension	0.4345	0.3096
Household income (log) (time-varying)	0.6114	0.4350
Bachelor's degree (time-varying)	0.3605	0.2989
White	0.3785	0.2603
Latino	-0.4286	-0.3419
African-American/Black	-0.1110	-0.0932
Asian/Pacific Islander	0.2313	0.2194

C. Correlation matrix of chosen tract attributes (time-varying), *N* = 3,317

Tract Variables	Tract Median Family Income (log)	Tract School Quality Score
Median family income (log)	*	0.6153
School quality score	0.6153	*
Housing value (log)	0.6200	0.5397
% Owner-occupied	0.6931	0.3499
% White	0.8132	0.5560
% Black	-0.2401	-0.2855
% Latino	-0.7634	-0.5734
% Asian	0.2129	0.3339
% Bachelor's degree or higher	0.7995	0.6507

Notes

[a] Means are weighted and reflective of all nonmissing observations between the years of 2001 and 2012.

[b] Correlation values capture weighted unconditional correlations based on continuous rather than categorical values of observations without missing data and/or with imputed data on the two variables in question.

[c] Tract school quality and tract housing value variables include imputed values for person-year-tracts originally missing data.

TABLE 3
Sorting Effects of Respondent Attributes and Structural Characteristics on Residential Choice, Conditional Logit Models

	Model 1		Model 2	
Variables	O.R.	S.E.	O.R.	S.E.
Destination tract attributes				
Origin tract	14381.97**	3923.90	14183.56**	3879.55
Network distance in miles from origin	0.803**	0.029	0.804**	0.029
# housing units (log)	2.868**	0.652	2.987**	0.678
Median family income (log)	1.145	0.510	0.647	0.269
Median housing value (log)	0.925	0.168	0.927	0.168
% Owner-occupied	1.010	0.006	1.010	0.006
% Black	0.985	0.008	0.984*	0.007
% Latino	0.988	0.008	0.988	0.008
% Asian	1.004	0.007	1.004	0.007
% Bachelor's degree or higher	0.983	0.012	0.981	0.013
Interaction of individual and tract attributes				
Black X Tract black %	1.028*	0.013	1.028*	0.012
Latino X Tract Latino %	1.029**	0.007	1.028**	0.007
Asian X Tract Asian %	1.013	0.019	1.012	0.020
White X Tract white %	1.008	0.008	1.002	0.008
Household income Q2 X Tract income (log)	1.008*	0.003	1.010**	0.003
Household income Q3 X Tract income (log)	1.011*	0.005	1.013**	0.005
Household income Q4 X Tract income (log)	1.017*	0.007	1.018**	0.007
Household income Q5 X Tract income (log)	1.027**	0.008	1.028**	0.008
Med. passage comp. X Tract income (log)			2.270	1.023
High passage comp. X Tract income (log)			3.042**	1.031
Bachelor's deg. X Bachelor's degree or higher %	1.017*	0.009	1.019	0.012
Bachelor's deg. X Tract income (log)			0.960	0.032
Observations				
Number of persons	284		284	
Number of person-years	3,317		3,317	
Number of person-year-tract alternatives	165,357		165,357	

Notes
[a] Models include weights and the offset term, $-\ln(q_{ijt})$, for sampling the choice set.
[b] Standard errors are clustered by persons.
[c] $*p < .05$, $**p < .01$ (two-tailed test).

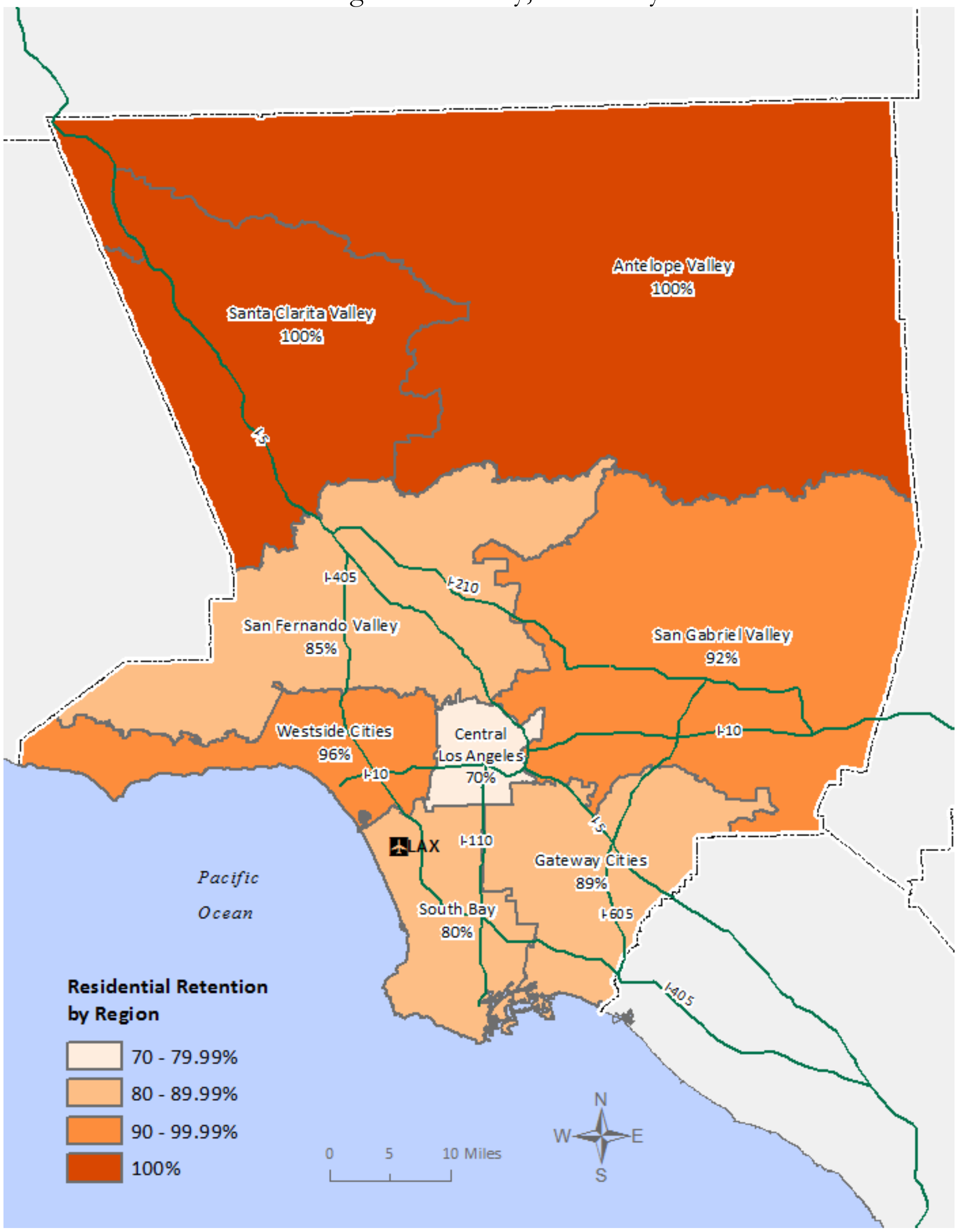
TABLE 4
Sorting Effects of Respondent Attributes, Structural Tract Characteristics, and Tract School Quality on Residential Choice by Educational Attainment, Conditional Logit Models

	Model 1 Bachelor's Degree+		Model 2 No Bachelor's Degree	
Variables	O.R.	S.E.	O.R.	S.E.
Destination tract attributes				
Origin tract	36.80	109.38	3676.72**	4220.25
Origin tract X School quality score	1.008*	0.004	1.002	0.002
Network distance in miles from origin	0.727**	0.062	0.818**	0.031
# housing units (log)	10.127**	4.114	2.536**	0.663
Median family income (log)	5.878	8.002	0.849	0.429
Median housing value (log)	1.291	0.588	0.727	0.143
% Owner-occupied	1.038**	0.011	1.003	0.007
% Black	0.949*	0.024	0.991	0.008
% Latino	0.965	0.023	0.996	0.008
% Asian	1.002	0.015	1.006	0.008
% Bachelor's degree or higher	0.955	0.025	0.980	0.013
School quality score	0.986	0.009	1.000	0.001
Interaction of individual and tract attributes				
Black X Tract black %	1.031	0.024	1.031*	0.015
Latino X Tract Latino %	1.044**	0.017	1.020**	0.007
Asian X Tract Asian %	0.996	0.036	1.044**	0.011
White X Tract white %	0.996	0.019	1.007	0.009
Household income Q2 X Tract income (log)	3.927	2.790	1.047	0.085
Household income Q3 X Tract income (log)	1.491	0.921	1.003	0.105
Household income Q4 X Tract income (log)	0.945	0.479	0.899	0.104
Household income Q5 X Tract income (log)	1.336	0.633	0.671	0.144
Household income Q2 X School quality score	0.981	0.010	0.999	0.001
Household income Q3 X School quality score	0.997	0.009	1.000	0.002
Household income Q4 X School quality score	1.004	0.007	1.002	0.002
Household income Q5 X School quality score	0.998	0.007	1.007*	0.003
Med. passage comp. X Tract income (log)	0.283	0.325	2.304	1.138
High passage comp. X Tract income (log)	0.141	0.164	2.916**	1.111
Med. passage comp. X Tract school quality	1.015*	0.007	1.000	0.001
High passage comp. X Tract school quality	1.015*	0.006	1.002	0.002
Observations				
Number of persons	67		230	
Number of person-years	698		2,619	
Number of person-year-tract alternatives	35,008		130,349	

Notes
[a] Models include weights and the offset term, $-\ln(q_{ijt})$, for sampling the choice set.
[b] Standard errors are clustered by persons.
[c] *p < .05, **p < .01 (two-tailed tests).
[d] Summing the number of persons in each analytic subsample above exceeds the total person N in the full sample (297 vs. 284) because some respondents switched from no bachelor's degree to bachelor's degree over the course of the panel.

FIGURE 1

Residential Retention Rate by Los Angeles County Region:
LA FANS-MIP Longitudinal Study, Randomly Selected Adults

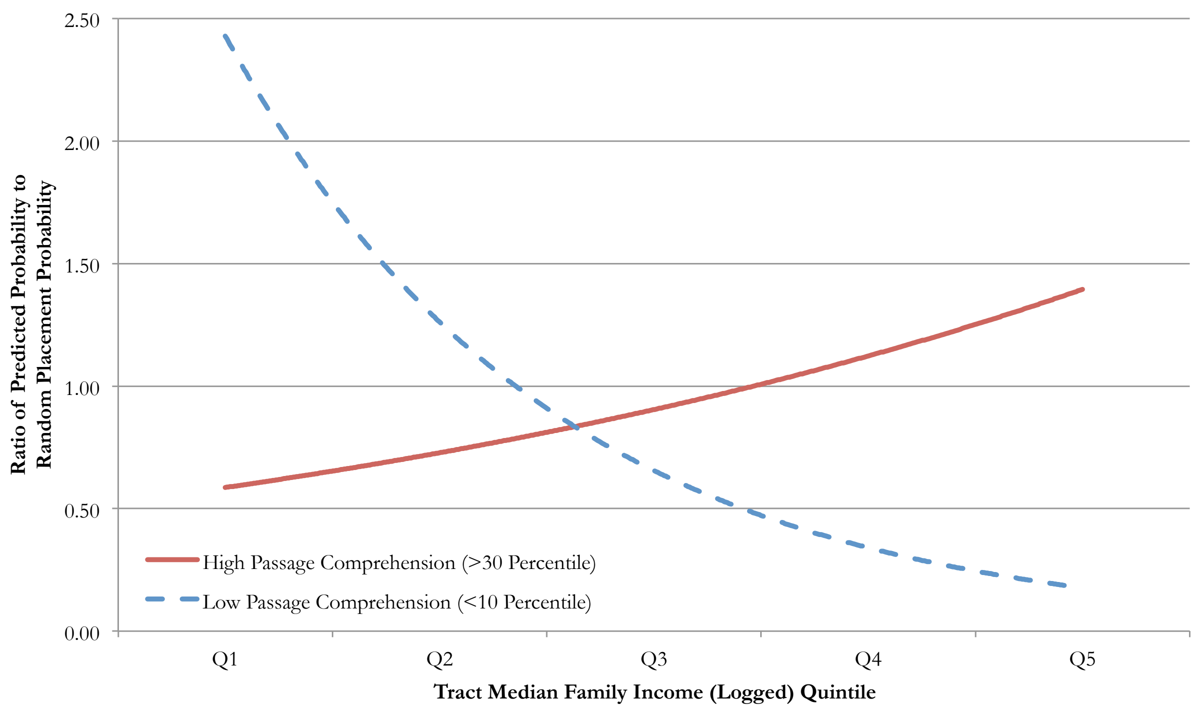


Source: Authors' calculations using L.A.FANS-MIP Longitudinal Study, as well as schematic maps from various Los Angeles County governmental agencies and the Los Angeles Times' "Mapping L.A." Project.

Notes

[a] The numbers indicate the percentage of randomly selected adult respondents who resided within the same region of Los Angeles County during both waves 1 and 3 of the LA FANS-MIP Longitudinal Study (*N*=612), regardless of whether they moved residences. For more details on this analytic sample of randomly selected adults, see (Sampson, Schachner, and Mare 2017).

FIGURE 2
Conditional Predicted Probability of Living in a Given Neighborhood (Ratio to a Random Placement)
By Cognitive Skill Level and Neighborhood Affluence

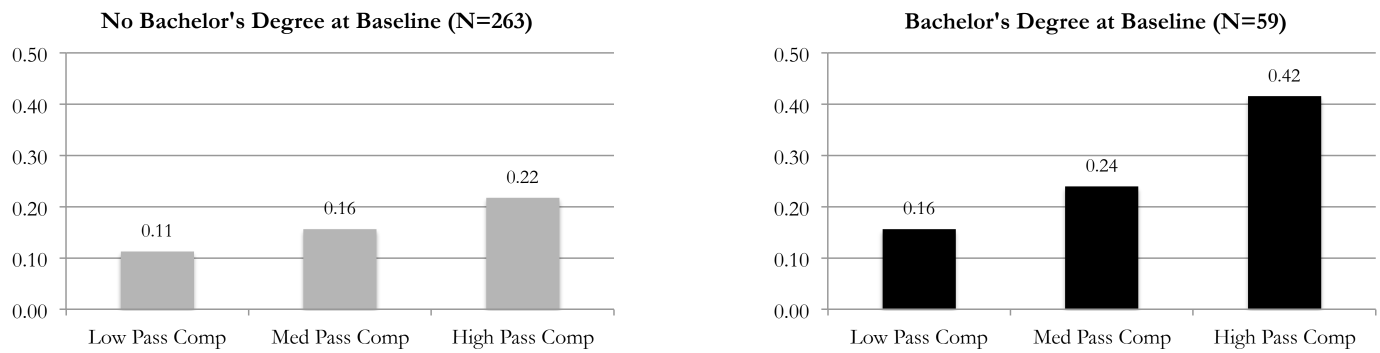


Notes
[a] Predicted probabilities are derived from Table 3, Model 2, and ratios are exponentially smoothed.

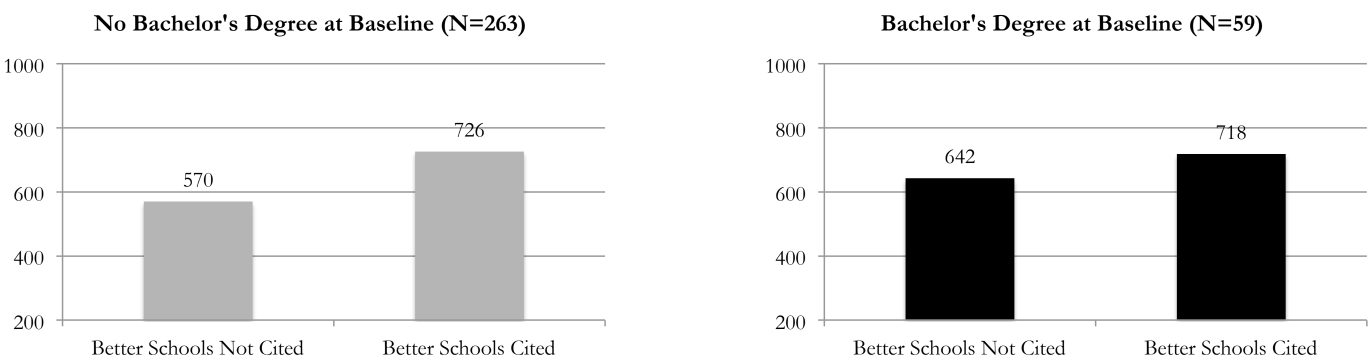
FIGURE 3

Neighborhood Mobility Preferences by Educational Attainment and Cognitive Skills,
LA FANS Panel Primary Caregivers Who Recently Moved

A. Proportion reporting access to better schools as a driver of neighborhood mobility decision in wave 1.



B. Median tract school quality score of chosen tract in 2001 by whether better schools cited as a driver of neighborhood mobility decision.



Notes

[a] LA FANS panel primary caregiver sample used in this analysis consists of respondents who completed waves 1 and 2 of data collection (regardless of whether they participated in wave 3/MIP) and moved within the five years prior to their wave 1 interview.

ONLINE SUPPLEMENT MATERIALS

APPENDIX: Analytic Sample and Discrete Choice Model Specifications

Analytic Sample

300 respondents were designated as primary caregivers (PCGs) at wave 1 and confirmed both to have resided within L.A. County and to have completed a survey during each of the three waves of data collection (i.e., waves 1 and 2 of L.A.FANS and MIP). Fifteen lacked Woodcock-Johnson Passage Comprehension scores and one additional respondent was dropped because s/he resided in a sparsely-populated, unincorporated portion of the Santa Clarita Valley within L.A. County that ArcGIS software could not locate for the purpose of calculating network distance.

We exclude year 2000 residential data from our analyses because origin tract identifiers are missing for nearly 15 percent of the analytic sample (i.e., tract of residence in year 1999). As described in the text, all models include a dummy variable indicating whether the selected tract is the origin tract. A high rate of missing data on this variable may yield imprecise, if not biased, estimates. We exclude year 2013 from our analyses because only a small portion of respondents completed the MIP survey in this year; the vast majority completed the MIP survey in 2011 or 2012.

As with any longitudinal survey, the bias generated by panel attrition must be addressed. We model the probability that PCGs exited the survey based on a range of individual- and household-level variables. See Sastry and Pebley (2010), Peterson et al. (2012), and Sampson, Schachner, and Mare (2017) for details on the attrition models used for attrition between waves 1 and 2 and between waves 2 and MIP, respectively. We weight all individual-level data based on the product of the inverse probability of attrition between waves 1 and 2 and waves 2 and 3, as well as sampling weights that adjust for L.A.FANS' original sampling design.

These specifications produce our analytic sample of 284 PCGs, most of whom have continuous census tract-coded residential history data (in 2000 boundaries) throughout the 2001-

2012 timeframe. If all 284 of these PCGs had continuous residential history data, 3,408 person-years (284 * 12) would be available for analysis. However, we remove person-years that lack valid GIS-coded census tracts and that entail moving out of L.A. County, into L.A. County from outside the county, or into a census tract for which network distance cannot be calculated by ArcGIS software, which reduces the analytic sample slightly, to 3,317 person-years of residential mobility data (97% of total). The residential history data span 2001 to 2012 and contain coded census tracts (based on household location as of January 1st of each year), enabling us to integrate annual estimates of neighborhood-level data using U.S. census 2000 data and American Community Survey (ACS) 2004 – 2008 through 2011 – 2015 data, administrative data provided by state and local governments, and GIS data into our dataset. Note that because the Census Bureau redraws tracts every decade, a standardized set of tract boundaries is required for any analyses that cross the decade threshold. Thus, we standardize all our tract-level data to 2000 census-defined boundaries, given that this was the first year of the L.A.FANS survey. To standardize data from the 2010-2014 and 2011-2015 ACS, which employed 2010 tract boundaries, we use the Backwards Longitudinal Tract Data Base's interpolation code (Logan, Xu, and Stults 2014).

Operationalizing Neighborhood School Quality

Beyond tract median family (logged), our other core neighborhood-level measure is an annual estimate of *K-12 school quality.* As we mention in the text, scholarly consensus regarding how to calculate neighborhood-level school quality estimates remains elusive. We develop a measure based on census tract boundaries, Los Angeles County-provided school catchment boundaries, and public school test score data from the California State Department of Education. The educational accountability movement, which gained strength in the late 1990s, spurred the California Department of Education to calculate a school-level measure of average student achievement levels based on state test scores across multiple content areas, termed the Academic Performance Index (API), for every campus with eleven or more valid scores, every year between 1998 and 2013. The school API is calculated on a standardized scale of 200 to 1000 for the entire school, as well as disaggregated by students' race-ethnicity and socioeconomic status. These scores are publicly disclosed via the Internet and newspapers, rendering them accessible to parents and the public.

We aggregate local schools' average API scores up to the neighborhood level by overlaying school catchment boundaries provided by Los Angeles County in 2002 with 2000 census tract boundaries via a GIS spatial merge. Given that catchment boundaries do not perfectly align with 2000 census tract boundaries, we estimate the spatial portion of each tract that is covered by each school's catchment boundaries that intersect the tract, which generates a relative weight for each school's test scores. Then, separately for all elementary, middle, and high schools, we generate a spatially-weighted tract-level measure of local schools' average test scores. Finally, we calculate a simple average of the separate elementary, middle, and high school-based API tract measures to create an aggregate neighborhood measure of school quality for each year between 2001 and 2012.

Modeling the Choice Set

Whether the choice sets employed in discrete choice analyses of residential selection should include the tract chosen in the prior period (t -1) – i.e., the origin tract, or D_{ij} in Bruch and Mare (2012)'s parlance – remains contested among residential mobility scholars. Inclusion or exclusion of the origin tract indicator determines whether the residential histories of households that remain in place during a given time period will be analyzed or if only movers' behavior will be examined. The discrete choice models of Spring et al. (2017) and Quillian (2015) incorporate only time periods in which a household moves and consequently exclude the origin tract from the choice set. However, Bruch and Mare (2012) provide a compelling argument for including it, which enables the decisions of (1) whether to move or stay and of (2) where to move to be modeled simultaneously rather than as a two-step process requiring two separate models; the latter strategy is employed by several residential mobility studies to examine selection into mobility and then neighborhood sorting predictors, conditional on moving (e.g., Crowder, South, and Chavez 2006; Spring et al. 2017). Incorporating the origin tract indicator is not only more a more streamlined approach that combines two separate behavioral models into one. It also accounts for the fact that the decision to stay in place is a common and theoretically important outcome that is partly determined by the characteristics of both one's current neighborhood and of other available neighborhood options (Bruch and Mare 2012). Sampson and Sharkey (2008) reinforce the importance of attending to stayers' patterns: "Choosing to remain in a changing or even declining neighborhood is a form of selection, after all, and can be just as consequential as the decision to relocate, an often overlooked point in debates about neighborhood effects."

We agree with their assessments, particularly given our theoretical questions and the ecological and temporal context in question. Theoretically salient features of L.A. neighborhoods have meaningfully changed around stayers over the decade-long period in question – a period marked by an immigration-fueled shift in the race-ethnic composition of the region, the exogenous shock of the Great Recession, volatile housing prices, a precipitous drop in crime, and the enactment of major reforms to local school systems. To the extent these changes meaningfully affect the conditions of origin neighborhoods and potential destinations, preserving stayers' residential histories and including the origin tract in the choice set is critical to acquiring a fuller picture of residential sorting in this spatial and temporal context and to mitigating potential bias generated by only tracking a strongly-selected group (i.e., movers).

Moreover, practically speaking, including the origin tract indicator enables interactions between moving/staying behavior and individual-, household-, and neighborhood-level features to be included in discrete choice models. These interactions can be interpreted as suggesting whether certain characteristics suppress or amplify the likelihood of moving out of one's origin neighborhood. It is also worth noting that because 94 percent of our analytic sample's person-years of residential history data consist of staying in place, rather than moving, we would lose a substantial amount of statistical power if we focused exclusively on movers.

For all of these reasons, we decide to include respondents who remained within the same census tract in a given year in our core analytic sample, and use the origin tract indicator to distinguish between the stayers and movers. Importantly, all models' core results are robust to origin tract indicator interactions with our core characteristics of interest at the neighborhood level (i.e., median family income logged and K-12 school quality) and individual/household levels (i.e., household income quintile and cognitive skills). Moreover, the results generated by Models 1 & 2 (Table 3) and Model 2 (Table 4) are replicated with an analytic sample that consists solely of respondents who moved within a given year (full results available upon request). Unfortunately, Model 1 (Table 4) contains too small of an analytic sample to replicate results within a mover-only analytic sample, but our descriptive analysis of recent movers' stated preferences (Figure 4) suggests that model's core findings plausibly hold when only movers' behaviors are examined.

Another important feature of the choice set beyond inclusion or exclusion of the origin tract is which non-selected tracts to include for each respondent. Prior discrete choice models typically conceptualize the choice set of non-selected tracts as every non-origin tract in a metropolitan area, given that households are far more likely than not to move within these geographic parameters (e.g., Bruch and Mare 2012; Quillian 2015; Spring et al. 2017). However, the computational intensity of constructing a choice set with over 2,000 county tract options, theoretical considerations regarding "importance sampling" (Bruch and Mare 2012; Spring et al. 2017), as well as emerging evidence suggesting that individuals generally consider only a small set of nearby neighborhoods options

(Bruch and Swait 2018; Krysan and Crowder 2017) and that Angelenos' actual residential moves are highly geographically circumscribed (Sampson et al. 2017) lead us to take a different tack. Based on a review of schematic maps from various Los Angeles County government agencies and of the crowd-sourced Mapping L.A. project overseen by the Los Angeles Times, we assign all county tracts to one of eight geographic regions – Central Los Angeles, San Fernando Valley, San Gabriel Valley, Gateway Cities, South Bay, Westside Cities, Santa Clarita Valley, and Antelope Valley – and use these regions to structure construction of respondents' choice sets. These regions are widely recognized as distinct sectors among locals, and Angelenos are likely to have a greater degree of familiarity with other neighborhoods within their region of residence than in other regions of the sprawling county (Bruch and Swait 2018). In fact, our data reveal a very high degree of within-, versus between-, region sorting, even among mobile households. As Figure 1 shows, between waves 1 and 3 of L.A.FANS-MIP, the two outlying regions retained fully 100% of randomly selected adults and two retained over 90%. Central L.A.'s retention rate is slightly lower, but still high at 70%.

Given this strong pattern, for each person-year combination we construct a circumscribed choice set of tract options, consisting of the tract selected; the tract within which the person resided during the prior year (i.e., the origin tract, which may or may not be the same as the tract selected); and 49 to 50 randomly-sampled non-selected, non-origin tracts, about half of which are drawn from the county region in which the respondent resided in the prior year, and about half from the entire county as a whole. To ensure each county tract's probability of selection into the choice set as a non-selected, non-origin tract is consistent across all person-years, we construct the choice set in a slightly distinct way based on one of the following three scenarios. In scenario 1, the selected tract is the same as the origin tract (i.e., the individual stayed in place) during a given year and we add 25 non-selected tracts randomly drawn from the stayer's county region and 25 randomly drawn from the county as a whole, yielding a total choice set of 51. The remaining two scenarios capture two types of moves: to a tract lying within the same county region as the origin tract (scenario 2) or to a tract outside of the origin tract's region (scenario 3). In the former scenario, we only draw 24 additional choice set tracts from the region-specific sample because the selected tract is also within the same region, ensuring the total within-region options equals 25. We then add 25 tracts drawn from the county as a whole. The final scenario refers to moves outside the origin tract's county region. In these cases, we count the selected tract as one of 25 choice set tracts drawn from the county as a whole and draw 24 additional tracts from this stratum. 25 tracts are drawn from the region of the origin tract. There are 158,712 person-period-tract alternatives within scenario 1 (3,112 person-periods * 51 tract options) and 10,250 person-period-tract alternatives (205 person-periods * 50 tract options) within scenarios 2 and 3, for a total of 168,692 person-period-tract alternatives in the analytic sample. Note that the total number of person-period-tract alternatives included in our model output is slightly lower (*N*=165,357) due to missing data on certain tract variables.

To account for sampling the choice set, Bruch and Mare (2012) argue that it is necessary to include an offset term, q, that differentially weights tract options based on the probability of the tract entering the circumscribed choice set for a given person-year. Following this guidance, Quillian (2015) and Spring et al. (2017) we assign q a value of 1 for all selected tracts, given their automatic inclusion in respondents' choice set. All other tracts receive a value equal to the number of non-selected tracts within the choice set divided by the total number of non-selected tract options within the relevant sampling frame. Jarvis (2018), however, argues that employing a simple random sample to generate the choice set, as these studies do, obviates the need for an offset term and can actually generate biased coefficient estimates. Because we instead apply a stratified random sample using county regions, an offset term is required. Based on Jarvis' guidance, we assign q a value of 1 for all origin tracts but assign selected, non-origin tracts a value equal to what q would be if it were any other tract within the choice set. If the selected, non-origin tract or the non-selected tract is located within the origin region sample stratum, then it is assigned a q value equal to 25 divided by the total number of tracts within that region (between 0.06 and 0.43). If the tract is drawn from the full countywide sampling frame, then it is assigned a q value equal to 25 divided by the total number of tracts within the county (0.01). The final offset term is calculated by applying a natural log transformation to the q values and multiplying them by -1, per Bruch and Mare (2012). Our models' core results are robust to excluding the offset term.

The Independence of Irrelevant Alternatives

Quillian (2015) and Bruch and Mare (2012) note that a key assumption underlying conditional logit models is that the odds ratios between any two options within the choice set will remain the same magnitude, regardless of whether a third option is added to, or removed from, the choice set. The implication of this assumption – commonly referred to as the independence of irrelevant alternatives (IIA) – is that reconstructing a given choice set by increasing/decreasing the number of options and/or by replacing certain options with other alternatives should generate model estimates that are consistent in magnitude and therefore valid predictions of selection behavior. Quillian (2015) warns that widely employed tests of IIA produce contradictory results and simulation analyses discourage their use. Despite the lack of consensus on what tests to use and whether the test results uphold or violate the IIA assumption, Train (2009) finds conditional logit model coefficients to accurately reflect average effects of options' characteristics on the probability of selection, regardless of whether IIA holds – a conclusion he draws by comparing estimates generated by conditional logit and mixed logit models, the latter of which is not predicated on the IIA assumption. Thus, despite the aforementioned concerns, Quillian (2015) and Bruch and Mare (2012) argue that conditional logit models remain useful in characterizing or at least approximating neighborhood sorting processes.

Until better tests of IIA are developed, Quillian (2015) and Bruch and Mare (2012) advise discrete choice analysts to hedge against the concern by (1) specifying their models as fully as possible, (2) acknowledging that results may shift based on how the choice set is constructed, and (3) refraining from extrapolating results to other ecological and temporal contexts. In this study, we address (1) by adding important predictors that several past discrete choice analyses of neighborhood sorting have missed (e.g., network distance of potential destination tracts from origin tract, individuals' cognitive skills, neighborhood K-12 school quality). As for (2), we develop plausible choice sets for every respondent in an innovative way that is both theoretically and empirically informed (see Bruch and Swait (2018) for another strategy of constructing choice sets that capture "cognitively plausible" outcomes). Lastly, with regard to (3), we repeatedly clarify that our results are particular to Los Angeles County during the time period in question.

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