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Where to Build Affordable Housing? Evaluating the Tradeoffs of Location

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Abstract

How does the location of affordable housing affect the distribution of assistance, tenant welfare, and segregation? Using administrative data, we first show that, despite fixed eligibility requirements, developments in higher-opportunity neighborhoods disproportionately house tenants who are higher-income, less likely to have children, and far less likely to be Black or Hispanic. We then build a structural model in which households choose from both market-rate and affordable housing options, where the latter must be rationed. For existing developments, the targeting of assistance is driven mainly by which eligible households apply, with developer screening playing a smaller role. Simulating new developments across neighborhoods, we find that building in higher-opportunity locations raises aggregate tenant welfare and reduces segregation, but primarily benefits more moderate-need and white households at the expense of higher-need and minority households. Policy levers available after construction, such as lowering income limits, have more limited effects than the initial choice of location.

JEL classification

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affordable housing location, tenant welfare, residential segregation, targeting efficiency, structural estimation

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1 Introduction

Central to many affordable housing programs is the choice of location. While early programs often built developments in disadvantaged neighborhoods, this led to concerns about the concentration of poverty, poor living environments for households, and the potential to perpetuate racial segregation.[1] More recently, policymakers have prioritized providing affordable housing in areas with lower poverty rates and greater economic opportunities, in part motivated by evidence on the positive effects that higher-opportunity neighborhoods have on residents (Kling, Liebman and Katz, 2007; Chetty, Hendren and Katz, 2016).[2] However, the choice of location comes with trade-offs. While affordable housing in higher-opportunity neighborhoods can provide tenants with access to better jobs and schools and reduce city-wide segregation, it can have negative spillovers on the neighbors of the new development (Diamond and McQuade, 2019) and costs more to construct.

One trade-off that has received less attention is that *where* affordable housing is built determines *who* applies for assistance when households have heterogeneous preferences for neighborhoods. Policy goals such as targeting those with the greatest need or reducing segregation rely on allocating units to households with characteristics that are difficult to observe (e.g., long-term need) or illegal to screen on (e.g., race). A common argument in favor of in-kind transfer programs is that take-up may be 'self-targeting' if demand for the good is correlated with unobserved need (Nichols and Zeckhauser, 1982; Besley and Coate, 1992). Unlike programs such as food stamps (Finkelstein and Notowidigdo, 2019) or Medicaid home care (Lieber and Lockwood, 2019), however, affordable housing programs offer a highly heterogeneous good, and take-up of assistance depends on demand for each specific housing unit. Moreover, affordable housing is not an entitlement, and units are heavily rationed; by one measure, only one in four eligible households receives any housing assistance (Joint Center for Housing Studies, 2020). Whether a household receives assistance depends not only on their own take-up decision, but on the decisions of other households and the mechanism used to allocate units.

In this paper, we evaluate the trade-offs of providing affordable housing in different types of neighborhoods, with particular attention to the endogenous relationship between location and the targeting of assistance. We focus on units built through the Low-Income Housing Tax Credit program (LIHTC), the largest and fastest-growing affordable housing program in the US. We begin by providing descriptive evidence on the link between location and the characteristics of LIHTC tenants. We then build and estimate a structural model that includes market-rate and affordable housing options, where the latter are priced below market and must be rationed among applicants. Both household preferences and the mechanism used to ration units affect which households receive a LIHTC unit. We use the estimated model to disentangle these two factors and to quantify the

[1] See Turner, Popkin and Rawlings (2009) for a history of early programs, including public housing. On racial segregation, Massey and Denton (1998) note that "public housing projects [...] had become black reservations, highly segregated from the rest of society and characterized by extreme social isolation."

[2] Initiatives in this vein include local 'inclusionary zoning' policies requiring that new market-rate developments set aside units for low-income households and state policies requiring that municipalities build their 'fair share' of affordable housing.

effects of adding affordable housing to different neighborhoods on tenant welfare, city-wide racial and economic segregation, and other common policy considerations. Finally, we compare the effects of location choice with other policy levers, such as lowering the income limits used for means-testing.

Our primary data come from individual-level tax records, residential address histories, and Census survey responses, which we combine to build a panel of renter households living in both LIHTC and market-rate units. For each individual, we observe their demographics, migration history, and several proxies for underlying need, including short- and long-run income, education, and parental income during childhood. For each rental unit, we observe the rent, characteristics of the unit, and, for LIHTC units, the income limit used to means-test for eligibility. Importantly, while we observe the set of LIHTC-eligible households and which households receive a unit, we do not observe individual applications for LIHTC units. Unlike centrally allocated programs such as public housing, the allocation of LIHTC units is decentralized, and individual developers have substantial discretion when allocating units.

We begin by documenting which eligible households receive a LIHTC unit, both on average and across neighborhoods. On average, households living in a LIHTC unit are far more likely to be Black and, consistent with self-targeting, exhibit greater need than other eligible households. However, the differences attenuate and often reverse for developments built in higher-opportunity neighborhoods. To classify neighborhoods, we define an index of neighborhood opportunity that combines measures of school quality, job access, transit access, poverty, and upward mobility.[3] Despite fixed rent and income limits, LIHTC developments in the top quartile of neighborhood opportunity house tenants who have higher long-run income, are twice as likely to have a college-educated household head, grew up in higher-income families, and are nearly three times as likely to be non-Hispanic white than the tenants of developments in the bottom quartile. In top-quartile neighborhoods, the average LIHTC tenant has observable characteristics similar to those of a randomly selected household from the eligible population.

We build a structural model of household and developer behavior to separate the role of preferences from screening in determining which households receive a unit and to simulate the effects of counterfactual siting and allocation policies. The model, which we estimate for the Chicago metro area, contains two sectors: a market-rate sector that is structurally similar to existing residential choice models (e.g., Bayer, Ferreira and McMillan, 2007), and an affordable housing sector in which units are priced below market and must be rationed. Households in the model first decide whether to apply for each affordable housing option, then developers screen applicants and make offers for units. We approximate the screening mechanism as a binary logit in which developers can up- or down-weight households based on their observable characteristics. In the absence of a price mechanism, the offer probabilities adjust in equilibrium to clear the market. Developments in high demand will screen more stringently than those with fewer applicants. Finally, households not allocated an affordable housing unit must select from among the market-rate options.

[3] Our measure of neighborhood opportunity is positively correlated with median household income, share college-educated, and the share non-Hispanic white (see Appendix Figure D.3). The results throughout the paper are qualitatively similar if these characteristics are used in place of our index of neighborhood opportunity.

To estimate the model, we develop a two-step method for estimating demand in a setting with rationing, without requiring data on applications for the rationed good. Our approach relies on a parallel market-rate sector in which we can estimate preferences for housing and neighborhood characteristics, up to shifters that capture the value a household places on affordable housing relative to an observably similar market-rate unit (e.g., any hassle, stigma, or unobserved quality differences). In the first step, we estimate household preferences for housing and neighborhood characteristics using observed choices in the market-rate sector. To address the endogeneity between market-rate rents and unobserved quality, we construct a new instrument that isolates shifts in the residual supply curve across housing types stemming from trends in the demographic and industry composition of cities, which is similar in spirit to Waldfogel instruments (Waldfogel, 2003; Berry and Haile, 2016). In the second step, we use the Generalized Method of Moments (GMM) to estimate household preferences specific to affordable housing and parameters governing the screening process. We allow both sets of parameters to vary by neighborhood opportunity, such that households may disproportionately prefer LIHTC developments in higher-opportunity neighborhoods, and developments in such neighborhoods may place greater weight on certain household characteristics when allocating units. To separate the role of discretionary screening from heterogeneity in household preferences for affordable housing, we construct moments based on both move-ins to LIHTC developments (affected by screening and preferences) and move-outs (affected only by preferences).

Using the estimated model, we first decompose the role of preferences versus screening in determining the allocation of existing LIHTC units to tenants.[4] For exposition, we collapse the many proxies for need into a single prediction of future income and define households as 'high-need' if they are in the bottom quartile of predicted future income and 'moderate-need' otherwise. LIHTC tenants are about 25% more likely to be classified as high-need and nearly 50% more likely to be Black or Hispanic than the average eligible household. Much of the gap can be explained by preferences for the housing and neighborhood characteristics of existing developments, which are predominantly built in lower-income, high-minority-share neighborhoods. Preferences specific to affordable housing also increase the share of high-need and Black/Hispanic households in LIHTC units. While the average household values a LIHTC unit in a median-opportunity neighborhood \$67 per month *less* than an observably equivalent market-rate unit, there is substantial heterogeneity across households, and many higher-need and Black/Hispanic households value LIHTC units more than market-rate. Taken together, household preferences alone explain about 80% of the race/ethnicity gap and about half of the gap in levels of need between households that are eligible and those that receive assistance. The remaining gap is due to differences in screening. We estimate that screening favors higher-need and Black/Hispanic households, who are more likely to be offered a unit (conditional on applying), especially in lower-opportunity neighborhoods.[5]

[4]While we use the term "preferences," our estimates may also capture information frictions, search costs, and discrimination in both sectors. We discuss these considerations in Section 7.4.

[5]In the model, we interpret this screening as developers selecting among applicants. However, higher-need and Black/Hispanic households may also be more likely to apply if they are disproportionately informed about LIHTC vacancies (e.g., through friends, family, or social workers).

Next, we quantify the effects of location by simulating adding new LIHTC units and varying the neighborhood in which they are placed, holding other housing options fixed. Total household surplus is \$143 more per month for a new unit built in the top instead of bottom quartile of neighborhood opportunity, but the increase in costs generally exceed the increase in household surplus. To measure costs, we predict the market-rate rent for each LIHTC unit and define the 'implicit subsidy' as the gap between the subsidized and predicted market-rate rents, which captures the opportunity cost of setting aside a housing unit for the LIHTC program. The estimated implicit subsidy increases from \$218 per month in the bottom quartile of neighborhood opportunity (18% discount off of market-rate) to \$700 per month in the top quartile (41% discount).

While total household surplus is greater for developments built in higher-opportunity neighborhoods, the benefits do not accrue evenly across households. For Black and Hispanic households, household surplus is \$164 *less* per month for a unit built in the top instead of bottom quartile of opportunity, primarily due to lower odds of being allocated a unit rather than lower ex-post value. The estimated number of moderate-need, non-Hispanic white applicants increases fivefold for developments built in the top instead of bottom quartile of neighborhood opportunity, which, because units are rationed, crowds out households willing to apply regardless of location. This crowding out creates an additional barrier for households looking to move from lower- to higher-opportunity neighborhoods, on top of other barriers that many low-income households face when searching for housing (DeLuca, Wood and Rosenblatt, 2019; Bergman et al., 2023).

Turning to other considerations that may enter the social planner's objective, we evaluate the effects of location on segregation, lifetime earnings of children, and spillovers on neighbors. First, we evaluate the potential effects on racial/ethnic and economic segregation. Past work has shown that existing LIHTC developments have had little effect on racial segregation or the concentration of poverty, and hypothesized that alternative siting policies may reduce segregation (Horn and O'Regan, 2011; Freedman and McGavock, 2015; Ellen, Horn and O'Regan, 2016). We find that LIHTC developments built in higher-opportunity neighborhoods can indeed reduce racial/ethnic and economic segregation. However, relative to a benchmark in which a development *and its tenants* are moved to a higher-opportunity neighborhood, much of the potential effects are dampened by changes in the tenant composition. This creates a nuanced trade-off for policymakers: affordable housing in higher-opportunity neighborhoods reduces segregation, but provides assistance to fewer minority households. Second, we use estimates from Chetty et al. (2026) to assess the impact on children's lifetime earnings. On net, we calculate that a LIHTC unit in the top quartile of neighborhood opportunity increases the discounted lifetime earnings of children by \$221 per month more than a unit in the bottom quartile (\$102,000 per child). The spillovers on neighbors, however, offset some of the effects on children. Using estimates from Diamond and McQuade (2019), we estimate a net effect on neighbors' welfare of −\$45,700 for a unit built in the top instead of bottom quartile (−\$316 per month if amortized over 15 years at a 3% discount rate).

Finally, we use the estimated model to evaluate the potential effects of counterfactual policies for managing units after they have been built. Lowering the income limits or using income-based rents provides assistance to higher-need households but also increases costs and has little impact on the racial/ethnic composition of tenants. For policymakers especially concerned about targeting assistance to the highest-need households, such policies may complement efforts to build in higher-opportunity neighborhoods. In contrast, allocating units through a fair lottery—i.e., shutting down the effects of differential screening—reduces both targeting by need and the share of Black-led households that receive assistance in the average development, but similar differences in tenant composition persist across neighborhoods due to heterogeneity in household preferences. Finally, giving priority to current neighborhood residents, as is common in cities such as New York City and San Francisco, generates more household surplus by selecting households that value the neighborhood more, but it also amplifies the effects of location on tenant composition, reducing the potential to promote integration.

Our results most directly contribute to the large literature studying the LIHTC program. Earlier studies primarily focus on the spillovers of a LIHTC development on the surrounding neighborhood. Baum-Snow and Marion (2009) find that new LIHTC units increase homeowner turnover and reduce neighborhood income in gentrifying areas but raise property values in declining areas. Similarly, Diamond and McQuade (2019) find that developments in low-poverty neighborhoods impose a negative externality on neighbors, whereas those in high-poverty and high-minority-share neighborhoods can have a positive, revitalizing effect.[6] More closely related, Ellen, Horn and O'Regan (2016) and Ellen, Horn and Kuai (2018) use data on LIHTC tenants across 12 states to show that developments built in more disadvantaged neighborhoods tend to house a greater share of lower-income and minority residents. We extend the literature on LIHTC in three ways. First, we assemble a nationwide panel of both LIHTC tenants and other eligible households, allowing us to characterize the targeting properties of LIHTC and the link between location and targeting. Second, we develop a structural model to decompose the roles of household preferences and developer screening in determining tenant composition. Finally, we use the estimated model to quantify the welfare and distributional consequences of counterfactual siting and allocation policies.

The shift towards building affordable housing in higher-opportunity neighborhoods is motivated in part by evidence on the benefits for households of 'moving to opportunity' (Katz, Kling and Liebman, 2001; Oreopoulos, 2003; Kling, Liebman and Katz, 2007; Chetty, Hendren and Katz, 2016; Chetty and Hendren, 2018; Chyn, 2018). We estimate that households derive greater value from affordable housing built in higher-opportunity neighborhoods, although the benefits accrue to more moderate-need, predominantly white households. Much as providing low-income households with rental vouchers rarely leads to moves to opportunity (Lens, Ellen and O'Regan, 2011; Bergman et al., 2023), changing the location of affordable housing alone is unlikely to pull many high-need households out of lower-opportunity neighborhoods, partly because of crowding out when rationing. Moreover, the potential effects on children are dampened because LIHTC households in higher-opportunity neighborhoods have fewer children and tend to move from less disadvantaged areas.

[6] See also Schwartz et al. (2006); Freedman and Owens (2011). LIHTC developments can also crowd out some nearby market-rate construction (Sinai and Waldfogel, 2005; Eriksen and Rosenthal, 2010; Soltas, 2024).

The intuition for the link between location and who applies for assistance comes from a broader literature on how the take-up of in-kind transfers depends on demand for the good being offered. In-kind transfers can improve targeting if demand is positively correlated with unobserved need (Nichols and Zeckhauser, 1982; Besley and Coate, 1992; Kleven and Kopczuk, 2011), but may worsen targeting if the ordeals disproportionately deter those with greater need (Mullainathan and Shafir, 2013). In most empirical applications, the transferred good is homogeneous (e.g., food stamps) and, for eligible households, is not subject to rationing (see, e.g., Alatas et al., 2016; Lieber and Lockwood, 2019; Finkelstein and Notowidigdo, 2019; Deshpande and Li, 2019). In contrast, we study a heterogeneous good with demand that varies by unit, and, because supply is limited, whether an applicant receives assistance depends on the decisions of all *other* households and the mechanisms for rationing units.

Finally, we contribute findings and a novel methodological approach to the empirical market design literature on housing allocation. While the mechanisms to ration housing are often studied in theory,[7] few empirical applications exist. A notable exception is Waldinger (2021), which shows how changes to the design of the Cambridge public housing allocation mechanism trade off between allocative efficiency and targeting by need. Our paper, in contrast, documents how changes to the *product* being allocated (i.e., the housing unit) affect efficiency, targeting, and other policy objectives. Moreover, in Waldinger (2021) and in other empirical market design settings such as school choice (Abdulkadiroğlu, Pathak and Roth, 2005; Agarwal and Somaini, 2020) and kidney exchange (Agarwal et al., 2021), researchers directly observe applications and the mechanism used to map applications to allocations. This is rarely possible in decentralized programs such as LIHTC. To overcome these limitations, we exploit observed choices in a parallel market-rate sector to estimate preferences for housing characteristics and use additional variation from move-outs to separately identify the parameters governing the rationing process from any preferences specific to affordable housing.

2 Affordable housing in the US

The US government spends nearly $50 billion annually on means-tested housing assistance programs targeted at low-income households (Collinson, Ellen and Ludwig, 2019). Early versions of affordable housing involved large government-owned and operated developments ('public housing'), which were criticized for concentrating poverty into distressed neighborhoods and for providing poor environments for both children and adults (Turner, Popkin and Rawlings, 2009). Since the late 1980s, policy has shifted towards public subsidies for *privately* built and managed affordable housing, often dispersed throughout the neighborhood income distribution of a city. In this paper, we focus on the Low-Income Housing Tax Credit (LIHTC), the largest and fastest-growing source of affordable housing in the US (Appendix Figure D.1).

[7] See, e.g., Bloch and Cantala (2017); Arnosti and Shi (2020); Leshno (2022); Kang (2022); Murra-Anton and Thakral (2025); Ferdowsian, Lee and Yap (2024); Tokarski (2025).

2.1 The Low-Income Housing Tax Credit (LIHTC)

The Low-Income Housing Tax Credit (LIHTC) program was established in 1987 to subsidize the construction and preservation of affordable housing developments. As of 2020, there are over 2.8 million LIHTC units, more than the number of housing vouchers and three times the number of public housing units (Schwartz, 2021).

The LIHTC program operates as a public-private partnership in which the government offers subsidies (in the form of tax credits) to private developers to build and manage affordable housing developments. Each state is allocated a per-capita budget of tax credits, then reviews applications from developers and scores them according to a Qualified Allocation Plan (QAP). States have significant latitude in determining the scoring criteria. Common criteria include points for onsite amenities, cost-effectiveness, and neighborhood characteristics. As of 2018, 29 states award points for building in explicitly defined "opportunity" areas, and 20 other states award points based on implicit measures of neighborhood opportunity, such as poverty rates, access to jobs and schools, or access to amenities (Freddie Mac, 2018). Many of these opportunity-related criteria are recent additions to state QAPs and have affected where developers build (Ellen and Horn, 2018; Owens and Smith, 2023). We describe the supply-side details of LIHTC in greater detail in Appendix Section A.1.

2.2 Rationing of LIHTC units

In exchange for the subsidy, developers must charge below-market rents and means-test potential tenants. Eligibility for a LIHTC unit is determined based on current household income, scaled by household size. Households can remain in their unit even if their income exceeds the limit in later years. Rent and income limits are set by HUD as a percentage of the median household income in the metropolitan area. The most common income limit is 60% of the Area Median Income (AMI), scaled by the number of members in the household.[8] Unlike in public housing, LIHTC rents are set and do not depend on a tenant's current income. Instead, each unit's rent ceiling is fixed at 30% of the income limit for a standard-sized household.

Demand for units generally far exceeds supply, so units must be rationed. The processes used to ration vacant units vary across cities and developers. For instance, New York City and San Francisco use online platforms to run lotteries for new developments, often receiving thousands of applications per unit (Haag, 2020). Most cities leave it up to developers to allocate both new and vacated units. There is little data on the exact processes developers choose, but anecdotal evidence suggests that waitlists, first-come-first-serve, and referrals are all common methods for filling vacancies. Regardless of the exact mechanism used, developers can legally set minimum incomes, favor applicants with higher credit scores, or require that applicants have no past evictions.

[8] To be eligible for credits, developers must have at least 20% of units with a 50% AMI limit or 40% of units with a 60% AMI limit. In practice, nearly all LIHTC developments are fully affordable, and most LIHTC units use the 60% AMI limit. Figure B.1 documents the distribution of unit sizes and income limits. There are a few cases in which a unit's rent ceiling may exceed 30% of the income limit, detailed in Stagg (2018).

3 Data

We combine administrative data from the U.S. Census Bureau, the Internal Revenue Service (IRS), and the Department of Housing and Urban Development (HUD) to build a panel of renter households. This section describes our primary data sources, the samples used for analyses, and definitions and summary statistics for the main variables used throughout. Appendix Section B contains additional details on the data construction.

3.1 Data sources

Tax and migration records. We combine administrative data on individual tax records, decennial Census responses, and migration records to build an annual panel with each individual's income, place of residence, household structure, and demographics. The data cover all residents with a Social Security Number (SSN) or Individual Taxpayer Identification Number (ITIN). Individuals are linked across data sources using a unique person identifier called a Protected Identification Key (PIK) assigned by Census staff (Wagner and Lane, 2014). The tax records cover income tax returns (e.g., 1040s) and third-party information returns (e.g., W-2s and 1099s). We identify an individual's residence using the addresses reported on either the 1040 form or, if missing, the W-2 form. For non-filers who also lack a W-2, we use the Master Address File-Auxiliary Reference File (MAF-ARF), which collects addresses from several administrative sources, including the U.S. Postal Service. Unique addresses are assigned an identifier by Census staff called the Master Address File ID (MAFID), which can link records across different data sources.

American Community Survey. We supplement the baseline panel with data from the American Community Survey (ACS), which surveys approximately 1% of housing units each year. We observe whether each unit is owned or rented and its characteristics, including the number of bedrooms, building size, and, where applicable, monthly rent. The ACS also includes additional information on the households surveyed, such as educational attainment.

HUD administrative data. We obtain data on LIHTC units through a data-sharing agreement between HUD and the Census Bureau. For each unit, we observe the income limit, rent limit, and number of bedrooms. The income and rent limits are recorded as the percentage of the AMI, which we convert to dollars using the annual income limits for the corresponding Metropolitan Statistical Areas (MSAs), which are available from HUD.[9] In a supplementary property-level file, we observe additional information on the year placed in service, developer characteristics (e.g., for-profit vs non-profit), sources of funding, development size, and whether the development targets a specific population of renters (e.g., elderly or disabled renters). For all analyses, we restrict to LIHTC properties that do not target any specific population of renters (e.g., seniors) and for which Census

[9] The income limits are posted on HUD's website (link). HUD uses Fair Market Rent (FMR) areas to define cities, which usually align with the boundaries of the MSAs in our sample. In cases where the boundaries of the FMR area differ from MSA boundaries, we define a unit's income limit using the corresponding FMR area.

staff were able to match the unit-level addresses to MAFIDs.[10] For other federal affordable housing programs—including Public Housing and Housing Choice Vouchers—we observe annual data on tenants and units in the HUD PICTRACS data.

3.2 Sample definitions

Our primary unit of analysis is a renter household living in one of the 50 most populous MSAs between 2010 and 2019. We build two primary samples: households living in LIHTC units and households living in market-rate units.

LIHTC households. We link each individual in the tax and migration records to LIHTC units using the MAFIDs. We then assemble individuals living in a development into households using a combination of spousal, claimer-dependent, and shared address relationships; see Appendix Section B.2 for details. For most analyses, we focus on household characteristics at the time of move-in.

Market-rate households. We use annual cross-sections of households sampled by the ACS each year to build a sample of renter households. We define a household as living in a market-rate unit if it is not in a LIHTC, public housing, or project-based Section 8 unit. The sample includes households that use a housing voucher to pay rent, which we observe. We match each individual in a household to the tax and migration records panel using their PIK. Each individual in the household is then matched to the tax and migration records panel so that we can define characteristics consistently across our two samples.

3.3 Variable definitions and summary statistics

We build a set of household characteristics that can be consistently defined for market-rate households sampled by the ACS and LIHTC households in the Census-IRS panel. All dollar-denominated variables are adjusted to 2019 dollars using the consumer price index (CPI-U).

Household income and LIHTC eligibility. We define household income as the sum of Adjusted Gross Income (AGI) for all tax filing units in the household. For non-filers, we use any reported W-2 wages as income. Non-filers with no W-2 wages are coded as having zero income that year. All measures of household income are pre-tax. We focus on two primary time periods of household income: current household income and average income in the three years preceding move-in. Current household income determines a household's eligibility for LIHTC in a given year, while the latter proxies for a household's 'long-run' income before moving in. Approximately half of renter households surveyed by the ACS are eligible to live in LIHTC units in the year surveyed.

Childhood family income (CFI) rank. For individuals claimed as dependents between 1994 and 1995 or 1998 and 2005, we measure their childhood family income (CFI) as the average household

[10] Some properties reported addresses that were either poorly formatted or lacking unit numbers such that they could not be linked by Census staff to MAFIDs. In Table B.1, we provide a balance table of development and neighborhood characteristics for in-sample and out-of-sample properties.

income of their parents when they were under 18 years old. We follow Chetty et al. (2026) and identify an individual's 'parents' based on the first tax return for which they were claimed as a dependent. We then measure each individual's CFI rank for their birth cohort, which helps account for mechanical changes in CFI across cohorts (e.g., for earlier cohorts we observe CFI only when the child is nearly 18 years old).

Race/ethnicity. We define each individual's race and ethnicity using the primary race/ethnicity they most recently reported to the ACS, 2010 Decennial Census, or 2000 Decennial Census. For most analyses, we categorize individuals into four mutually exclusive racial/ethnic groups: Black (non-Hispanic), white (non-Hispanic), Hispanic, or other. The largest racial groups in the 'other' category are Asian and American Indian or Alaska Native.

Education. We measure an individual's education based on whether they reported having a high school degree or a four-year college degree. For market-rate households, this information is available from the ACS for all household members. For LIHTC households, we restrict attention to individuals surveyed by the ACS within three years of their move into LIHTC.

Household structure. We define the household head as the individual with the highest W-2 wages or, in the case of a tie, the eldest. We use the household head to define characteristics such as race/ethnicity, education, and childhood family income at the household level. We proxy for marital status using whether the head of household files jointly with a spouse in a given year. We define a household as containing children if the head has any dependents under 18 or if we observe someone under 18 living at the address in the migration records.

Future income rank. As a proxy for underlying need, we predict each household's future income rank based on their current observables, including income, household structure, race, and neighborhood characteristics. We use ACS-sampled households as training data, then predict average household income over the three subsequent years for all households, adjusting for household size using an equivalence scale. We construct future income ranks by ranking each household within the distribution of renter households. To account for life-cycle differences in earnings, we rank each household within 5-year age bins (based on the head of household's age).

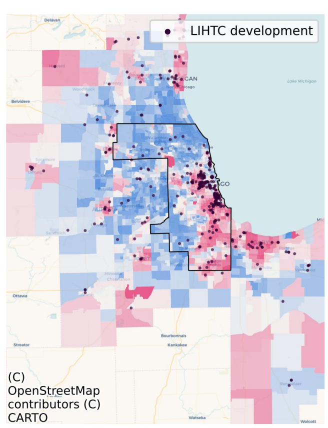
Rent. For each LIHTC unit, we compute the rent based on the unit's income limit and number of bedrooms. The regulated rent ceiling for LIHTC units includes the estimated cost of utilities. In rare cases, developers may price a vacant unit below the rent ceiling if they cannot fill the unit. For market-rate units, we use the gross rent reported to the ACS, which also includes utilities.

Neighborhood opportunity index. To categorize neighborhoods, we create a single tract-level index of neighborhood opportunity. Categorizing neighborhoods using a single vertical index is helpful for exposition but necessarily masks substantial heterogeneity across neighborhoods. Many neighborhoods we classify as "lower-opportunity" are likely better matches for certain households than those we classify as "higher-opportunity." We combine five neighborhood characteristics commonly used by policymakers, including indices of job access, school proficiency, transit access, and poverty from the Affirmatively Furthering Fair Housing Tool (AFFH-T) published by HUD, and a measure of the upward economic mobility for children born to parents at the 25th percentile of the income distribution from the Opportunity Atlas (Chetty et al., 2026), which we normalize to match the construction of the AFFH-T indices. We construct a single index of opportunity by taking the average and computing where each neighborhood falls within the MSA's distribution of neighborhood opportunity. The index is static; the HUD indices each use data from 2010 or shortly thereafter, while the Opportunity Atlas is based on the upward economic mobility of the 1978-1983 birth cohorts. As measured here, neighborhood opportunity is positively correlated with household income, share white (non-Hispanic) residents, and land prices (Figure D.3). While we use our index of opportunity throughout, categorizing neighborhoods by these alternative characteristics leads to substantively similar results.

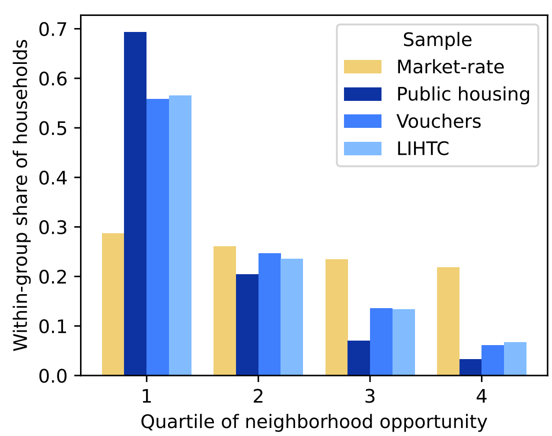
Figure 1 Panel (a) plots a map of neighborhood opportunity in Chicago, overlaid with the locations of LIHTC developments. The highest opportunity neighborhoods are those just outside of the urban core, which benefit from both access to the jobs-rich core and the higher school quality and lower poverty rates of the city's periphery. This pattern of a lower-opportunity core surrounded by a higher-opportunity periphery is a common feature of many major cities (see Figure D.2). Panel (b) plots the share of households living in quartiles of neighborhood opportunity for market-rate, public housing, voucher, and LIHTC households across the 50 sample MSAs. While most LIHTC households live in the bottom quartile of neighborhood opportunity, LIHTC households and those with vouchers are far more likely to live in each of the top two quartiles of opportunity than public housing residents.

Figure 1: Neighborhood opportunity

(a) Map of the Chicago MSA



(b) Distribution of renters (sample MSAs)



Notes: The first panel maps neighborhood opportunity in the Chicago MSA, with an overlay of Cook County and the locations of LIHTC developments. The second panel plots the distribution of households across quartiles of neighborhood opportunity for the market-rate, public housing, voucher, and LIHTC samples. The data cover the 50 sample MSAs, 2010-2019. The public housing and voucher samples are constructed by linking individuals surveyed by the ACS to HUD's register of assisted households (PICTRACS).

Summary statistics. The sample includes 2.5 million market-rate households from the ACS and 420,000 LIHTC households from the Census-IRS panel. Table 1 presents descriptive statistics for the market-rate and LIHTC households. We show results for three sub-samples of market-rate households: all households, LIHTC-eligible households, and LIHTC-eligible households who moved within the past year. Relative to LIHTC-eligible households in market-rate units, households in LIHTC units are lower income, have lower predicted future income, grew up in poorer families, have less education, and are more likely to have a Black head of household. For family structure, LIHTC households are more likely to have children and less likely to have a married couple. LIHTC households also move from neighborhoods farther away, with lower median income and fewer white (non-Hispanic) residents. The gaps generally increase when comparing LIHTC households at the time of move-in to other recently moved households.

Table 1: Market-rate and LIHTC household characteristics

	Market-rate			LIHTC
	All	LIHTC-elig.	LIHTC-elig. movers	At move-in
Financials and education				
Adjusted Gross Income (AGI)	$51,460	$15,020	$15,890	$14,920
Avg. AGI in years [-3, 0)	$45,920	$19,230	$19,750	$14,550
Avg. AGI in years (0, 3]	$55,630	$22,600	$25,810	$19,350
Predicted future income rank	0.5169	0.3303	0.3297	0.2340
Filed taxes	0.8131	0.6514	0.6979	0.6816
Childhood family income ptile*	0.5161	0.4324	0.4677	0.3169
Graduated college*	0.3229	0.1853	0.2210	0.1084
Graduated high school*	0.8660	0.7981	0.8382	0.7791
Surveyed gross rent (ACS)	$1,184	$1,025	$1,114	$733
Household structure				
Household has married couple	0.2438	0.1377	0.1357	0.0924
Household has children (<18yo)	0.3982	0.4209	0.4330	0.4561
Household has seniors (>64yo)	0.1467	0.1890	0.099280	0.1051
# of persons	2.218	2.195	2.184	2.315
Race/ethnicity				
White (non-Hispanic)*	0.4936	0.4221	0.4369	0.2502
Black (non-Hispanic)*	0.2102	0.2547	0.2473	0.4753
Hispanic*	0.1995	0.2259	0.2174	0.2313
Previous tract chars.				
Miles from prev. tract*	6.165	5.826	6.345	6.680
<1mi from prev. tract*	0.2327	0.2449	0.2047	0.1568
Prev. tract opportunity ptile*	0.4752	0.4153	0.4313	0.3123
Prev. tract median household income*	$57,750	$53,110	$54,510	$45,440
Prev. tract frac. white*	0.6301	0.5924	0.6045	0.4942
N	2,450,000	1,260,000	430,000	420,000

Notes: This table documents household characteristics for market-rate and LIHTC households. Characteristics with an asterisk (*) are defined for the household head. LIHTC-eligible movers include households in the ACS who are eligible for LIHTC at the time surveyed and who moved within the past year. To account for differences in the relative sample sizes in each MSA, each statistic is computed within-MSA first, then across MSAs weighted by population. The sample size is rounded per Census disclosure requirements.

4 Who lives in affordable housing?

In this section, we describe the characteristics of LIHTC tenants along two dimensions: how LIHTC households differ from other eligible households *on average*, and how LIHTC tenants differ *across neighborhoods*. On average, LIHTC households exhibit greater need and are less likely to be white (non-Hispanic) than eligible households in market-rate units. Across neighborhoods, however, developments in higher-opportunity neighborhoods house tenants who exhibit lower levels of need and are far more likely to be white (non-Hispanic).

4.1 Average differences in who receives LIHTC

We investigate which eligible households receive a LIHTC unit by comparing the characteristics of recipients to eligible households in market-rate units.[11] We regress household characteristics on an indicator for whether the household lives in LIHTC, with fixed effects for the MSA interacted with the year. The sample includes all LIHTC households at the time of move-in and cross-sections of eligible households observed in the ACS. In Figure 2, we show results for a subset of household characteristics related to common policy goals such as racial/ethnic integration and targeting assistance based on need. Table D.1 documents the raw coefficients and results for additional characteristics, including family structure and the characteristics of a household's previous neighborhood.

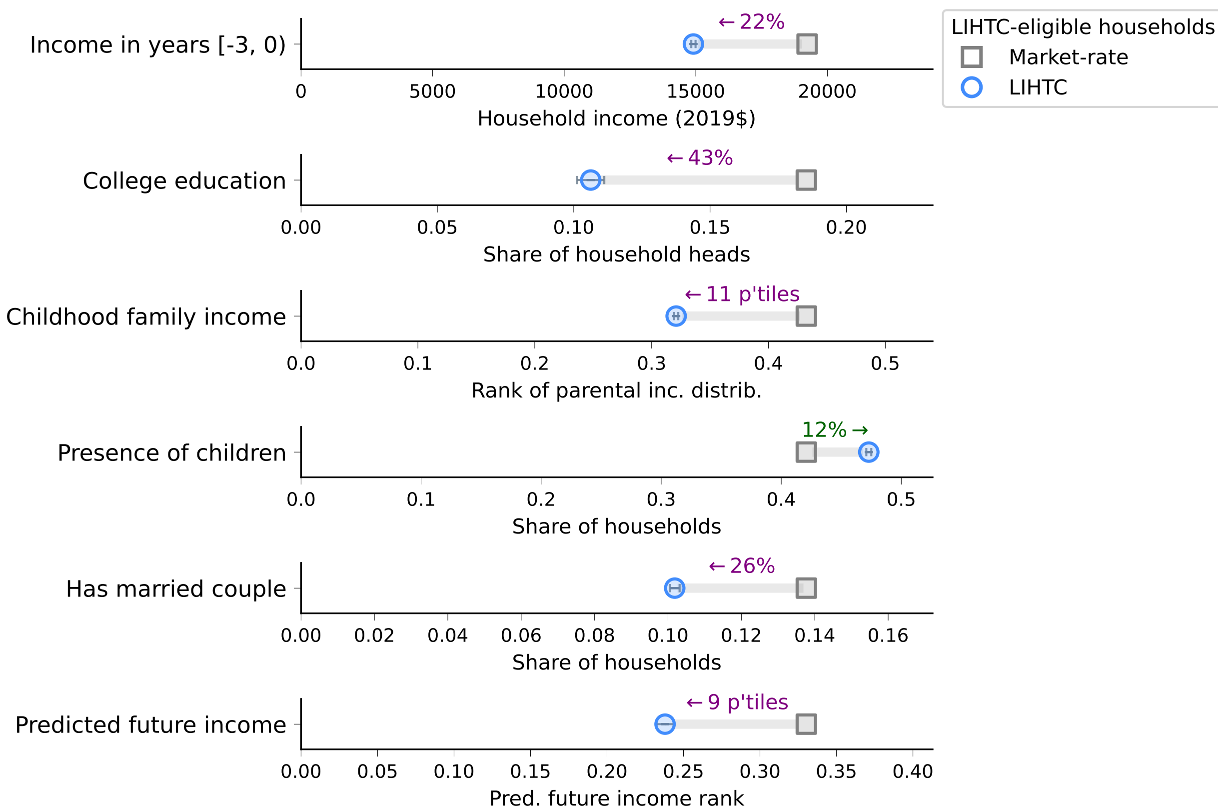
Households living in a LIHTC unit exhibit greater need than the average eligible household, consistent with 'self-targeting' in the spirit of Nichols and Zeckhauser (1982). Compared to eligible households living in market-rate units, the average LIHTC household earned 22% less in the three years prior to move-in, is 43% less likely to have a college-educated household head, and has a household head that grew up in a family 11 percentiles (25%) lower in the parental income distribution for their birth cohort. LIHTC households are also 12% more likely to include a child but 26% less likely to include a married couple. Similar gaps arise in other characteristics; LIHTC households also move from lower income tracts and are less likely to have a household head with a high school degree (Table D.1). Combining the many household characteristics observed prior to move-in into a single measure of predicted future income, we find that LIHTC households are an average of 9 percentiles (28%) lower in the distribution of predicted future income than other eligible households.

The average LIHTC household is also 82% more likely to be non-Hispanic Black than LIHTC-eligible households in market-rate units. This stark difference comes with a commensurate reduction in the share of non-Hispanic white households. In contrast, the share of Hispanic households is similar in the two populations. These gaps by race echo the disproportionate representation of Black households in public housing in earlier decades (Massey and Denton, 1998).

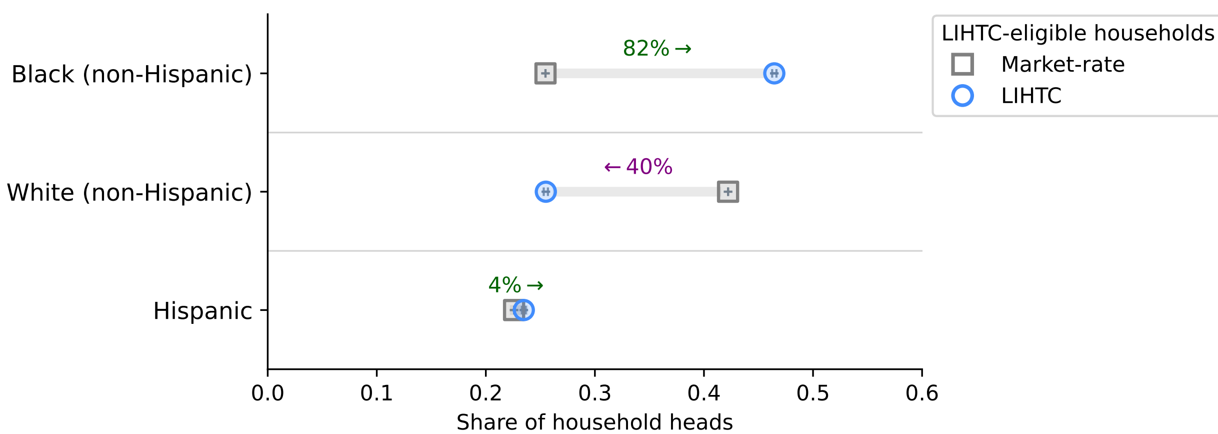
[11] We classify a household in the ACS as eligible for LIHTC if their adjusted gross income in the year surveyed is below the 60% AMI income limit for their city. While households close to the limit may be ineligible for units that use lower income limits (e.g., 50% AMI), the results are similar if we restrict the sample to just 60% AMI units.

Figure 2: LIHTC recipients versus eligible non-recipients

(a) Proxies for need



(b) Race/ethnicity (household head)



Notes: This figure documents differences between LIHTC recipients and eligible non-recipients living in a market-rate unit. Childhood family income, college education, and race/ethnicity are for the household head. The difference in means is computed using a regression of each characteristic on whether a household is in LIHTC, with fixed effects for the year interacted with MSA. The sample includes market-rate households in the ACS with incomes below the 60% AMI limit at the time of the survey and LIHTC households at the time of move-in constructed using the Census-IRS panel (2010-2019, 50 sample MSAs). 95% confidence intervals are represented by gray bars.

4.2 Differences in LIHTC household characteristics across neighborhoods

The average differences between LIHTC households and eligible non-recipients mask substantial variation across neighborhoods. To illustrate this, we estimate the relationship between household characteristics and neighborhood opportunity *within* the population of LIHTC households. We regress household characteristics at the time of move-in on indicators for the within-MSA quartile of neighborhood opportunity of the corresponding LIHTC development. In the baseline specification, we include controls for the number of bedrooms, the unit's income limit, and fixed effects for MSA interacted with year. Figure 3 illustrates the results. The raw coefficients, results for additional characteristics, and similar statistics for market-rate renters are documented in Tables D.4-D.8.

Relative to LIHTC developments in the bottom quartile of opportunity, developments in the top quartile house tenants who earned 16% higher income prior to move-in, grew up in families 11 percentiles (39%) higher in the parental income distribution, are twice as likely to have a college-educated head, and are 8 percentiles (39%) higher in the distribution of predicted future income. While higher-opportunity neighborhoods offer many benefits to children (Chetty, Hendren and Katz, 2016), LIHTC developments in the top quartile of neighborhood opportunity house 10% fewer families with children than those in the bottom quartile. Tenants of developments in higher-opportunity neighborhoods also move from further away and come from neighborhoods that are themselves higher-opportunity (Table D.4).[12]

There are also large differences across neighborhoods in the racial and ethnic composition of LIHTC developments. 80% of LIHTC households in the bottom quartile of neighborhood opportunity are Black or Hispanic, compared to just 52% in the top quartile. Non-Hispanic white households go from making up only 17% of LIHTC households in the bottom quartile to 42% of households in the top quartile. This shift across neighborhoods parallels the change in the composition of market-rate households; market-rate households in the bottom quartile of opportunity are three times as likely to be Black or Hispanic as households in the top quartile (Table D.7).

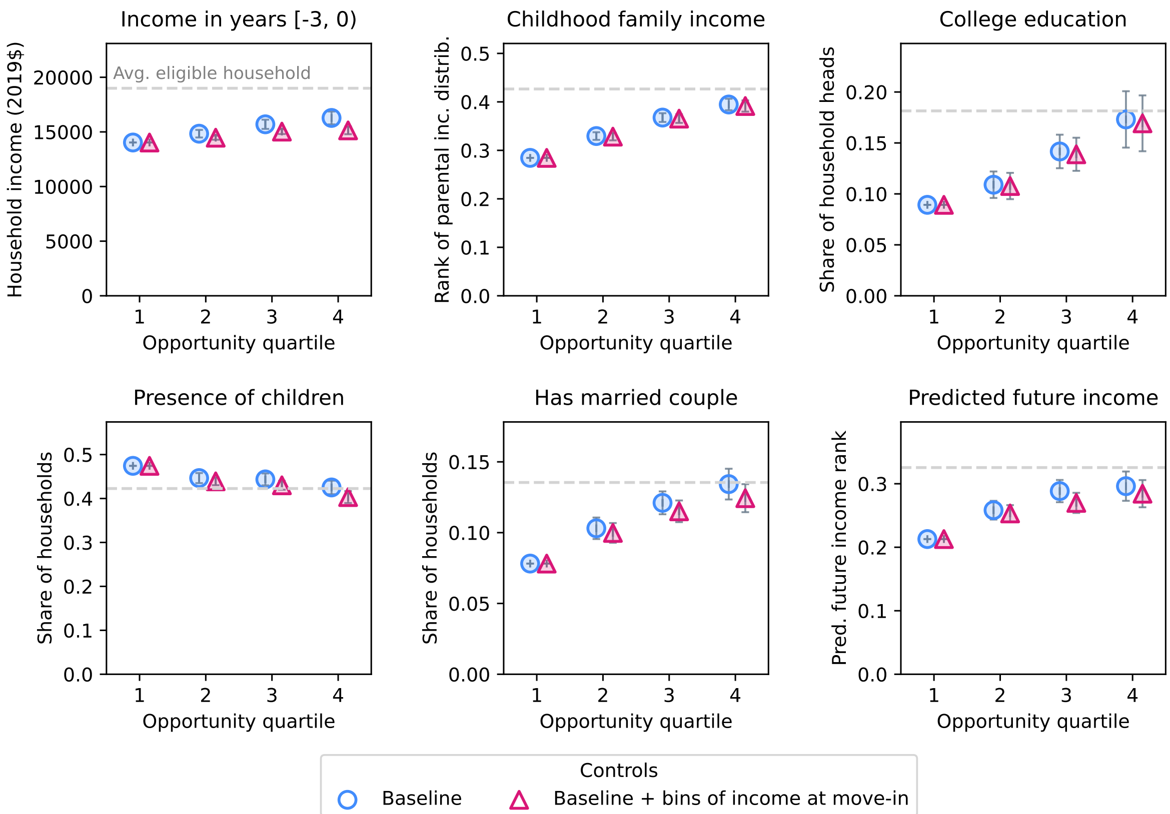
Adding controls for narrow income bins at the time of move-in—the characteristic used for means-testing—does little to attenuate differences in tenant composition across neighborhoods. While current income is strongly correlated with many other household characteristics in the broader population, these correlations are much weaker once we condition on being eligible for LIHTC, which restricts attention to the left-tail of the income distribution (Table D.3). One consequence of this, discussed in Section 8.4, is that changing the income limits used for means-testing has limited impact on the composition of LIHTC households by other characteristics.

Differences in the LIHTC population across neighborhoods can stem from both household preferences (i.e., who applies for assistance) as well as the process used to ration units among applicants. To help disentangle the role of these two forces, we next build a structural residential choice model with both market-rate and affordable housing options.

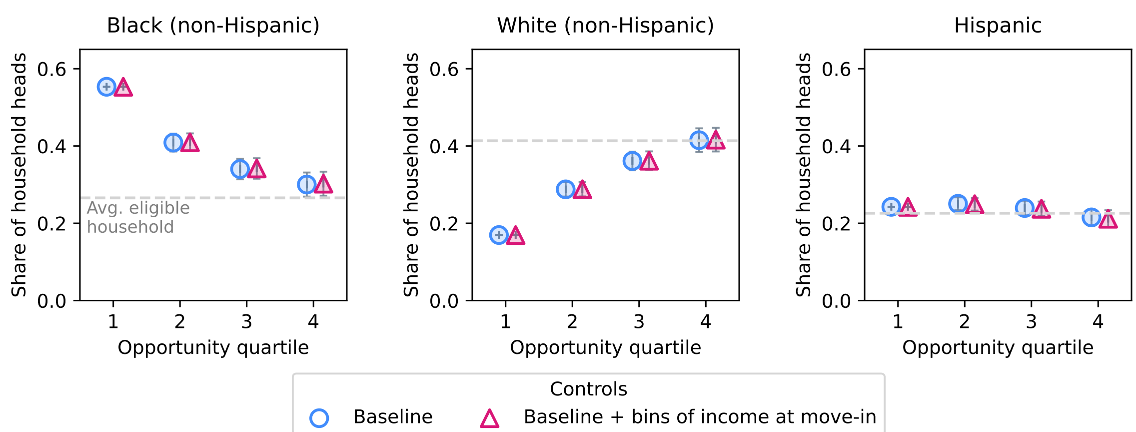
[12] In Table D.6, we explore whether these patterns across levels of neighborhood opportunity can be explained by specific characteristics of the neighborhood. Adding controls for bins of the share white (non-Hispanic) has the largest effect, attenuating the relationship between opportunity and race/ethnicity by about two-thirds and the relationship between opportunity and proxies for need by about one-third.

Figure 3: LIHTC household characteristics by neighborhood opportunity

(a) Proxies for need



(b) Race/ethnicity (household head)



Notes: This figure documents how characteristics of LIHTC households vary by the neighborhood opportunity of the development. Each point is a coefficient from a regression of a characteristic on indicators for each quartile, shifted by the average value in the first quartile. The sample covers LIHTC households at move-in, constructed using the Census-IRS panel (2010-2019, 50 sample MSAs). The dashed line is the average for LIHTC-eligible households living in market-rate units. The baseline specification includes controls for MSA interacted with year, the income limit, and the number of bedrooms. Income bins are based on a household's current adjusted gross income. We use 14 bins, starting with \$5k increments up to \$50k, then larger increments. 95% confidence intervals are represented by gray bars.

5 Model of residential choice with affordable housing options

We build a static model of residential choice with market-rate and affordable housing options, consisting of two stages. In the first stage, eligible households decide whether to apply to different affordable housing units, and developers allocate units by screening applicants based on their observable characteristics. In the second stage, households not allocated an affordable unit select among market-rate units.

5.1 Demand for affordable and market-rate housing

We model residential choice within a given city. The city has a set $\mathcal{J}$ of housing options, partitioned into affordable options $\mathcal{J}^{\mathrm{AH}}$ and market-rate options $\mathcal{J}^{\mathrm{MR}}$. Each housing option $j \in \mathcal{J}$ is a tuple of neighborhood, number of bedrooms, building type, building age, and, for affordable housing units, an income limit. The supply of units of each option is denoted s_j and is taken as exogenous. Options outside the city are included as a single outside option in $\mathcal{J}^{\mathrm{MR}}$ with utility normalized to zero. Each renter household $i \in \mathcal{I}$ is characterized by a vector of characteristics $\mathbf{w}_i$ and is endowed with current housing j_i^0. Based on their current income and household size, a household may be eligible to apply for affordable housing options $\mathcal{J}_i^{\mathrm{AH}} \subseteq \mathcal{J}^{\mathrm{AH}}$.

Household i receives the following indirect utility from option j:

$$u_{ij} = \boldsymbol{\gamma}_i \mathbf{x}_j - \beta_i r_j - \kappa_i^0 \mathbb{1}_{j \neq j_i^0} - \kappa_i^1 d_{jj_i^0} + \alpha_{ig(j)} \mathbb{1}_{j \in \mathcal{J}^{\mathrm{AH}}} + \xi_j + \varepsilon_{ij} \tag{1}$$

where $\mathbf{x}_j$ is a vector of housing and neighborhood characteristics, r_j is the median rent, $\mathbb{1}_{j \neq j_i^0}$ is an indicator for whether j is not the household's endowed housing option, $d_{jj_i^0}$ is the distance between j_i^0 and j, $\mathbb{1}_{j \in \mathcal{J}^{AH}}$ is an indicator for whether j is an affordable housing option, ξ_j are unobserved amenities, and ε_{ij} are idiosyncratic errors distributed as type 1 extreme values.

This formulation deviates from the canonical residential choice model presented in Bayer, Ferreira and McMillan (2007) in two ways. First, we add shifters that capture the difference in utility for an affordable housing option relative to an observably equivalent market-rate unit (α_{ig}), which may vary by neighborhood g. The difference could stem from unobserved differences in the average quality of market-rate and affordable housing options or any hassle or stigma associated with affordable housing. Second, similar to Galiani, Murphy and Pantano (2015), we incorporate move-out costs ($\boldsymbol{\kappa}_i$) incurred by households that select any option other than their endowed choice, which can increase with the distance from their endowed option. This allows the model to generate realistic move-out rates, which will be an important empirical moment.[13]

To ease exposition, we separate utility into a common component δ_j and a household-specific component λ_{ij}. Conditional on choosing from market-rate options, the probability i chooses $j \in$

[13]Move-out costs are also a common feature of dynamic residential choice models (Bayer et al., 2016; Almagro and Domınguez-Iino, 2024). Estimating a dynamic model would require additional assumptions on the trajectories of household and neighborhood characteristics, as well as how households form beliefs. Implicitly, our static model assumes that households are myopic, which may be reasonable given that most renters only stay in their unit for a few years (Table B.2).

$\mathcal{J}^{MR}$ is given by the usual logit formulation (McFadden, 1973):

$$P_{ij}^{\mathrm{MR}} = \frac{\exp(\delta_j + \lambda_{ij})}{\sum_{j' \in \mathcal{J}^{\mathrm{MR}}} \exp(\delta_{j'} + \lambda_{ij'})} \tag{2}$$

5.2 Allocation of affordable housing units

In the affordable housing sector, households apply independently to each affordable housing option and are then offered units by developers. We assume households can apply to each affordable housing option without cost, such that household i will apply to $j \in \mathcal{J}^{\mathrm{AH}}$ if they prefer it to their current housing and their best market-rate option. With logit errors, the probability household i applies to $j \in \mathcal{J}^{\mathrm{AH}}$ is

$$\begin{aligned} P_{ij}^{\mathrm{apply}} &= \mathbb{1}_{j \in \mathcal{J}_i^{\mathrm{AH}}} \times \mathbb{P}\left[u_{ij} > u_{ij'} \ \forall j' \in \left\{j_i^0\right\} \cup \mathcal{J}^{\mathrm{MR}}\right] \\ &= \mathbb{1}_{j \in \mathcal{J}_i^{\mathrm{AH}}} \times \left(\frac{\exp(\delta_j + \lambda_{ij})}{\exp(\delta_j + \lambda_{ij}) + \sum_{j' \in \left\{j_i^0\right\} \cup \mathcal{J}^{\mathrm{MR}}} \exp(\delta_{j'} + \lambda_{ij'})} \right) \end{aligned} \tag{3}$$

where $\mathbb{1}_{j \in \mathcal{J}_i^{\mathrm{AH}}}$ is an indicator for whether household i is eligible to apply for j.

Estimating preferences specific to affordable housing ($\boldsymbol{\alpha}$) requires taking a stance on the mechanism used to ration units among interested households. While we do not observe how individual developers allocate units, in practice, they appear to screen applicants on observable characteristics through some combination of waitlists, first-come first-served offers, and informal selection. We adopt an approximation flexible enough to nest these possibilities: each applicant receives an offer with a probability that depends on their characteristics, the development's neighborhood, and a development-specific stringency term that adjusts in equilibrium to clear the market.

Assumption 1 (mechanism). *Applicant i to development j in neighborhood g receives an offer with probability*

$$P_{ij}^{\mathit{offer}} = \frac{\exp(\phi_{ig(j)} - \zeta_j)}{1 + \exp(\phi_{ig(j)} - \zeta_j)}$$

where

- $\phi_{ig(j)} = \boldsymbol{\phi}'_{g(j)}\mathbf{w}_i$ *shifts an applicant's relative offer probability, with loadings* $\boldsymbol{\phi}_g = \boldsymbol{\phi}_0 + \boldsymbol{\phi}_1 \mathit{Opp}_g$ *that vary linearly in the neighborhood opportunity index*
- ζ_j *is a stringency term set in equilibrium to clear the market*

The loadings $\boldsymbol{\phi}_g$ govern which applicants developers favor, which can vary by neighborhood opportunity. A positive element of $\boldsymbol{\phi}_1$, for instance, means that developers in higher-opportunity neighborhoods place more weight on the corresponding household characteristic. The scalar ζ_j captures congestion at development j. Developments with many applicants relative to available units must have higher ζ_j to lower each applicant's offer probability enough to clear the market.

Specifically, in the absence of a price mechanism, ζ_j adjusts to satisfy

$$\dot{s}_j = \sum_{i \in \mathcal{I}} \overbrace{P_{ij}^{\text{apply}} \times P_{ij}^{\text{offer}}(\zeta_j) \times P_{ij}^{\text{accept}}}^{\text{Probability } i \text{ is allocated to } j} \tag{4}$$

where $\dot{s}_j$ is the flow of units in option j that become available for allocation.

In the model, the only situation in which a household would apply for a development but not accept an offer is if they receive multiple offers. In practice, LIHTC developers make offers sporadically as vacancies arise, and households that would receive multiple offers are unlikely to be able to compare them and select their favorite. We assume each household accepts the first offer that arrives, where the arrival order is random:

Assumption 2 (acceptances).

i) Offers arrive in random order, and a household accepts the first offer it receives

ii) Households are not strategic with respect to offer/acceptance probabilities when choosing whether to apply to each affordable housing option

Absent the second part of Assumption 2, households may wish to apply to only their favorite developments to avoid the case where they randomly accept a dominated option. For tractability, we rule out this form of strategic behavior. In practice, the estimated probability of receiving multiple offers is negligible, so this assumption rarely affects outcomes.

6 Estimation

We estimate our residential choice model in two steps. First, we use the observed choices of market-rate households to estimate preferences for housing/neighborhood characteristics ($\boldsymbol{\gamma}$), rent ($\boldsymbol{\beta}$), and adjustment costs ($\boldsymbol{\kappa}$). Second, taking those preference parameters as fixed, we estimate household preferences specific to living in affordable housing ($\boldsymbol{\alpha}$) and the screening parameters ($\boldsymbol{\phi}$) using the Generalized Method of Moments (GMM) to match moments based on both move-in and move-out decisions. The first step exploits the fact that market-rate choices identify common preference parameters, without requiring assumptions about the allocation mechanism for LIHTC units. The second step uses differences between predicted and actual LIHTC move-ins and move-outs to separately identify preferences specific to affordable housing and the parameters governing the screening process.

We estimate the model using repeated cross-sections of household decisions in the Chicago MSA, the third-largest metro area.[14] We aggregate observations into 2-year periods between 2010 and 2019, denoted by t. While we suppressed time subscripts for ease of exposition, we now rewrite utility as $u_{ijt} = \delta_{jt} + \lambda_{ijt} + \varepsilon_{ijt}$ and add t subscripts to the supply of units (s_{jt}), offer probabilities (P_{ijt}^{offer}), and sets of households ($\mathcal{I}_t$) and housing options ($\mathcal{J}_t$).

[14] Chicago is also a convenient setting, as its rental market consists mostly of market-rate and LIHTC units. New York City, in contrast, includes many rent-controlled/stabilized units, public housing units, and units of other affordable housing programs funded by the city.

6.1 Model parameterization

To define housing options, we use Public Use Microdata Areas (PUMAs) as neighborhoods,[15] discretize bedrooms as 0-1, 2, and 3+, define building types as single-family, small apartment building (<10 units), or large apartment building, and discretize building age into over or under 25 years old. The housing and neighborhood characteristics in $\mathbf{x}$ include indicators for the number of bedrooms, building type, and whether the building is less than 25 years old; indices of school quality, transit access, jobs access, and poverty from HUD; and log median income, race/ethnicity shares, and log population density from the 2010 Census. For the household characteristics ($\mathbf{w}$), we include measures of current and past household income, household size, race/ethnicity, presence of children, presence of seniors, presence of a married couple, head of household age, and whether the household has a housing voucher.

We parameterize the preference coefficients as the sum of a common component and a component that varies by the observable household characteristics $\mathbf{w}_i$:

$$\theta_i = \theta_0 + \sum_{\ell} \theta_\ell w_{i\ell}, \text{ for each } \theta_i \in \{\beta_i, \gamma_i, \kappa_i^0, \kappa_i^1\}$$
$$\alpha_{ig} = \alpha_0 + \sum_{\ell} \left(\alpha_\ell + \alpha_\ell^o \text{Opp}_g\right) w_{i\ell}$$

where we normalize elements in $\mathbf{w}_i$ to be mean zero across households such that each common component corresponds to the population average. We allow preferences specific to affordable housing (α_{ig}) to vary linearly by neighborhood opportunity, where Opp_g is our neighborhood opportunity index. This allows the "gap" between affordable housing and an observably-equivalent market-rate unit to vary heterogeneously by the level of neighborhood opportunity. We re-center neighborhood opportunity around zero, such that α_0 and each α_ℓ corresponds to preferences for affordable housing in a neighborhood at the 50th percentile of opportunity.

To ease exposition, we separate the non-idiosyncratic components of u_{ijt} into a common component (δ_{jt}) and household-specific term (λ_{ijt}):

$$\delta_{jt} = \boldsymbol{\gamma}_0 \mathbf{x}_{jt} - \beta_0 r_{jt} + \alpha_0 \mathbb{1}_{j \in \mathcal{J}^{\text{AH}}} + \xi_{jt} \tag{5}$$

$$\begin{aligned} \lambda_{ijt} = &\Big(\sum_{\ell} \boldsymbol{\gamma}_\ell w_{i\ell}\Big)\mathbf{x}_{jt} - \Big(\sum_{\ell} \beta_\ell w_{i\ell}\Big) r_{jt} - \Big(\kappa_0^0 + \sum_{\ell} \kappa_\ell^0 w_{i\ell}\Big) \mathbb{1}_{j \neq j_i^0} \\ &- \Big(\kappa_0^1 + \sum_{\ell} \kappa_\ell^1 w_{i\ell}\Big) d_{jj_i^0} + \Big(\sum_{\ell} \left(\alpha_\ell + \alpha_\ell^o \, \text{Opp}_{g_j}\right) w_{i\ell}\Big) \mathbb{1}_{j \in \mathcal{J}^{\text{AH}}} \end{aligned} \tag{6}$$

Embedded in this parameterization of preference heterogeneity is an assumption that two households with identical observable characteristics will have the same preferences, up to the idiosyncratic shocks (ε). This formulation is key to our estimation strategy and allows us to recover the preferences of households living in affordable housing units by observing how similar households make choices in the market-rate sector. Two features of our setting help make this assumption more reasonable. First, because units are rationed, many would-be LIHTC residents instead must make

[15] PUMAs are geographically larger than the Census tracts used in prior sections (see Figure D.4). The ACS is only a 1% annual sample, so defining housing options using tracts leads to many options with zero observed shares.

choices in the market-rate sector. Second, we observe a larger set of household characteristics than most existing residential choice models, leaving less to load on unobservables. In Appendix Table D.9, we provide some evidence that these observed household characteristics explain much of the differences in the housing choices of LIHTC households and other eligible households. Without conditioning on household observables, eligible households that move into a LIHTC unit within the next two years live in poorer, less white, less college-educated, and lower opportunity neighborhoods than other eligible households. However, conditional on the observables used in the demand model, these differences in neighborhood characteristics become statistically indistinguishable from zero in Chicago, suggesting that persistent unobservables play a limited role in the housing choices of LIHTC households.

In our parameterization, we also treat neighborhood characteristics as exogenous, and include in $\mathbf{x}$ only fixed neighborhood characteristics measured near the start of our sample period (e.g., median household income in the 2010 Census). For racial/ethnic neighborhood shares, the shares may be endogenous if the estimated race/ethnicity preferences reflect direct preferences over neighbors per se (e.g., homophily) rather than preferences for some correlated, time-invariant unobservables. Recent empirical work points toward at least some role for direct same-race preferences: Bayer et al. (2025) use a "new neighbor" design that isolates within-block variation in the race of arriving neighbors to provide evidence of preferences for same-race neighbors, and Davis, Gregory and Hartley (2026) reach a similar conclusion using a structural model that explicitly separates the two channels. In contrast, Caetano and Maheshri (2021) find that much of the observed sorting in their setting can be accounted for by correlated preferences for neighborhood characteristics. We maintain the assumption of exogenous neighborhood characteristics for tractability. Allowing for endogenous characteristics would require separate instruments that shift each characteristic. Even with such instruments, counterfactuals that change a neighborhood's characteristics would require re-solving the equilibrium distribution of households across neighborhoods. Davis, Gregory and Hartley (2026) find that, based on their estimates of racial homophily, existing neighborhood shares are already unstable, making it difficult to solve for such an equilibrium in practice.

6.2 Market-rate sector

We estimate preferences for housing and neighborhood characteristics using data on market-rate renter household decisions observed in the ACS. We first estimate mean utilities ($\boldsymbol{\delta}$), the heterogeneous component of preferences for rent and housing/neighborhood characteristics ($\boldsymbol{\gamma}_\ell$ and β_ℓ), and moving costs ($\boldsymbol{\kappa}$) using Maximum Likelihood Estimation. For a candidate vector of parameters $\widetilde{\boldsymbol{\theta}}^{\text{MR}} = \left\{\widetilde{\boldsymbol{\delta}}, \widetilde{\boldsymbol{\gamma}}_\ell, \widetilde{\beta}_\ell, \widetilde{\boldsymbol{\kappa}}\right\}$, the pseudo log-likelihood of the observed choices is given by

$$\ell = \sum_t \sum_{i \in \mathcal{I}_t^{\text{MR}}} \sum_{j \in \mathcal{J}_t^{\text{MR}}} \mathbb{1}_{j_i = j} \times \log\left(P_{ij}^{\text{MR}}(\widetilde{\boldsymbol{\theta}}^{\text{MR}})\right) \tag{7}$$

where $\mathbb{1}_{j_i=j}$ is an indicator for household i choosing option j and $\mathcal{I}_t^{\text{MR}}$ is the set of renters in the market-rate sample. Conditional on selecting a market-rate option, preferences for affordable housing ($\boldsymbol{\alpha}$) do not affect the likelihood function.

We use a contraction mapping to recover the mean utilities in each step of the estimation, which leverages the equilibrium condition that supply equals demand:

$$\widetilde{\delta}_{jt}^{new} = \widetilde{\delta}_{jt}^{old} + \log s_{jt} - \log \left(\sum_{i \in \mathcal{I}_t^{\text{MR}}} P_{ij}^{\text{MR}}(\widetilde{\boldsymbol{\theta}}^{\text{MR}}) \right) \tag{8}$$

Given the estimated mean utilities ($\widehat{\boldsymbol{\delta}}$), we can estimate the baseline preference parameters γ_0 and β_0 by regressing $\widehat{\boldsymbol{\delta}}$ on characteristics $\mathbf{x}_{jt}$ and rent r_{jt}. However, we need an instrument to address the endogeneity of rents with the unobservables ξ_{jt}.

Instrumenting for rent. We develop a new instrument for rents that isolates shifts in the residual supply of housing options stemming from broad trends in cities' demographic and industry composition.[16] The instrument is similar in spirit to Waldfogel instruments: prices faced by consumers depend in part on the preferences of other consumers in the market (Waldfogel, 2003; Berry and Haile, 2016). In our setting, the key intuition is that housing options popular among growing demographic groups (e.g., unmarried 20-30 year-olds) will see increased demand—and, from the perspective of any one household, less residual supply—in later periods than those popular among shrinking demographic groups (e.g., families with kids). Given the inelasticity of housing supply (Saiz, 2010; Baum-Snow and Han, 2024), these shifts will affect rents.

We construct the instrument in a similar manner to shift-share instruments (Bartik, 1991). The 'shifts' are nationwide trends in the population of different demographic groups, and the 'shares' are the proportion of each group who would choose each housing option, estimated using pre-period data. We describe this procedure in detail in Appendix Section C.1. To construct the shares, we use data on renter and homeowner choices from 2005-2009—before our main study period—to estimate the likelihood that individuals of different groups select each option $j \in \mathcal{J}^{\text{MR}}$. We classify individuals over the age of 21 using the industry of their primary employer, ten-year age bins, whether they are married, and whether they have children.[17] We then estimate an auxiliary model to estimate the share of individuals in each housing option, $\widehat{P}_{jb}$, where b indexes unique combinations of the (discrete) individual characteristics. To construct the shifts, we compute the growth rate of group b between the pre-period and period t (denoted g_{bt}). We use only data from the other cities in our sample to compute g_{bt} so that the instrument does not depend on any variation specific to Chicago. During our sample period, cities became substantially older, experienced large changes in industry composition, and contained fewer married couples and fewer households with kids (Figure C.1).

[16] Residual supply refers to the portion of available housing units that remain for a household to choose from after accounting for the choices of other market participants. Our instrument does not rely on any variation originating in the supply-side of the housing market itself, such as construction.

[17] We define industry using the 3-digit North American Industry Classification System (NAICS) code of their primary employer, which we identify by matching the Employer Identification Number (EIN) for the individual's highest-paying W-2 to the Business Registrar.

Putting these components together, we construct our instrument as

$$z_{jt} = \frac{\sum_b g_{bt} N_b \widehat{P}_{jb}}{\sum_b N_b \widehat{P}_{jb}} \tag{9}$$

where N_b is the number of individuals in the pre-period with characteristics b.

To isolate just within-neighborhood variation, we add neighborhood fixed effects to Equation 5 so that any time-invariant neighborhood characteristics (including unobservables) are absorbed by the fixed effects. With neighborhood fixed effects $\psi_{g(j)}$, the estimating equation becomes

$$\delta_{jt} = \boldsymbol{\gamma}_0 \mathbf{x}_{jt} - \beta_0 r_{jt} + \psi_{g(j)} + \xi_{jt} \tag{10}$$

where we instrument for rents r_{jt} with our instrument z_{jt}.

Table 2 compares the parameter estimates using OLS versus our instrument. In the first stage (Table D.11), a one standard deviation increase in our instrument increases rents by \$31 (F-statistic of 35). When estimated using OLS, we find that renters are insensitive to rent. However, once we instrument for rents, we obtain the expected result that households dislike paying higher rents. For other housing characteristics, the average household is willing to pay about \$750/mo more for an apartment with 3+ bedrooms instead of a studio or 1-bedroom, \$460/mo more for a newer building, and more for units in larger apartment buildings.

Satisfying the exclusion restriction requires that, conditional on observables $\mathbf{x}_{jt}$ and the neighborhood fixed effects $\psi_{g(j)}$, the remaining variation in the unobserved demand shocks is orthogonal to the variation in z_{jt}, i.e. that $\mathbb{E}[z_{jt}\xi_{jt} \mid \mathbf{x}_{jt}, \psi_{g(j)}] = 0$. With neighborhood fixed effects, the primary threats to identification come from changes over time rather than across housing options. In Table D.10, we show that our instrument is associated with small and often insignificant changes in the counts of various types of establishments (e.g., restaurants and grocery stores) and other neighborhood characteristics. For robustness, the final column of Table 2 compares our preferred estimates to a version in which we instrument for rent using characteristics of nearby neighborhoods, a commonly used instrument in the residential choice literature. This approach is inspired by the differentiated products literature: characteristics of other products affect equilibrium prices but are arguably uncorrelated with unobserved quality (Berry, Levinsohn and Pakes, 1995). Such instruments were first used in the context of residential choice in Bayer, Ferreira and McMillan (2007) (henceforth BFM) and remain popular today.[18]

The difference in threats to exogeneity between BFM instruments and our own makes them complementary. BFM instruments rely on *cross-sectional* variation in housing and neighborhood characteristics.[19] A potential concern is that unobserved demand shocks may be spatially correlated, which can lead to violations of the exclusion restriction if the neighborhood features used to form an instrument are also spatially correlated. In contrast, our instrument uses external, within-

[18]See, for example, Geyer (2017); Calder-Wang (2021); Carneiro, Das and Reis (2022); Anagol, Ferreira and Rexer (2026); Barwick et al. (2024).

[19]The variables used to construct BFM instruments are often included in the demand specification, too. Using transformations of variables included in the demand specification as instruments can make the estimates especially sensitive to model misspecification (Andrews et al., 2025).

neighborhood variation *over time* stemming from broader population trends, but the exclusion restriction may be violated if changes in unobservables are correlated with baseline shares ($\widehat{P}_{jb}$). Despite differences in the threats to identification, the two instruments yield similar estimates; the implied willingness to pay for different characteristics is not statistically different between the two sets of estimates (Table 2).

Heterogeneity in household preferences. We present the estimated preference parameters in Tables D.12, D.13, and D.14. Much like existing work, we find substantial preference heterogeneity along household characteristics such as race, income, and household structure (see, e.g., Galiani, Murphy and Pantano, 2015; Calder-Wang, 2021; Davis, Gregory and Hartley, 2026).[20] Each racial/ethnic group exhibits strong preferences for living in neighborhoods with a high share of residents of the same race/ethnicity. For example, the average Black household values a 10 percentage point increase in the share of Black residents by about \$50/mo, which may stem from either homophily or correlated preferences for unobservables. Households with children and married couples place more weight on lower-density neighborhoods with access to good schools, and larger households naturally have strong preferences for larger units. Lower-income, Black, and Hispanic households are all more sensitive to rents and, as a result, will be more responsive to the below-market rents offered by affordable housing. Similar to Galiani, Murphy and Pantano (2015), we find high moving costs that are primarily due to a high fixed cost of moving at all, plus a much smaller variable cost that increases in distance.

6.3 Affordable housing sector

To estimate preferences for affordable housing ($\boldsymbol{\alpha}$) and the screening parameters ($\boldsymbol{\phi}$), we use the Generalized Method of Moments (GMM) to match two sets of moments each period, described in detail in Appendix Section C.3. The first set is based on *move-ins* to LIHTC and includes the average characteristics ($\mathbf{w}$) of households allocated to affordable housing and the covariance between household characteristics and neighborhood opportunity level of the development. The second set is based on *move-outs* of LIHTC, and includes the average rate at which affordable housing households move out, the covariance between moving out and household characteristics, and the covariance between moving out and the interaction of household characteristics with the opportunity level of the household's current neighborhood. We document the estimated preferences specific to affordable housing in Table D.12 and the screening parameters in Table D.15.

The move-out moments are primarily informative about heterogeneity in household preferences ($\boldsymbol{\alpha}$).[21] Households that remain in LIHTC units longer than we would predict, based solely on their

[20] It is difficult to directly compare our estimates to others in the literature. Many papers, including Bayer, Ferreira and McMillan (2007), are estimated using data on both homeowners and renters. The most apt comparison we've found is Calder-Wang (2021), who estimates a similar model for New York City renters. However, even in this case, the vector of both household and housing/neighborhood characteristics in Calder-Wang (2021) is much more sparse. Many of the characteristics we use are also correlated (e.g., income and lagged income; neighborhood college share and racial shares; etc.), so the relationship between broad concepts like household 'income' and neighborhood 'education level' may load on the many included characteristics that are correlated with each.

[21] In practice, developers can also evict tenants. If similar tenants are less likely to be evicted from affordable

Table 2: Estimated preferences for average household

Covariate	IV	Alternatives: OLS	Alternatives: BFM
Gross rent (00s)	-0.1673	-0.0217	-0.1784
	(0.0494)	(0.0033)	(0.0586)
2 bedrooms	0.6844	0.2858	0.7113
	(0.1381)	(0.0272)	(0.1653)
3+ bedrooms	1.253	0.4452	1.310
	(0.2770)	(0.0329)	(0.3276)
Building <25yo	0.7725	0.4468	0.7991
	(0.1145)	(0.0229)	(0.1325)
Big apartment building	0.6939	0.6445	0.7059
	(0.0403)	(0.0276)	(0.0394)
Small apartment building	0.2889	0.5129	0.2728
	(0.0805)	(0.0262)	(0.0961)
Neighborhood (PUMA) fixed effects	✓	✓	
F-statistic	35.03		30.52
N	5300	5300	5300

Notes: This table compares OLS and IV estimates of Equation 10. The dependent variable is the mean utility of each housing option in each period ($\widehat{\boldsymbol{\delta}}$), i.e., the value of option j to the average household in the sample. For the IV and OLS specifications, the neighborhood fixed effects absorb time-invariant neighborhood characteristics. The BFM instruments use cross-sectional variation, so we can not include neighborhood fixed effects. For the BFM instruments we use five characteristics in a 3-6 mile ring around the focal neighborhood: the average level of development and the fraction of land that is forested in the 2011 National Land Cover Database; the fraction of land defined as 'flat plains' from the US Geological Survey's National Elevation Database (Cress et al., 2009); and the median year built and share of housing units that are single-family residences in the 2010 5-year ACS. The sample size is rounded per Census disclosure requirements. Standard errors are clustered at the PUMA level and are reported in parentheses.

preferences for housing/neighborhood characteristics estimated in the market-rate sector, must place a relatively higher value on affordable housing. Appendix Table C.3 illustrates this directly. Married couples, for instance, move out of LIHTC units more quickly than their preferences for housing/neighborhood characteristics would predict, which the model rationalizes through a dislike for LIHTC units relative to similar market-rate units.[22]

The move-in moments are informative about both preferences for affordable housing and the screening parameters. Appendix Table C.2 shows that the predicted composition of LIHTC tenants under $\boldsymbol{\alpha} = 0$ differs systematically from the realized composition. Once preferences for affordable housing ($\boldsymbol{\alpha}$) are disciplined by the move-out moments, any remaining gaps between the predicted and realized move-in composition must be rationalized by the screening parameters ($\boldsymbol{\phi}$).

housing than market-rate housing, our estimates will overstate the value of affordable housing relative to market-rate. Ellen, Lochhead and O'Regan (2024) document that an average of 14.8 eviction orders were filed per 100 units for LIHTC units in New York City between 2016-2019, which is above the overall market-rate average (6.5 per 100 units) but below the rate for public housing (19.2 per 100 units) and similar to the filing rates in many of the poorer parts of the city documented in Collinson et al. (2024).

[22]For both the sample analogues and the model-predicted moments, we use annual move-out rates to match the construction of move-outs in the ACS, where a household's endowed option j_i^0 is their housing choice the prior year. In practice, moves to other affordable housing options are rare—in Chicago, only 2.6% of moves into a LIHTC building are from another LIHTC building—so we model the move-out decision as a decision to move to a market-rate option.

7 Quantifying the role of preferences versus screening

In this section, we present the estimated parameters governing preferences for affordable housing and developer screening, then use the model to decompose the contributions of means-testing, preferences, and screening to the composition of LIHTC tenants in existing developments. These channels carry different policy and welfare implications, and a given pattern in the data—e.g., strong targeting by need—can arise from any of them. If the targeting arises largely from preferences, it reflects a form of self-targeting; households sort into LIHTC on their own, based on the characteristics of existing developments. If, instead, it arises from means testing or screening, then policies such as changes to the allocation rules can meaningfully affect who receives assistance. We find that household preferences are the primary driver of the observed LIHTC tenant composition (especially for race/ethnicity), followed by means-testing and then screening.

7.1 Preferences for affordable housing

Household preferences for affordable housing relative to observably similar market-rate units ($\boldsymbol{\alpha}$) vary across both households and neighborhoods. To express these parameters in interpretable units, we convert them into rent-equivalent dollars per month by dividing by each household's rent disutility (β). Consider an affordable housing unit built in a median-opportunity neighborhood. On average, LIHTC-eligible households value this unit by \$67/month *less* than they would value it if it were a market-rate unit (Table 3). This gap is increasing in neighborhood opportunity, ranging from -\$100/month in neighborhoods at the 25th percentile of opportunity to -\$35/month in 75th percentile neighborhoods.

We estimate substantial heterogeneity along household characteristics in the value of affordable housing (Table 3). For exposition, we divide households into four types by race/ethnicity (Black/Hispanic and white/other) and by whether their predicted future income is in the bottom quartile of the nationwide distribution of renters ('high-need') or not ('moderate-need'). In median-opportunity neighborhoods, relative to observably similar market-rate units, affordable housing units are valued the least by moderate-need, white/other households (-\$192/month) and most by high-need, Black/Hispanic households (+\$24/month). Larger households, those with children, those without a married couple, and voucher holders also place greater value on affordable housing (Appendix Table D.16).

Many households place *positive* value on LIHTC units relative to observably equivalent market-rate units (Figure 4), suggesting that any stigma or hassle costs associated with LIHTC are outweighed by other unobserved differences for these households. This is especially true of LIHTC tenants, of whom half place positive value on a LIHTC unit built in a median-opportunity neighborhood. This finding echoes survey evidence from Reid (2018), in which current LIHTC tenants highlighted less tangible benefits to the developments, including reliable property managers, protection from rent increases, and a greater sense of community.[23] Consistent with there being

[23]LIHTC units have also experienced less rent growth historically than market-rate units. If households' value for

unobserved quality differences that can favor LIHTC, we show in Appendix Section B.5 that LIHTC units sampled by the American Housing Survey also have fewer maintenance issues and are less likely to have roaches or barred windows than market-rate units in the same neighborhood.

Figure 4: Value of affordable housing

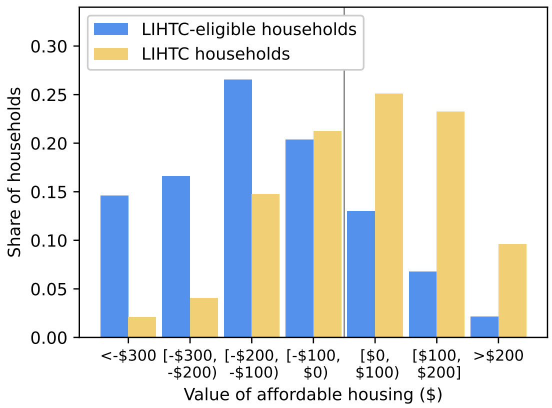


Table 3: Value by household type

	Nbhd opportunity ptile		
Population	p25	p50	p75
All eligible	-\$99.7	-\$67.5	-\$35.3
	(2.38)	(1.62)	(1.33)
High-need, Black/Hisp.	-\$0.50	\$24.2	\$48.8
	(3.73)	(2.21)	(1.72)
Moderate-need, Black/Hisp.	-\$5.02	-\$0.25	\$4.53
	(3.99)	(2.58)	(2.15)
High-need, White/other	-\$221	-\$154	-\$86.9
	(5.90)	(3.23)	(2.75)
Moderate-need, White/other	-\$241	-\$192	-\$144
	(4.24)	(2.66)	(2.55)

Notes: Figure 4 documents the distribution of the rent-equivalent value of an affordable housing unit built at the 50th percentile of neighborhood opportunity relative to an observably similar market-rate unit. The value is converted into units of monthly rent using each household's rent disutility. Table 3 reports the average α_i/β_i at different levels of neighborhood opportunity for different populations of households. 'High-need' refers to households whose predicted future income is in the bottom quartile of the nationwide distribution of renters, adjusted for household size and age. Bootstrapped standard errors are reported in parentheses.

7.2 Developer screening

Conditional on applying, households receive offers at different rates depending on the screening parameters $\boldsymbol{\phi}$. Appendix Table D.15 documents the full set of estimated parameters. In a median-opportunity neighborhood, applicant screening favors households with children, larger households, households with a Black (non-Hispanic) head, and households with a housing voucher to cover rent. The weight placed on each of these characteristics declines with neighborhood opportunity, while the weight placed on an applicant's income rises.

To better illustrate the magnitudes of the screening parameters, Table 4 reports simulated offer probabilities for a hypothetical development to which all eligible households apply with equal probability, with probabilities set such that five households apply per unit. For a development built at the 25th percentile of neighborhood opportunity, high-need Black/Hispanic households are about 25% more likely to receive an offer than the average applicant. The lowest offer rates in such a neighborhood are for moderate-need, White/other households. In higher-opportunity neighborhoods, these gaps compress, and screening becomes less favorable to high-need and Black/Hispanic households.

LIHTC is partly based on expectations of future rent growth, this will load onto the $\boldsymbol{\alpha}$ parameters in our model.

Table 4: Simulated offer probabilities under equal applications

	Nbhd opportunity ptile		
Population	p25	p50	p75
Average applicant	20%	20%	20%
High-need, Black/Hispanic	25.3%	23.9%	22.5%
	(0.65)	(0.95)	(1.38)
Moderate-need, Black/Hispanic	18.9%	20.1%	21.5%
	(0.81)	(1.46)	(2.05)
High-need, White/other	19.8%	18.7%	17.5%
	(0.85)	(1.42)	(1.99)
Moderate-need, White/other	15.2%	16.0%	17.0%
	(0.54)	(0.61)	(0.84)

Notes: This table documents the simulated offer probabilities for different types of households for a scenario in which households apply with equal probability to a hypothetical new development located at different levels of neighborhood opportunity. The application probabilities are set such that there are five applicants per unit. 'High-need' refers to households whose predicted future income is in the bottom quartile of the nationwide distribution of renters, adjusted for household size and age. Bootstrapped standard errors are reported in parentheses.

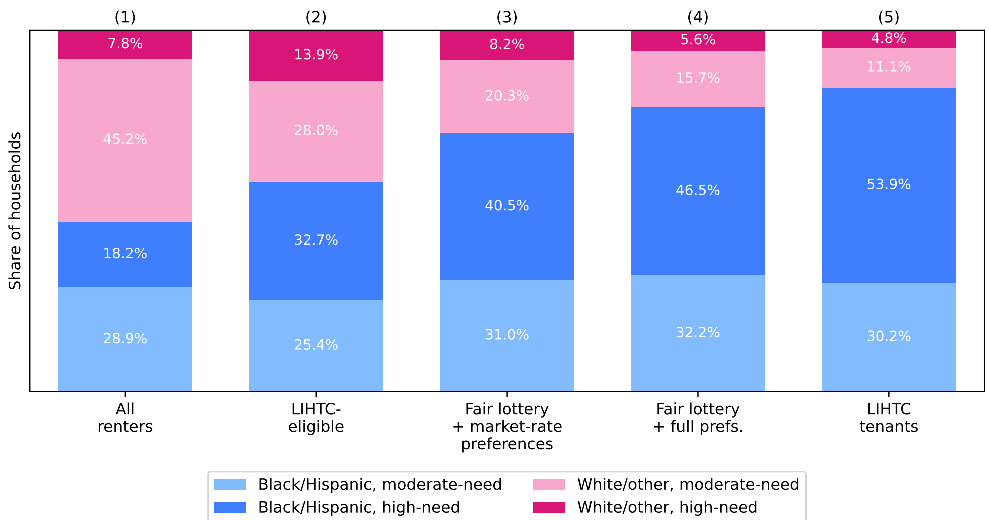
7.3 The role of preferences versus screening

We now decompose the contribution of means-testing, household preferences, and developer screening to the composition of LIHTC tenants in existing Chicago developments. Figure 5 reports the share of the four household types in the broader renter population (Column 1), among LIHTC-eligible renters (Column 2), under counterfactual versions of the model that shut down preferences and/or screening (Columns 3 and 4), and finally among observed LIHTC tenants (Column 5).

Relative to all renters, LIHTC tenants in Chicago are about twice as likely to be Black or Hispanic (84% of tenants versus 47% of all renters) and more than twice as likely to be high-need (59% of tenants versus 26% of all renters). Means-testing alone—i.e., restricting attention to LIHTC-eligible renters—closes over half of the gap by need and about a third of the gap by race/ethnicity. To isolate the role of preferences for housing and neighborhood characteristics, Column 3 simulates the share of each household type in a world where households apply as if LIHTC units were standard market-rate units ($\boldsymbol{\alpha} = 0$) and are selected via a fair lottery ($\boldsymbol{\phi} = 0$). Even with no LIHTC-specific preferences and no screening, LIHTC developments would house 71% Black/Hispanic households and 48% high-need households. This reflects the fact that LIHTC developments are disproportionately built in neighborhoods that are favored by Black/Hispanic and lower-income households in the market-rate sector. Column 4 adds back preferences specific to affordable housing while continuing to allocate units via a fair lottery. The share of Black/Hispanic households rises to 79% and the share of high-need households rises to 52%. The remaining gap between Column 4 and Column 5 is attributable to screening, which increases the share of Black or Hispanic tenants by an additional 5.4 percentage points and the share of high-need tenants by 6.6 percentage points.

Two implications follow. First, because preferences for housing and neighborhood characteristics account for such a large share of the observed targeting within the eligible population (especially by race/ethnicity), the characteristics of existing developments do much of the work in determining who receives assistance. This motivates the paper's central counterfactual —changing the location of a new development—which we turn to next. Second, the relative magnitudes suggest that the levers available to a policymaker who wants to change targeting are correspondingly constrained. In Section 8.4, we simulate the effects of alternative policies for allocating units and find that many policy levers available post-construction are much weaker instruments than the initial choice of location.

Figure 5: Decomposition of preferences and screening



Notes: This figure decomposes the role of means-testing, preferences, and screening in explaining the characteristics of LIHTC tenants in developments in the Chicago MSA. Columns 3-5 are predicted shares using the estimated model. Column 3 shuts down any preferences specific to affordable housing ($\boldsymbol{\alpha} = 0$) and allocates units according to a fair lottery ($\boldsymbol{\phi} = 0$). Column 4 brings back preferences specific to affordable housing but continues to allocate units with a fair lottery. 'High-need' refers to households whose predicted future income is in the bottom quartile of the nationwide distribution of renters, adjusted for household size and age.

7.4 Discussion

Our estimates rely on a strategy for recovering demand under rationing, a setting that is challenging because observed allocations reflect both applicants' underlying preferences and the rationing mechanism. Unlike in other empirical market design settings (e.g., school choice), we observe neither applications nor the exact rules of the mechanism, and instead estimate preferences for the characteristics of the rationed good from a parallel market-rate sector and approximate the unobserved mechanism with a flexible reduced-form screening function. This approach comes with important caveats that bear on how the preceding results should be interpreted.

First, while we treat observed market-rate choices as reflective of true preferences, frictions such as discrimination, financial constraints, and imperfect information may constrain residential choices for many households. For example, even 50 years after the passage of the Fair Housing Act, studies continue to find evidence of discrimination against Black and Hispanic households (Ahmed and Hammarstedt, 2008; Ewens, Tomlin and Wang, 2014; Christensen and Timmins, 2023). Lower-income households may also struggle to find landlords willing to accept their applications for units whose rent would represent a large share of their income, even if they would be willing to pay. If certain households face systematic frictions for options in higher-opportunity neighborhoods, our estimates based on observed choices in the market-rate sector will understate the value these households place on the characteristics of these neighborhoods.

Second, our formulation of the rationing mechanism approximates how LIHTC units are rationed in practice. Common mechanisms for filling vacancies include waitlists, first-come-first-serve, and lotteries, each combined with screening of potential tenants based on credit score, eviction history, and some minimum income. While these mechanisms can be nested within our formulation so long as offers are random conditional on the observables in $\mathbf{w}$, in practice, developers may screen on other characteristics, and mechanisms such as waitlists entail additional dynamic considerations (e.g., heterogeneity in attrition). If households are screened on characteristics we do not observe (e.g., credit scores or eviction histories), the estimated screening parameters will capture both direct screening on the characteristics in $\mathbf{w}$ and screening on any correlated unobservables. Similarly, although we interpret $\boldsymbol{\phi}$ as capturing developer behavior, similar patterns in move-ins would arise if higher-need and Black/Hispanic households are disproportionately informed about LIHTC vacancies (e.g., through referrals from current tenants or social workers). If $\boldsymbol{\phi}$ reflects developer choices, then policies that change how developers screen (e.g., requiring developers to allocate via a fair lottery) would meaningfully reshape the composition of tenants, while the same policies may have little effect if instead $\boldsymbol{\phi}$ reflects other frictions, such as differential information.

8 The trade-offs of location

To evaluate the effects of where affordable housing is built, we simulate adding a new LIHTC development to households' choice sets and vary the neighborhood in which it is placed.[24] We then simulate which households receive affordable housing and how much they value it, holding fixed market-rate supply, rents, and neighborhood characteristics.[25]

[24] We simulate a development with 100 units, with unit sizes that match the distribution of LIHTC units in the sample. We set the income limit at 60% of AMI. In practice, the government does not directly select where to locate a new LIHTC development. In Appendix Section A.2 we use data on developer applications for subsidies to show that policy levers such as spatial variation in the subsidy size can influence developer behavior.

[25] Our results should be interpreted as the partial equilibrium response to a new development, and do not include any re-sorting in the market-rate sector in response to the development's entry or changes in market-rate rents. On rents, a new development adds housing supply to the focal neighborhood while drawing tenants from throughout the city, opening vacancies elsewhere. The resulting rent effects are likely diffuse, but should be concentrated in the neighborhoods from which LIHTC tenants are drawn. For developments built in higher-opportunity neighborhoods, for example, tenants tend to come from other higher-opportunity neighborhoods (Table D.4), so any rent relief is likely to accrue disproportionately to those neighborhoods rather than to lower-opportunity ones.

8.1 Tenant welfare, the distribution of assistance, and costs

Consistent with the descriptive evidence, which households receive a unit in the simulated development depends on its location (Figure 6 Panel a). For developments in the top quartile of neighborhood opportunity, 49% of households are Black/Hispanic households and 42% are high-need. In contrast, for developments in the bottom quartile, 88% of households are Black/Hispanic and 63% are high-need.

The model allows us to disentangle two potential causes for the decrease in Black/Hispanic and high-need households in the higher-opportunity neighborhoods. First, these households may prefer developments built in neighborhoods that we classify as providing less opportunity. Indeed, Figure 6 Panel (b) shows that the average Black/Hispanic applicant is slightly less likely to apply for a new unit in the top quartile of neighborhood opportunity than in the bottom quartile. This reduction is primarily due to the lower share of same-race/ethnicity residents in these neighborhoods, which outweighs the improvements in school quality, transit access, and other amenities. However, the decrease for Black/Hispanic households is small relative to the increase for white/other households, who are five times more likely to apply for a unit built in the top instead of bottom quartile.

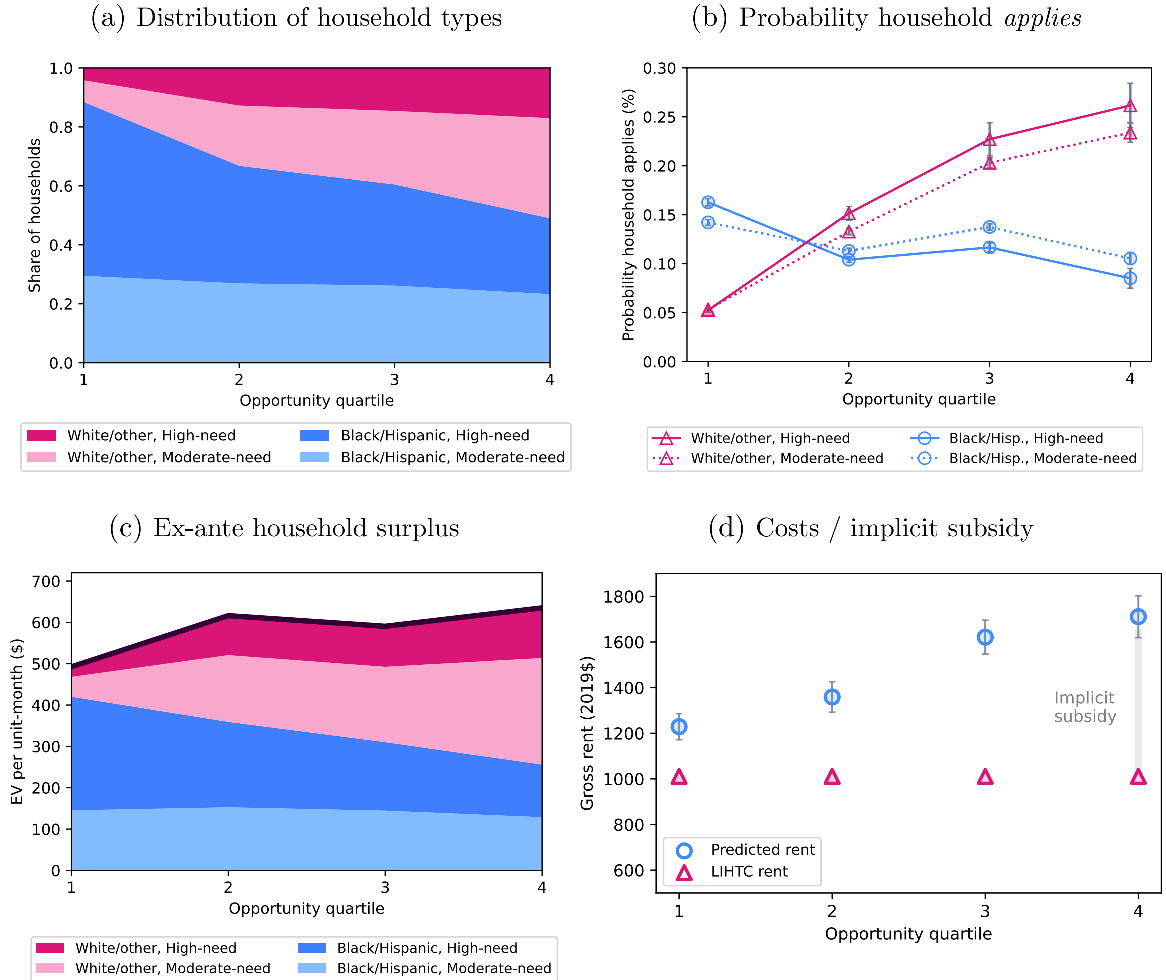
The increase in applications from white/other households creates a crowding out effect, in which the fraction of high-need and Black/Hispanic households in the developments drops due to the demand response of moderate-need and white/other households. The increase from white/other households alone—holding fixed applications from Black/Hispanic households—accounts for the majority of the decline in the share of Black/Hispanic households between the bottom and top quartiles of neighborhood opportunity.[26] This crowding out effect occurs because of the limited supply of affordable housing units. In contrast, other in-kind transfers such as food stamps and Medicare are entitlements, and take-up by one household does not directly affect another household's ability to take up assistance. Maintaining the same number of Black/Hispanic (high-need) households for a development in the top quartile of neighborhood opportunity as a development in the bottom quartile would require building 84% (48%) more units.

Household surplus. We compute household surplus accruing from the construction of the new development using each household's equivalent variation (EV), measured in units of monthly rent.[27] A household's EV depends on its probability of being allocated to the development, the value it would derive from living there, and the value it places on its market-rate options if not allocated to the development.

[26] While the simulated number of applications from Black/Hispanic households declines only slightly in neighborhood opportunity, it is not necessarily the *same* households that apply in each neighborhood. This is an important distinction from other studies that evaluate the residential choices of households with housing vouchers, where the recipient of assistance is held fixed. In general, this literature finds that households given vouchers rarely use the vouchers to move to higher-opportunity areas without additional assistance (Lens, Ellen and O'Regan, 2011; Bergman et al., 2023). Similarly, households in our sample who move into a LIHTC development built in a higher-opportunity neighborhood generally come from a neighborhood that is itself higher-opportunity (Table D.4).

[27] We compute the EV exclusive of any adjustment costs of moving. This is justified if moving into LIHTC does not increase the total number of lifetime moves. In practice, the average LIHTC household remains in their unit longer than the average LIHTC-eligible household (Table B.2), so their number of lifetime moves may even decrease.

Figure 6: Composition, value, and costs of a new LIHTC unit



Notes: This figure documents how the composition of tenants and the value derived from a new development varies based on location. Each point is the average for a simulated development built in each PUMA in the corresponding quartile. Household surplus is computed as the equivalent variation in monthly rent based on differences in expected utilities pre/post-new development. Panel (d) documents the 'implicit subsidy' of LIHTC units in the Chicago MSA, which we define as the difference between the regulated rent for a LIHTC unit and an estimate of the rent if the same unit were a market-rate unit. Gray bars represent 95% confidence intervals.

Total household surplus increases by $143 per unit-month for a development built in the top instead of bottom quartile of neighborhood opportunity (Figure 6 Panel c). However, the gains do not accrue evenly across households. While white/other households value a new unit in the top quartile $307 more per month than a unit in the bottom quartile, Black/Hispanic households value the unit $164 *less*, primarily because of their reduced odds of being allocated the unit. Similarly, moving a new unit from the bottom to the top quartile of neighborhood opportunity is better for moderate-need households (+$194) than high-need households (-$51).

Costs. For each LIHTC unit, we measure costs as the 'implicit subsidy,' defined as the difference between its regulated LIHTC rent and an estimate of how much the same unit would rent for as a market-rate unit. Conceptually, the implicit subsidy captures the opportunity cost of setting aside a market-rate unit to be rented out as a LIHTC unit instead. We predict the market value of a LIHTC unit based on its characteristics, using a sample of market-rate units observed in the ACS as training data (see Appendix Section C.4). The monthly implicit subsidy for a typical unit increases from \$218 (18% discount off of market-rate) in the bottom quartile to \$700 (41% discount) in the top quartile (Figure 6 Panel d).[28]

Net effects of location. Figure 7 summarizes the trade-offs of building affordable housing in the top quartile versus bottom quartile of neighborhood opportunity. A new LIHTC unit in higher-opportunity neighborhoods generates additional household surplus for moderate-need and white/other households, but reduces surplus for high-need and Black/Hispanic households. The net difference between the change to aggregate household surplus and the change in costs is −\$339 from the bottom to the top quartile of neighborhood opportunity, although the social planner may not equally weigh the value to households and the costs if, for example, some of the costs represent a transfer to other individuals (e.g., to employees of the developer).

Beyond household surplus and costs, many other considerations may enter into the social planner's decision of where to build affordable housing, including any externalities or effects on other policy goals, such as reducing segregation. We next consider effects on racial/ethnic and economic integration, the upward mobility of children in the development, and spillovers on neighbors.

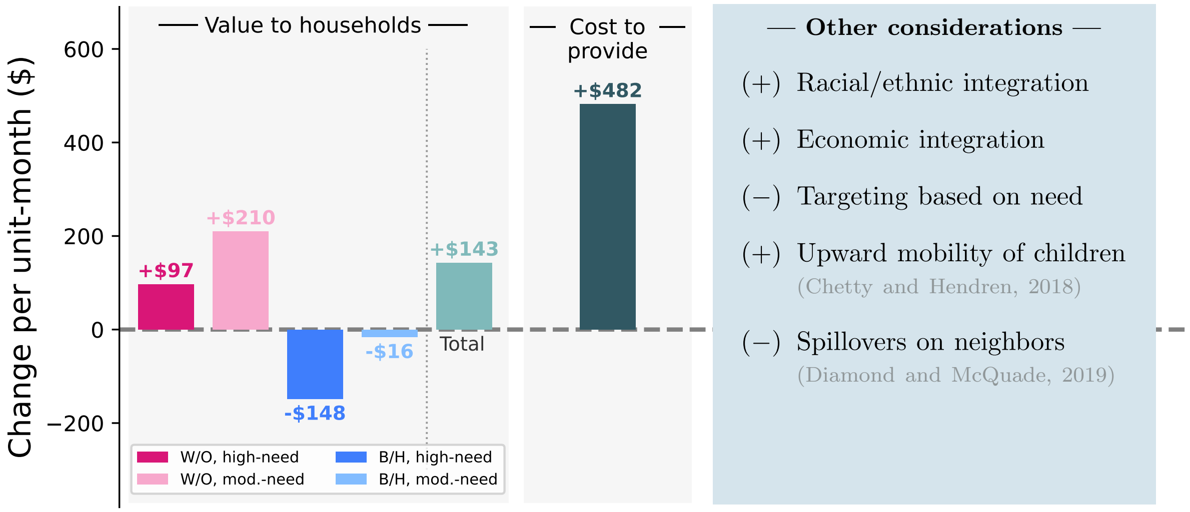
8.2 Racial/ethnic and economic integration

We next look at the effect of location on city-wide racial/ethnic and economic integration, motivated by evidence on the detrimental effects of racial/ethnic segregation on minority households (Ananat, 2011; Chetty et al., 2020; Chyn, Collinson and Sandler, 2024) and the rise in economic segregation in recent years (Reardon et al., 2018). The potential role affordable housing plays in perpetuating racial/ethnic segregation has been the subject of several court cases over the years. Most recently, a 2015 Supreme Court case evaluated whether the LIHTC program in Texas "perpetuates racial segregation" because of its "failure to correct the disproportionate allocation of housing tax credits to low-income minority areas" (ICP v. DHCA, 2008). On appeal, the case reached the Supreme Court, which ruled that policies that have a 'disparate impact' on minorities—even if unintentionally—can be contested under the Fair Housing Act. This ruling prompted state policymakers to examine their criteria for LIHTC funding and, in some cases, shift priority towards high-opportunity neighborhoods, which rarely have large minority shares (Owens and Smith, 2023).

Using our estimated model, we evaluate the effect of where LIHTC is built on residential segregation, which depends on the composition of the development compared to that of the surrounding

[28] An alternative measure of costs is the number of tax credits awarded per unit. In Appendix C.4, we show that this measure of cost is nearly flat across levels of neighborhood opportunity, perhaps because the tax credits awarded are a function of the construction costs (excluding land), which are unlikely to vary significantly within a city. However, the number of tax credits is not an accurate measure of the full cost to the government, as developments often layer additional government assistance, such as tax abatements, bonds, land grants, and expedited permitting (Cummings and DiPasquale, 1999). We do not observe these additional subsidies, but anecdotal evidence suggests they are more common for developments built in expensive neighborhoods.

Figure 7: Effects of building in top versus bottom quartile of neighborhood opportunity



Notes: This figure plots the difference in household surplus and costs for building a new LIHTC development in the average neighborhood in the top quartile of neighborhood opportunity versus the average neighborhood in the bottom quartile. Household surplus is computed as the equivalent variation in monthly rent, summed across all households. 'B/H' refers to Black or Hispanic households and 'W/O' refers to white (non-Hispanic) and other households. 'High-need' refers to households whose predicted future income is in the bottom quartile of the nationwide distribution of renters, adjusted for household size and age. Costs are computed based on the 'implicit subsidy,' i.e., the gap between LIHTC rents and an estimate of the fair-market rents for the development.

neighborhood and where tenants would otherwise live. We use the following index of residential isolation[29] between groups A and B (in our case, Black/Hispanic and white/other or high-need and moderate-need):

$$\text{Isolation} = \overbrace{\frac{1}{|\text{A}|}\sum_{i\in \text{A}} \underbrace{\text{fracA}_{g(i)}}_{\substack{\text{Home nbhd} \\ \text{frac. A}}}}^{\text{Avg. exposure to A by A}} - \overbrace{\frac{1}{|\text{B}|}\sum_{i\in \text{B}} \text{fracA}_{g(i)}}^{\text{Avg exposure to A by B}} \tag{11}$$

where $g(i)$ indexes the neighborhood of resident i and frac$A_{g(i)}$ is the fraction of neighborhood g's population that belongs to group A. In the Chicago MSA, the average white/other household lives in a neighborhood with 78% white/other residents, while the average Black/Hispanic household lives in a neighborhood with 48% white/other residents (i.e. an isolation index of 0.30). For economic isolation, the average high-need household lives in a neighborhood where 81% of residents are moderate-need, while the average moderate-need household lives in a neighborhood where 89% of residents are also moderate-need (i.e. an isolation index of 0.08).

To provide a baseline for comparison, we first simulate a version where we move both a development *and its tenants* from the bottom quartile of neighborhood opportunity to higher quartiles, i.e. holding fixed the tenants who sort into the average development in the bottom quartile. Developments built in the bottom quartile of opportunity increase both economic and racial/ethnic isola-

[29]See Cutler, Glaeser and Vigdor (1999) and Gentzkow and Shapiro (2011)

tion on the margin, whereas moving these developments (with their tenants) to higher-opportunity neighborhoods would steadily decrease both isolation measures (Figure 8). We then allow the tenants of the development to change as we move the development to different neighborhoods, which dampens the effects of location on integration ('with sorting,' in Figure 8). The effects of sorting are especially large in the case of racial/ethnic segregation, reducing the effect on integration of building in the top instead of the bottom quartile of neighborhood opportunity by over half.

While we treat racial/ethnic composition in the market-rate units as exogenous, in practice there may be additional re-sorting by market-rate households if the estimated preferences for same-race/ethnicity shares reflect homophily (Davis, Gregory and Hartley, 2026). For developments built in higher-opportunity neighborhoods, the entry of a LIHTC development that disproportionately houses Black/Hispanic tenants would modestly raise the local Black/Hispanic share. If market-rate residents have preferences for same-race neighbors, this would trigger further sorting and amplify the initial compositional change.

8.3 Effects on children & neighbors

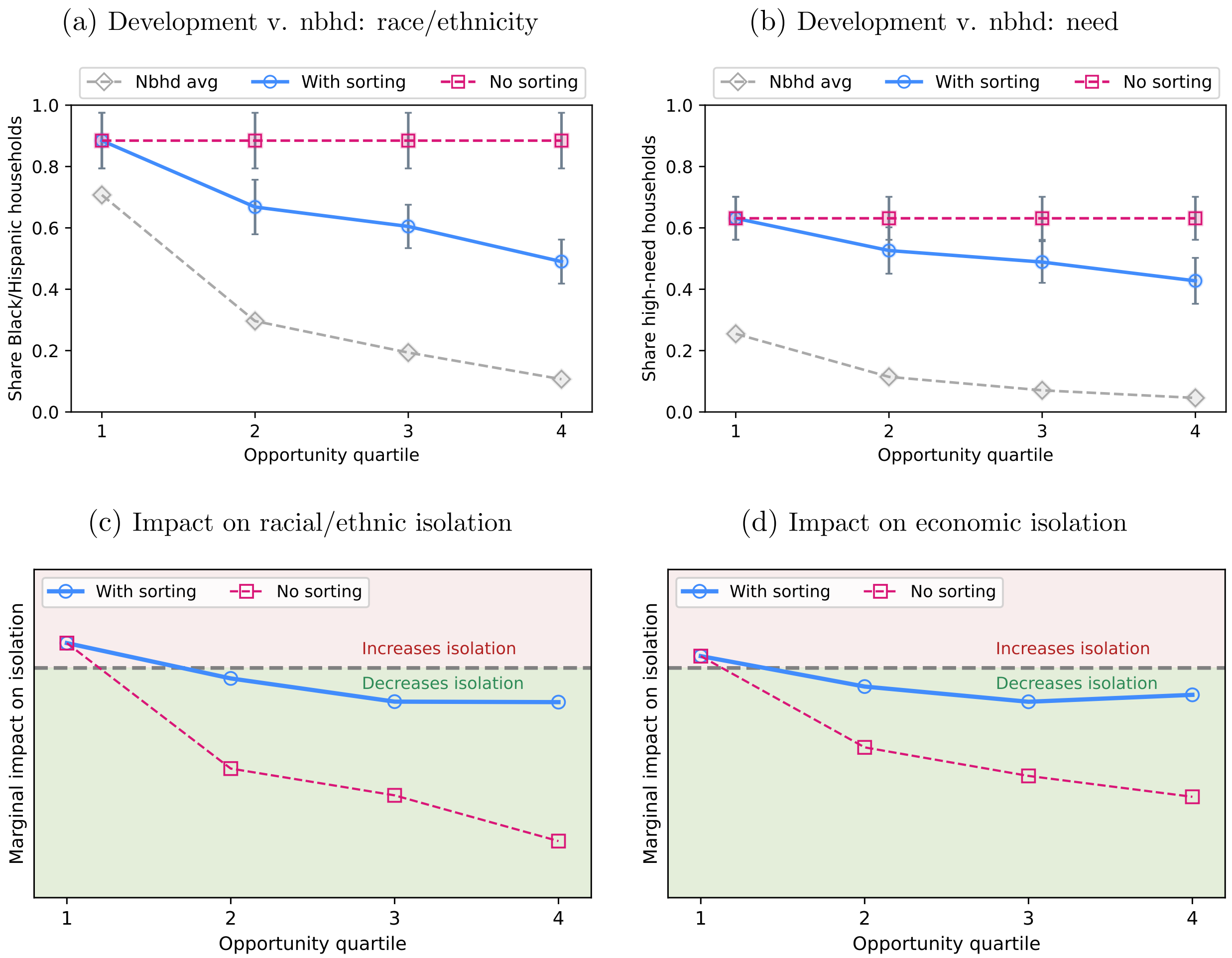
Other considerations that may enter into the social planner's decision of where to build affordable housing include spillovers on the surrounding neighborhood and any long-run effects on children of the development. In this section, we use estimates from Chetty et al. (2026) and Diamond and McQuade (2019) to evaluate the effects on the upward mobility of children and the welfare of the neighbors. We describe the main results here and defer additional details to Appendix Section C.5.

Lifetime earnings of children. We estimate the effects of location on the future earnings of children living in the development using data from the Opportunity Atlas (Chetty et al., 2026), which is based on the upward mobility of the 1978-1983 birth cohorts.[30] While our estimates of household surplus will capture some of the effects on children, households may not fully internalize the long-run benefits for children when choosing where to live. Developments in higher-opportunity neighborhoods provide a greater 'treatment effect' on the lifetime earnings of children, but also house fewer families with children and attract tenants already living in higher-opportunity neighborhoods than developments in lower-opportunity neighborhoods. Using the simulated move-ins from our model, we estimate that a development in the top quartile of neighborhood opportunity increases the discounted lifetime earnings of children in the development by +\$450 per unit-month, compared to +\$229 per unit-month for a development in the bottom quartile (i.e. a difference of +\$221 from moving from bottom to top quartile).

Spillovers on neighbors. Diamond and McQuade (2019) find that the welfare effect of a new LIHTC development on neighboring renters, homeowners, and landlords depends on where it is built. While developments built in many high-income, low-minority share areas have a negative effect on the welfare of neighbors, developments built in some low-income, high-minority share

[30] While Chetty et al. (2026) show that the neighborhood upward mobility measures are generally stable over time, large changes to neighborhoods that affect local policies may change the upward mobility of residents (Derenoncourt, 2022) and sampling error can lead to an upward bias in the differences in neighborhood ranks (Mogstad et al., 2023).

Figure 8: Effect of location on residential isolation



Notes: This figure documents how a new development affects city-wide economic and racial/ethnic integration. For racial/ethnic, we split households based on Black/Hispanic and white/other, while for economic we split households by high- versus moderate-need. The top panels report the shares in the development compared to the average neighborhood. The bottom panels compute the marginal impact on an isolation index, which depends both on the development and neighborhood economic and racial/ethnic mixes and where applicants to the development would have lived otherwise. 'No sorting' version holds fixed applications based on the average for developments built in the bottom quartile.

block groups can have a positive effect. Using their estimates, we calculate that a development built in the average neighborhood in the top quartile of opportunity would reduce neighbors' welfare by \$8.30 million, while developments in the bottom quartile would reduce neighbors' welfare by \$4.55 million. The average LIHTC development in their sample has 82 units, implying a net welfare effect of −\$45,700 per unit for a new development in the top versus bottom quartile of neighborhood opportunity. The present discounted value of this welfare difference is −\$316 per unit-month if we amortize the effects over the first 15 years of the development.

8.4 Alternative policies for managing units

We evaluate four counterfactual changes to the LIHTC program that, depending on the social planner's objective, may complement the choice of location.[31]

1. **Lower income limit.** Lower the income limits from 60% of the Area Median Income (AMI) to 30% AMI, which also reduces the rents charged to households
2. **Income-based rents.** Set rents equal to 30% of each household's income at the time of application, similar to how rent is determined for new households in public housing
3. **Fair lottery.** Allocate units according to a fair lottery, where all applicants have the same odds of receiving an offer for a unit ($\boldsymbol{\phi} = 0$)
4. **Local preferences.** Give households from the surrounding neighborhood priority for 50% of the units in the development, similar to the 'community preferences' used in San Francisco and New York City for allocating new affordable housing units

Table 5 presents the results on tenants for simulated developments in the bottom quartile of neighborhood opportunity (Q1) and the change from the bottom to top quartile of neighborhood opportunity (Q1→Q4). Figure 9 illustrates the effects on racial/ethnic and economic segregation.

The first two policies modify either the eligibility or rent structure of the program. Lowering the income limit to 30% AMI mechanically disqualifies higher-income applicants, while income-based rents leave eligibility unchanged but charge each household 30% of its income. Both policies select for higher-need households along economic dimensions. Average future income rank in both higher- and lower-opportunity neighborhoods drops by about 5 percentage points relative to the baseline. For policymakers concerned about targeting assistance based on need, either of these changes may complement building units in higher-opportunity neighborhoods. However, neither policy meaningfully shifts the racial/ethnic composition of tenants, likely because current income is a poor predictor of race/ethnicity once subset to the left tail of the income distribution (Table D.3). Both policies also substantially increase the value of assistance to recipients by charging lower rents on average.

Allocating units via a fair lottery ($\boldsymbol{\phi} = 0$) reduces the share of Black/Hispanic tenants and lowers the share of high-need tenants, consistent with the decomposition of preferences versus screening in Section 7. However, the differences in tenant composition persist, and screening alone does little to explain the differences between higher- and lower-opportunity neighborhoods.

Requiring developers to prioritize households within the same neighborhood amplifies differences in tenant characteristics across neighborhoods. New York City was recently sued over whether its policy of prioritizing local residents perpetuates racial segregation in the city.[32] By keeping the distribution of race/ethnicity and income across the city closer to the status quo, we show that using local preferences further dampens any effects (either positive or negative) on integration.

[31] More drastic changes to the allocation mechanism—e.g., implementing the centralized Cambridge Mechanism studied in Waldinger (2021), where, among other differences, applicants can only apply to three developments—would generally require incorporating additional complications into our model, such as beliefs about win probabilities.

[32] The case was settled in 2024, and NYC agreed to reduce the share of units set aside for local residents to 15%.

However, prioritizing local residents generates greater household surplus by selecting households that value the neighborhood's characteristics more, and may accomplish other policy goals not captured by our framework, such as reducing the displacement of long-time neighborhood residents (Pennington, 2025) or increasing community support for new developments.

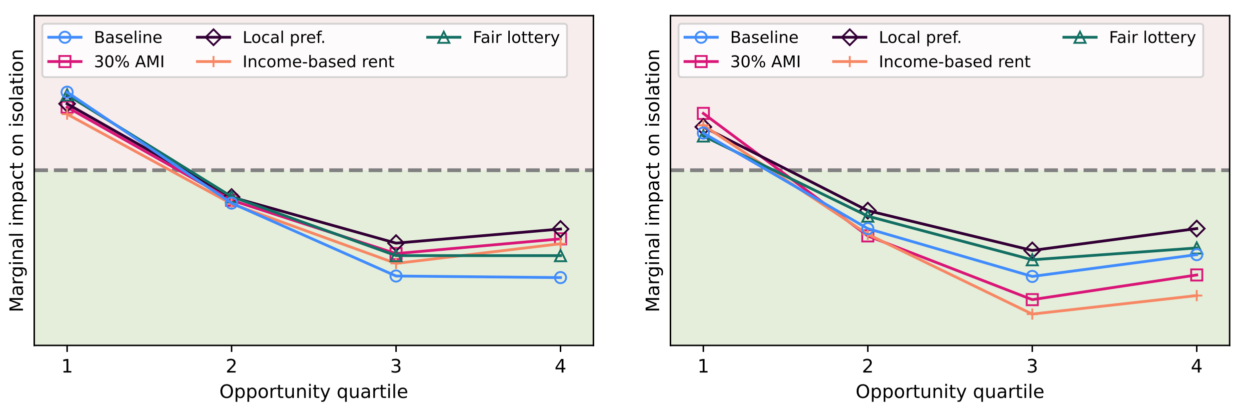
Table 5: Comparison of counterfactual policies

	Frac. Black/Hisp.		Future inc. rank		WTP (\$/unit-mo.)	
	Q1	Q1→Q4	Q1	Q1→Q4	Q1	Q1→Q4
Baseline	0.8844	-0.3943	0.2295	+0.0897	492.4	+142.7
	(0.0234)	(0.0302)	(0.0154)	(0.0093)	(27.47)	(39.71)
Lower income limits	0.8892	-0.4079	0.1781	+0.0748	729.5	+214.0
	(0.0247)	(0.0313)	(0.0205)	(0.0109)	(44.54)	(39.62)
Income-based rents	0.8716	-0.4182	0.1796	+0.0754	857.1	+291.1
	(0.0243)	(0.0300)	(0.0204)	(0.0100)	(67.01)	(42.18)
Fair lottery ($\phi = 0$)	0.8459	-0.4265	0.2547	+0.0697	697.6	+155.9
	(0.0224)	(0.0336)	(0.0143)	(0.0100)	(62.26)	(56.75)
Local preferences	0.8875	-0.4657	0.2327	+0.0975	726.5	+117.0
	(0.0230)	(0.0329)	(0.0145)	(0.0096)	(51.19)	(57.95)

Notes: This table documents the effects of counterfactual processes or parameter estimates on a range of outcomes for developments built in the bottom quartile of neighborhood opportunity (Q1) as well as the change from the bottom to top quartile of neighborhood opportunity (Q1→Q4). The baseline uses an income limit of 60% AMI, which we lower to 30% of AMI for the lower income limit counterfactual. For income-based rents, we charge households 30% of their income at the time of application. Local preferences requires that 50% of new tenants come from the surrounding neighborhood. Bootstrapped standard errors are reported in parentheses.

Figure 9: Effect of counterfactuals on residential isolation

(a) Racial/ethnic isolation (b) Economic isolation



Notes: This figure documents how a new development affects city-wide residential integration on the margin under counterfactual parameters or processes for rationing units. '30% AMI' lowers the income limits (and rents) by half, 'income-based rent' sets rent at 30% of income at the time of move-in, and 'local preferences' prioritizes allocating half of the units to households that already live in the neighborhood. 'Fair lottery' replaces differential screening with equal offer probabilities. Each panel computes the marginal impact on an isolation index under counterfactual processes or structural parameters.

9 Conclusion

Policymakers choosing where to provide affordable housing face a trade-off that has received little attention: because households have heterogeneous preferences over neighborhoods and units are rationed, the choice of location is implicitly a choice of tenants. We document this link using a newly constructed nationwide panel of renters and a structural model estimated for Chicago. In higher-opportunity neighborhoods, greater LIHTC demand from white/other and moderate-need households crowds out Black/Hispanic and high-need households—even though the latter are slightly favored in screening—because the supply of units is fixed. This compositional shift has consequences for policy goals that depend on who receives assistance, including targeting by need and promoting racial/ethnic and economic integration.

Policymakers must weigh competing objectives when choosing where to provide affordable housing. Building in opportunity-rich neighborhoods delivers greater value to tenants, reduces city-wide racial/ethnic and economic segregation, and offers some low-income households access to neighborhoods they could not otherwise afford. However, it also costs more, reduces targeting on need, and disproportionately benefits more moderate-need, predominantly white households. The planner's preferred site depends on how these objectives are weighted, as well as any externalities, such as spillovers to neighbors.

There may be complementary policies that preserve the targeting advantages of affordable housing, even when built in neighborhoods desirable to a broader swath of households. A natural starting point is the eligibility requirements, although means-testing based solely on current income has limited ability to target other characteristics. Defining eligibility using additional household characteristics (e.g., 'proxy means-testing') may improve targeting, but risks deterring households that face disproportionate costs in documenting their need (Mullainathan and Shafir, 2013). An alternative approach is to provide low-income households living in opportunity-scarce neighborhoods with information, financial assistance, or guidance in applying for affordable housing. Such interventions have proven effective at encouraging households with vouchers to move to higher-opportunity neighborhoods (Bergman et al., 2023) and are worth exploring for place-based affordable housing.

References

Abdulkadiroğlu, Atila, Parag A. Pathak, and Alvin E. Roth. 2005. “The New York City High School Match.” *American Economic Review*, 95(2): 364–367.

Agarwal, Nikhil, and Paulo Somaini. 2020. “Revealed Preference Analysis of School Choice Models.” *Annual Review of Economics*, 12(Volume 12, 2020): 471–501.

Agarwal, Nikhil, Itai Ashlagi, Michael A. Rees, Paulo Somaini, and Daniel Waldinger. 2021. “Equilibrium Allocations Under Alternative Waitlist Designs: Evidence From Deceased Donor Kidneys.” *Econometrica*, 89(1): 37–76.

Ahmed, Ali M., and Mats Hammarstedt. 2008. “Discrimination in the rental housing market: A field experiment on the Internet.” *Journal of Urban Economics*, 64(2): 362–372.

Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A. Olken, Ririn Purnamasari, and Matthew Wai-Poi. 2016. “Self-Targeting: Evidence from a Field Experiment in Indonesia.” *Journal of Political Economy*, 124(2): 371–427.

Almagro, Milena, and Tomas Domınguez-Iino. 2024. “Location Sorting and Endogenous Amenities: Evidence from Amsterdam.” *Econometrica*, forthcoming.

Anagol, Santosh, Fernando Ferreira, and Jonah Rexer. 2026. “Estimating the Economic Value of Zoning Reform.” *American Economic Journal: Economic Policy.*

Ananat, Elizabeth Oltmans. 2011. “The Wrong Side(s) of the Tracks: The Causal Effects of Racial Segregation on Urban Poverty and Inequality.” *American Economic Journal: Applied Economics*, 3(2): 34–66.

Andrews, Isaiah, Nano Barahona, Matthew Gentzkow, Ashesh Rambachan, and Jesse M Shapiro. 2025. “Structural Estimation Under Misspecification: Theory and Implications for Practice.” *The Quarterly Journal of Economics*, 140(3): 1801–1855.

Arnosti, Nick, and Peng Shi. 2020. “Design of Lotteries and Wait-Lists for Affordable Housing Allocation.” *Management Science*, 66(6): 2291–2307.

Bartik, Timothy. 1991. “Who Benefits from State and Local Economic Development Policies?” *Upjohn Press.*

Barwick, Panle Jia, Shanjun Li, Andrew R. Waxman, Jing Wu, and Tianli Xia. 2024. “Efficiency and Equity Impacts of Urban Transportation Policies with Equilibrium Sorting.” *American Economic Review*, forthcoming.

Baum-Snow, Nathaniel, and Justin Marion. 2009. “The effects of low income housing tax credit developments on neighborhoods.” *Journal of Public Economics*, 93(5): 654–666.

Baum-Snow, Nathaniel, and Lu Han. 2024. “The Microgeography of Housing Supply.” *Journal of Political Economy*, 132(6): 1897–1946.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan. 2007. “A Unified Framework for Measuring Preferences for Schools and Neighborhoods.” *Journal of Political Economy*, 115(4): 588–638.

Bayer, Patrick, Marcus Casey, W. Ben McCartney, John Orellana-Li, and Calvin Zhang. 2025. “Distinguishing Causes of Neighborhood Racial Change: A Nearest-Neighbor Design.” *American Economic Review*, 115(11): 3999–4039.

Bayer, Patrick, Robert McMillan, Alvin Murphy, and Christopher Timmins. 2016. “A Dynamic Model of Demand for Houses and Neighborhoods.” *Econometrica*, 84(3): 893–942.

Bergman, Peter, Raj Chetty, Stefanie DeLuca, Nathaniel Hendren, Lawrence F. Katz, and Christopher Palmer. 2023. “Creating Moves to Opportunity: Experimental Evidence on Barriers to Neighborhood Choice.” *American Economic Review.*

Berry, Steven, and Philip Haile. 2016. “Identification in Differentiated Products Markets.” *Annual Review of Economics*, 8(1): 27–52.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica*, 63(4): 841–890.

Besley, Timothy, and Stephen Coate. 1992. "Workfare versus welfare: Incentive arguments for work requirements in poverty-alleviation programs." *The American Economic Review*, 82(1): 249–261.

Bloch, Francis, and David Cantala. 2017. "Dynamic Assignment of Objects to Queuing Agents." *American Economic Journal: Microeconomics*, 9(1): 88–122.

Caetano, Gregorio, and Vikram Maheshri. 2021. "A Unified Empirical Framework to Study Segregation." *Working paper.*

Calder-Wang, Sophie. 2021. "The Distributional Impact of the Sharing Economy on the Housing Market." https://papers.ssrn.com/abstract=3908062.

Carneiro, Pedro, Jishnu Das, and Hugo Reis. 2022. "The Value of Private Schools: Evidence from Pakistan." *The Review of Economics and Statistics*, 1–45.

Chen, Tianqi, and Carlos Guestrin. 2016. "XGBoost: A Scalable Tree Boosting System." In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. KDD '16*, 785–794.

Chetty, Raj, and Nathaniel Hendren. 2018. "The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects*." *The Quarterly Journal of Economics*, 133(3): 1107–1162.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter. 2026. "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility." *American Economic Review*, 116(1): 1–51.

Chetty, Raj, Nathaniel Hendren, and Lawrence F. Katz. 2016. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment." *American Economic Review*, 106(4): 855–902.

Chetty, Raj, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter. 2020. "Race and Economic Opportunity in the United States: an Intergenerational Perspective*." *The Quarterly Journal of Economics*, 135(2): 711–783.

Christensen, Peter, and Christopher Timmins. 2023. "The Damages and Distortions from Discrimination in the Rental Housing Market." *The Quarterly Journal of Economics*, 138(4): 2505–2557.

Chyn, Eric. 2018. "Moved to Opportunity: The Long-Run Effects of Public Housing Demolition on Children." *American Economic Review*, 108(10): 3028–3056.

Chyn, Eric, Robert Collinson, and Danielle Sandler. 2024. "The Long-Run Effects of Residential Racial Desegregation Programs: Evidence from Gautreaux." *Quarterly Journal of Economics.*

Clarke, Phillipa, and Robert Melendez. 2019. "National Neighborhood Data Archive (NaNDA): Land Cover by Census Tract, United States, 2001-2016." Inter-university Consortium for Political and Social Research.

Collinson, Robert, Ingrid Gould Ellen, and Jens Ludwig. 2019. "Reforming Housing Assistance." *The ANNALS of the American Academy of Political and Social Science*, 686(1): 250–285.

Collinson, Robert, John Eric Humphries, Nicholas Mader, Davin Reed, Daniel Tannenbaum, and Winnie van Dijk. 2024. "Eviction and Poverty in American Cities*." *The Quarterly Journal of Economics*, 139(1): 57–120.

Cress, Jill J, Roger G Sayre, Patrick Comer, and Harumi Warner. 2009. "Terrestrial Ecosystems-Land Surface Forms of the Conterminous United States." US Geological Survey.

Cummings, Jean L., and Denise DiPasquale. 1999. "The Low-Income Housing Tax Credit An Analysis of the First Ten Years." *Housing Policy Debate*, 10(2): 251–307.

Cutler, David M., Edward L. Glaeser, and Jacob L. Vigdor. 1999. "The Rise and Decline of the American Ghetto." *Journal of Political Economy*, 107(3): 455–506.

Davis, Morris A, Jesse Gregory, and Daniel A Hartley. 2026. "Preferences over the racial composition of neighborhoods: Estimates and implications." Federal Reserve Bank of Chicago.

DeLuca, Stefanie, Holly Wood, and Peter Rosenblatt. 2019. "Why Poor Families Move (And Where They Go): Reactive Mobility and Residential Decisions." *City & Community*, 18(2): 556–593.

Derenoncourt, Ellora. 2022. "Can You Move to Opportunity? Evidence from the Great Migration." *American Economic Review*, 112(2): 369–408.

Deshpande, Manasi, and Yue Li. 2019. "Who Is Screened Out? Application Costs and the Targeting of Disability Programs." *American Economic Journal: Economic Policy*, 11(4): 213–248.

Diamond, Rebecca, and Tim McQuade. 2019. "Who Wants Affordable Housing in Their Backyard? An Equilibrium Analysis of Low-Income Property Development." *Journal of Political Economy*, 127(3): 1063–1117.

Ellen, Ingrid G., Keren M. Horn, and Katherine M. O'Regan. 2016. "Poverty concentration and the Low Income Housing Tax Credit: Effects of siting and tenant composition." *Journal of Housing Economics*, 34: 49–59.

Ellen, Ingrid Gould, and Keren Mertens Horn. 2018. "Points for Place: Can State Governments Shape Siting Patterns of Low-Income Housing Tax Credit Developments?" *Housing Policy Debate*, 28(5): 727–745.

Ellen, Ingrid Gould, Elizabeth Lochhead, and Katherine O'Regan. 2024. "Eviction Practices in Subsidized Housing: Evidence From New York State." *Cityscape*, 26(1): 261–286.

Ellen, Ingrid Gould, Keren Mertens Horn, and Yiwen Kuai. 2018. "Gateway to Opportunity? Disparities in Neighborhood Conditions Among Low-Income Housing Tax Credit Residents." *Housing Policy Debate*, 28(4): 572–591. _eprint: https://doi.org/10.1080/10511482.2017.1413584.

Eriksen, Michael D., and Stuart S. Rosenthal. 2010. "Crowd out effects of place-based subsidized rental housing: New evidence from the LIHTC program." *Journal of Public Economics*, 94(11): 953–966.

Ewens, Michael, Bryan Tomlin, and Liang Choon Wang. 2014. "Statistical Discrimination or Prejudice? A Large Sample Field Experiment." *The Review of Economics and Statistics*, 96(1): 119–134.

Ferdowsian, Andrew, Kwok Hao Lee, and Luther Yap. 2024. "Build-to-Order: Endogenous Supply in Centralized Mechanisms." *Working paper.*

Finkelstein, Amy, and Matthew J Notowidigdo. 2019. "Take-Up and Targeting: Experimental Evidence from SNAP." *The Quarterly Journal of Economics*, 134(3): 1505–1556.

Freddie Mac. 2018. "Opportunity Incentives in LIHTC Qualified Allocation Plans."

Freedman, Matthew, and Emily Owens. 2011. "Low-income housing development and crime." *Journal of Urban Economics*, 70(2): 115–131.

Freedman, Matthew, and Tamara McGavock. 2015. "Low-Income Housing Development, Poverty Concentration, and Neighborhood Inequality." *Journal of Policy Analysis and Management*, 34(4): 805–834.

Galiani, Sebastian, Alvin Murphy, and Juan Pantano. 2015. "Estimating Neighborhood Choice Models: Lessons from a Housing Assistance Experiment." *American Economic Review*, 105(11): 3385–3415.

Gentzkow, Matthew, and Jesse M. Shapiro. 2011. "Ideological Segregation Online and Offline." *The Quarterly Journal of Economics*, 126(4): 1799–1839.

Geyer, Judy. 2017. "Housing demand and neighborhood choice with housing vouchers." *Journal of Urban Economics*, 99: 48–61.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review*, 110(8): 2586–2624.

Gyourko, Joseph, Albert Saiz, and Anita Summers. 2008. "A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index." *Urban Studies*, 45(3): 693–729.

Gyourko, Joseph, Jonathan S. Hartley, and Jacob Krimmel. 2021. "The local residential land use regulatory environment across U.S. housing markets: Evidence from a new Wharton index." *Journal of Urban Economics*, 124: 103337.

Haag, Matthew. 2020. "25 Million Applications: The Scramble for N.Y.C. Affordable Housing." *The New York Times*.

Horn, Keren M, and Katherine M O'Regan. 2011. "The low income housing tax credit and racial segregation." *Housing Policy Debate*, 21(3): 443–473.

ICP v. DHCA. 2008. https://clearinghouse.net/doc/77143/. *U.S. District Court for the Northern District of Texas, 3:08-CV-00546*.

Joint Center for Housing Studies. 2020. "America's Rental Housing." Harvard University.

Kang, Zi Yang. 2022. "Optimal Redistribution Through Public Provision of Private Goods." *Working Paper*.

Katz, Lawrence F., Jeffrey R. Kling, and Jeffrey B. Liebman. 2001. "Moving to Opportunity in Boston: Early Results of a Randomized Mobility Experiment." *The Quarterly Journal of Economics*, 116(2): 607–654.

Kleven, Henrik Jacobsen, and Wojciech Kopczuk. 2011. "Transfer Program Complexity and the Take-Up of Social Benefits." *American Economic Journal: Economic Policy*, 3(1): 54–90.

Kling, Jeffrey R, Jeffrey B Liebman, and Lawrence F Katz. 2007. "Experimental Analysis of Neighborhood Effects." *Econometrica*, 75(1): 83–119. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-0262.2007.00733.x.

Le Cam, Lucien. 1960. "An approximation theorem for the Poisson binomial distribution." *Pacific Journal of Mathematics*.

Lens, Michael C., Ingrid Gould Ellen, and Katherine O'Regan. 2011. "Do Vouchers Help Low-Income Households Live in Safer Neighborhoods? Evidence on the Housing Choice Voucher Program." *Cityscape*, 13(3): 135–159.

Leshno, Jacob D. 2022. "Dynamic Matching in Overloaded Waiting Lists." *American Economic Review*, 112(12): 3876–3910.

Lieber, Ethan M. J., and Lee M. Lockwood. 2019. "Targeting with In-Kind Transfers: Evidence from Medicaid Home Care." *American Economic Review*, 109(4): 1461–1485.

Massey, Douglas S., and Nancy A. Denton. 1998. *American Apartheid: Segregation and the Making of the Underclass.* Cambridge, MA:Harvard University Press.

McFadden, Daniel. 1973. "Conditional Logit Analysis of Qualitative Choice Behavior." *Frontiers in Econometrics*, 105–142.

Mogstad, Magne, Joseph P Romano, Azeem M Shaikh, and Daniel Wilhelm. 2023. "Inference for Ranks with Applications to Mobility across Neighbourhoods and Academic Achievement across Countries." *The Review of Economic Studies*, rdad006.

Mullainathan, Sendhil, and Eldar Shafir. 2013. *Scarcity: Why Having Too Little Means So Much.* Times Books.

Murra-Anton, Zeky, and Neil Thakral. 2025. "The Public Housing Allocation Problem." Working paper.

Nichols, Albert L., and Richard J. Zeckhauser. 1982. "Targeting Transfers through Restrictions on Recipients." *The American Economic Review*, 72(2): 372–377.

Novogradac. 2022. "LIHTC Equity Pricing Trends."

Oreopoulos, Philip. 2003. "The Long-Run Consequences of Living in a Poor Neighborhood." *The Quarterly Journal of Economics*, 118(4): 1533–1575.

Owens, Ann, and Rebecca Brooks Smith. 2023. "Producing affordable housing in higher-opportunity neighborhoods: Incentives in California's LIHTC program." *Journal of Urban Affairs*, 0(0): 1–29.

Pennington, Kate. 2025. "Rents, Movers, and Stayers: The Spillover Effects of Construction in San Francisco." Working paper.

Reardon, Sean F., Kendra Bischoff, Ann Owens, and Joseph B. Townsend. 2018. "Has Income Segregation Really Increased? Bias and Bias Correction in Sample-Based Segregation Estimates." *Demography*, 55(6): 2129.

Reid, Carolina. 2018. "The Links Between Affordable Housing and Economic Mobility." *Terner Center.*

Saiz, Albert. 2010. "The Geographic Determinants of Housing Supply." *The Quarterly Journal of Economics*, 125(3): 1253–1296.

Schwartz, Alex. 2021. *Housing Policy in the United States.* Routledge.

Schwartz, Amy Ellen, Ingrid Gould Ellen, Ioan Voicu, and Michael H. Schill. 2006. "The external effects of place-based subsidized housing." *Regional Science and Urban Economics*, 36(6): 679–707.

Sinai, Todd, and Joel Waldfogel. 2005. "Do low-income housing subsidies increase the occupied housing stock?" *Journal of Public Economics*, 89(11-12): 2137–2164.

Soltas, Evan. 2024. "Tax Incentives and the Supply of Low-Income Housing." *Working paper.*

Stagg, Thomas. 2018. "What you Need to Know About Income Limits."

Tokarski, Filip. 2025. "Screening with damages and ordeals." *arXiv preprint arXiv:2508.04456.*

Turner, Margery Austin, Susan J. Popkin, and Lynette Rawlings. 2009. *Public Housing and the Legacy of Segregation.* The Urban Insitute. Google-Books-ID: GwpgiiqjxD8C.

Wagner, Deborah, and Mary Lane. 2014. "The Person Identification Validation System (PVS): Applying the Center for Administrative Records Research and Applications' (CARRA) Record Linkage Software." *CARRA Working Papers.*

Waldfogel, Joel. 2003. "Preference Externalities: An Empirical Study of Who Benefits Whom in Differentiated-Product Markets." *The RAND Journal of Economics*, 34(3): 557–568.

Waldinger, Daniel. 2021. "Targeting In-Kind Transfers through Market Design: A Revealed Preference Analysis of Public Housing Allocation." *American Economic Review*, 111(8): 2660–2696.

Appendices

A Background on US affordable housing policy

A.1 The Low-Income Housing Tax Credit (LIHTC)

Most privately constructed affordable housing receives funding from the Low-Income Housing Tax Credit (LIHTC) program. LIHTC developers receive a 10-year stream of tax credits in exchange for meeting certain affordability requirements. Developers must set aside a minimum of 20% of units earning below 50% of the Area Median Income (AMI) or 40% of units for households earning below 60% of AMI.[33] In practice, most developments are fully affordable as the size of the subsidy scales with the fraction of units set aside as low-income, and maintaining mixed-income developments comes with additional administrative requirements. After 30 years, projects can convert to market-rate housing.[34]

The amount of tax credits a project receives depends on its qualified basis and the tax credit rate. The qualified basis includes all non-land construction costs, including hard costs like construction materials, as well as soft costs such as architects and environmental reviews. The qualified basis can also include an explicit fee paid to the developer for their services, usually capped at 15% of other costs. Applications for LIHTC are made based on an estimate of the qualified basis conducted by an independent accounting firm, often including a contingency for construction cost overruns (e.g., 10% of estimated costs). Based on the realized costs, the final qualified basis is then locked in the first year after development.

The qualified basis is then multiplied by the tax credit rate to determine the annual allocation of tax credits. Developers can apply either for 9% or 4% tax credit rates. The 4% credits are most often used for rehab projects, while 9% credits are used for new construction and more extensive rehab projects. Developers can receive an additional 30% boost in credits for building in either a Qualified Census Tract (QCT) or Difficult to Develop Area (DDA). QCTs are tracts with high rates of poverty, while DDAs are areas where the market-rate rents are high relative to median household income.[35] Since 2008, the Housing and Economic Recovery Act has allowed states to provide the basis boost to any property receiving 9% credits that the state deems needs the boost for financial viability. The total face value of tax credits can reach 117% of a project's non-land construction costs, doled out over ten years.

Developers sell the rights to these tax credits to outside investors. Institutional banks frequently purchase tax credits to satisfy the Community Reinvestment Act (CRA) requirements. The average price paid per dollar of tax credits fluctuates over time but is often quite high; in 2019, the average price was about \$0.95 (Novogradac, 2022). The price that investors may pay may also vary across metro areas due to the CRA, which requires banks to invest in communities within the metro areas where they have branches – the price for credits will be higher (even >\$1) in areas where more banks are active.

Each state receives a per-capita amount of tax credits to allocate. When there are more project applications than tax credits available, states use Qualified Allocation Plans (QAPs) to select the winners. Applications are awarded points for several criteria, ranked by these scores, and allocated in order. Common criteria for earning points include estimated costs per unit, on-site amenities, developer experience with past projects, set-asides for tenants making far below the income limit (e.g., <30% median income), and geographic characteristics such as proximity to

[33]Since 2018, there is a third option in which developers can rent some units at up to 80% of AMI as long as the average of income limits in the property does not exceed 60% of AMI.

[34]Federal law initially required only 15 years of affordability, but this was extended to 30 years in 1990. As of 2017, 17 states require even longer periods of affordability (Schwartz, 2021).

[35]Since 2016, DDAs in metro areas are now zipcode-level to reflect that the ratio of market-rate rent to household income can vary widely across an MSA.

transit, neighborhood poverty, and the presence of existing subsidized options nearby. The process is competitive; many states award credits to fewer than half of the applicants.

A.2 Policy levers affecting LIHTC locations

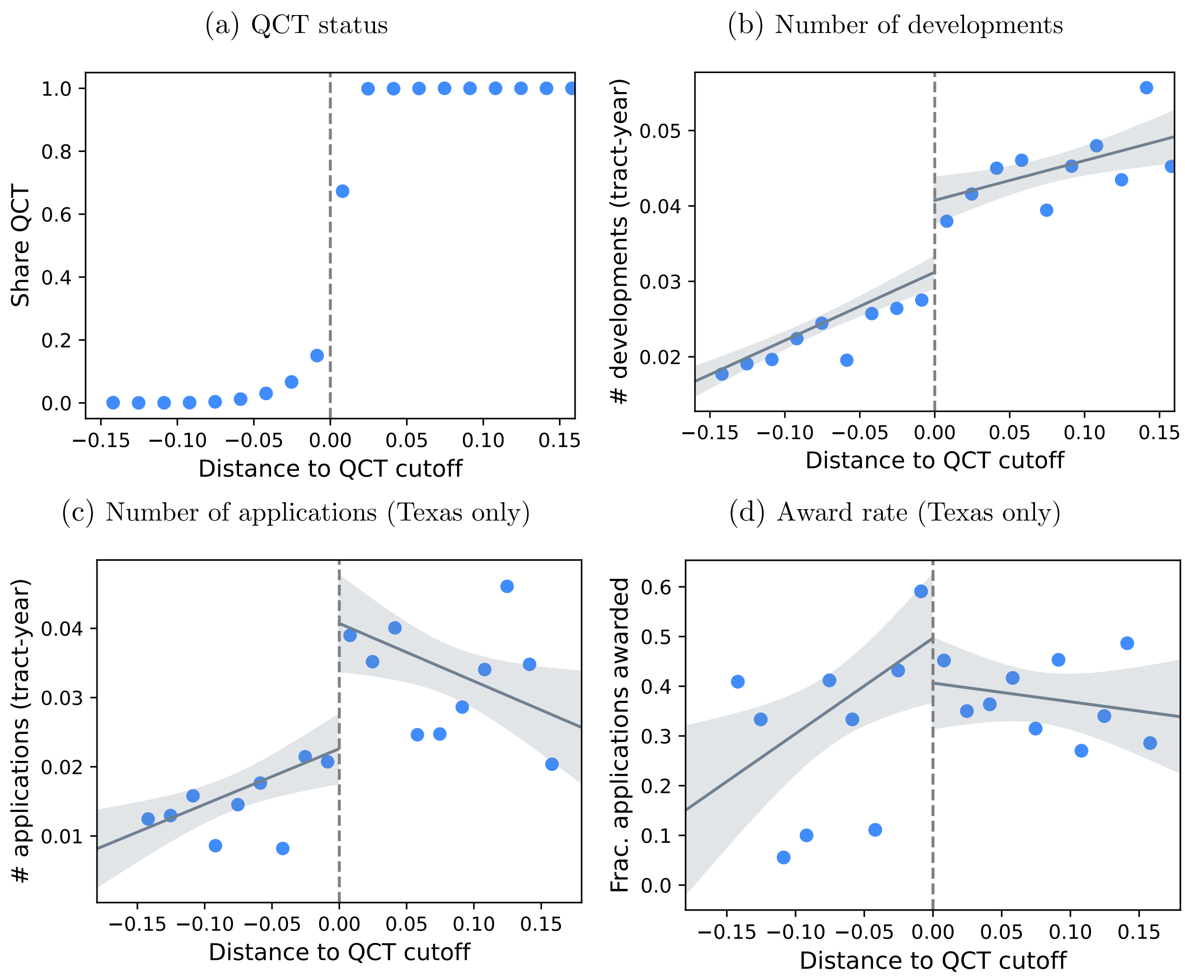
While the government does not mandate where LIHTC developments are built, at least two policy levers can affect private developers' choice of location: state QAP plans and the subsidy boost awarded to developers who build in either QCTs or DDAs. Ellen and Horn (2018) provide evidence that changes to QAPs affect developer location choices. Here, we provide evidence that subsidy boosts also affect both applications for tax credits and the location of constructed developments using discontinuities in the rules used to define QCTs. A similar identification strategy is used in Baum-Snow and Marion (2009) as an instrument for the number of nearby LIHTC units.

Broadly, QCTs are defined using thresholds based on a tract's poverty rate and its median household income. At most, 20% of a metro area's population can lie within a QCT. For each year, we rank tracts within a metro area by the criteria used that year, then define a cutoff based on either the HUD thresholds or 20% of the population (whichever binds first). Our running variable is the distance to the threshold in percentile ranks. We use data from 2000-2015 for the 100 most populous MSAs and exclude counties that lie within DDAs as tracts on both sides of the threshold will receive the basis boost in DDAs.[36] Figure A.1 Panel (a) shows the share of tracts that are classified as a QCT around the threshold. The discontinuity is fuzzy, and we both classify QCTs as non-QCTs and vice-versa. One known cause is the exceptions made for small tracts near the 20% population threshold; HUD will try to include any smaller tracts past the threshold that would not push the total QCT population over 20% of the metro area. Despite the fuzzy threshold, Panel (b) shows that there is a discontinuous jump in the number of developments allocated tax credits; at the threshold, the average number of developments allocated credits jumps from 0.028 to 0.039 per tract-year.

The effect on whether a tract has a development could be due to either an increase in the number of applications for tax credits or an increase in the probability an application is accepted. We collect data on applications for tax credits in Texas metro areas between 2000-2015. We geocode the address of each application using Geocodio and attempt to fix addresses that do not match to coordinates manually. The final sample includes 1728 applications for 9% credits to fund new construction, totaling $2.2 billion in requested credits (2019$). Of these, 545 applications were awarded subsidies. Figure A.1 Panels (c) and (d) plot the change in applications and the share of applications that are awarded credits around the QCT threshold. While the results are more noisy on this smaller sample, we see a jump in the number of applications with little movement in the award rate. This suggests that the response in number of constructed developments is due to developer response to the 30% boost in subsidy, not any change to the probability a given application is accepted.

[36] DDAs are assigned at varying levels of geographies including counties, towns, and metro-areas. Mike Hollar at HUD was kind enough to share digitized records of which Census geographies are classified as a DDA each year. To be conservative, we exclude any county that intersects a DDA geography.

Figure A.1: LIHTC development around QCT threshold



Notes: These figures document the distance to the threshold HUD uses to define Qualified Census Tracts (QCTs). Developments built in QCTs receive a 'basis boost' or 30%. The sample for Panels (a) and (b) covers developments built in the 100 most populous metro areas between 2000 and 2015. Panels (c) and (d) subset to Texas and use data collected on LIHTC applications for credits between 2000 and 2015. Gray shading represents the 95% confidence interval.

B Data construction and supplemental analyses

B.1 LIHTC properties and units

The baseline data from HUD covers LIHTC units in service between 2018 and 2019. The property-level details are obtained from each developer's initial application for LIHTC. The unit-level data is collected by state housing and finance agencies as part of their compliance actions each year and then sent to HUD.

We link individuals to LIHTC units using the MAFIDs that Census staff assign to each unique address in the country. MAFIDs are persistent over time, so while the data from HUD cover 2018 and 2019, we can identify residents of the units in earlier years. In many developments, this match rate is low, often because the development reported poorly formatted addresses or addresses that lacked unit-level details. Developments with poor MAFID match rates must be excluded from the sample, as the MAFIDs are critical for linking individuals to units to then form into households. Table B.1 documents the sample balance for properties that did and did not make the sample.

Included and excluded properties are similar on most measures, with excluded properties being slightly older and smaller.

Table B.1: Balance table of properties

Characteristic	In-sample	Out-of-sample	Normalized diff.	T-statistic
Development characteristics				
MAFID match rate	0.8499	0.1626	2.22	110
Year placed in service	2006	2004	0.2415	11.83
# LIHTC units	107.6	92.87	0.1471	7.045
# total units	110	94.28	0.1504	7.181
Nonprofit developer	0.1936	0.1987	-0.01269	-0.6134
Neighborhood characteristics				
Median household income (2010)	41940	44660	-0.116	-5.631
Frac. white (2010)	0.4699	0.4768	-0.02416	-1.183
Frac. Black (2010)	0.3296	0.3265	0.009831	0.4795
Population density, pop. per sq. mile (2010)	15020	14260	0.03229	1.595
Upward mobility (p25 parents)	0.3808	0.3845	-0.05469	-2.659
KFR index	30.91	32.56	-0.06061	-2.942
HUD jobs index	55.66	52.72	0.1332	6.441
HUD school index	34.95	36.78	-0.07148	-3.477
HUD transit index	73.23	71.64	0.06962	3.387
HUD poverty index	28.05	31.7	-0.1381	-6.731
Overall opportunity index (average)	44.56	45.08	-0.03542	-1.722

Notes: This table documents differences in development and neighborhood characteristics for LIHTC properties that are and are not in the final sample. The upward mobility measure comes from Chetty et al. (2026) and measures the upward mobility of households born in the tract to parents at the 25th percentile of the income distribution. MAFID refers to a unique unit-level address ID assigned by the Census. The normalized difference is computed as the difference in means divided by the average square root of the two within-group variances. All statistics are computed within-MSA first, then across-MSA weighting by the population.

The HUD data includes information on the income limit threshold for each unit as well as the number of bedrooms. Figure B.1 documents the distribution of these two characteristics across sample LIHTC units. Compared to market-rate units, LIHTC units have fewer bedrooms on average.

B.2 Forming individuals into households

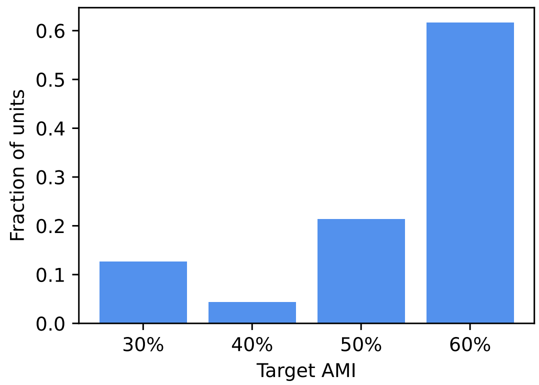
To combine individuals within a property into households, we start with the set of individuals who match based on their address to a given LIHTC development in a given year. While we link individuals to MAFIDs that are, in principle, at the individual unit level, in practice many individuals match to the MAFID corresponding to the front desk of a development or to a MAFID that has an implausible number of residents. As such, we need to account for cases where a household member may not be observed in the exact MAFID as other household members.

We first construct a graph in which individuals are nodes and edges are formed between individuals who are 'linked,' which we define using a combination of spousal relationships, claimer-dependent relationships, and shared addresses. Specifically, we define two individuals who moved into the development within two years[37] of each other as linked if any of the following are true:

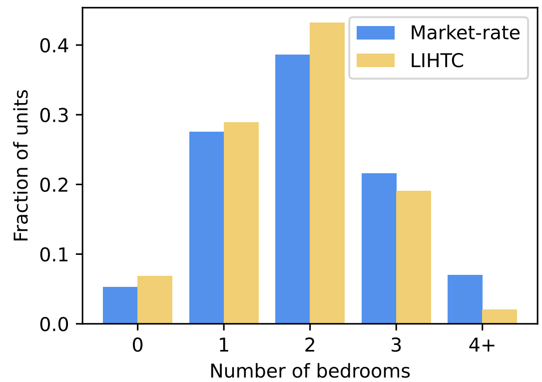
- The individuals filed taxes jointly either prior to move-in or within two years of moving in ('spousal link')

[37] There is some measurement error in the year an individual moves into the development. This is especially true for individuals who do not file taxes each year as the non-tax address sources (e.g., USPS records) may be updated with some lag.

Figure B.1: LIHTC unit types: target AMI and # of bedrooms



(a) Target Area Median Income (AMI) limit



(b) Number of bedrooms

Notes: This figure documents the distribution of target Area Median Income (AMI) levels and number of bedrooms across the sample of LIHTC and market-rate units in the 50 sample MSAs.

- One individual was ever claimed as a dependent of another ('claimer-dependent link')
- The individuals have co-resided at two or more unit-level MAFIDs, where at least one of the MAFIDs is outside of the LIHTC building and where there are at least three years of co-residence. We exclude cases where there were ten or more individuals observed in the MAFID in the same year

In practice, we found that this set of definitions captured the vast majority of links observed in samples where we know the true set of household members, such as LIHTC households sampled by the ACS. One common issue was that individuals under 18 may not match to any MAFID in the LIHTC development, as addresses for children are less reliable because they do not file taxes. To address this, we define an individual under 18 as linked to someone in the development if they were claimed as an at-home dependent (while the claimer was living in the LIHTC development), even if the dependent was never observed in a MAFID associated with the development.

We then define households as the connected components of the graph, which allows for two individuals to be in the same household even if they are not directly linked. For example, consider three individuals labeled A, B, and C. If A and B are married, they will be placed in the same household. If C was observed living in the same unit as B in earlier years, they would also be included in the same household (even if they were never observed living with A prior to move-in). We assign unit characteristics for the household based on the most commonly observed unit-level MAFID.

B.3 Predicted future income rank

We define future income as the average household income in the three years after being surveyed, then estimate the relationship between current household characteristics and future income using XGBoost (Chen and Guestrin, 2016), trained on ACS households in the 50 sample MSAs that were surveyed between 2010 and 2016. We use cross-validated grid search to select hyperparameters, train the model on an 80% sample, and then evaluate the model accuracy on a 20% holdout. The estimated model has an R^2 of 0.861 in the holdout sample. We then predict future income for all ACS and LIHTC households. For LIHTC households, we use their characteristics *prior* to moving in.

For household characteristics, we include average household income in the three prior years, current household income, average household wages in the three prior years, current household wages, and indicator for having any income in three prior years, the number of household members with W2 forms, indicators for the head of household race/ethnicity (white non-Hispanic, Black non-Hispanic, and Hispanic), the number of individuals in the household, whether the household has any children, whether the household has any members over 65 years old, the head of household's age (and age squared), and whether the household has joint filers. Finally, we include the median income, fraction white, and neighborhood opportunity index of the current tract. We do not use education or childhood family income as they are available for only a subset of households.

Given a prediction of future income, we standardize by an equivalence scale and then construct future income ranks. We use the following equivalence scale (ES) from the Census, which adjusts income based on the number of adults (N_{adults}) and children (N_{children}) in the household:[38]

- One and two adults: $ES = N_{\text{adults}}^{0.5}$
- Single parents: $ES = (N_{\text{adults}} + 0.8 + 0.5 * (N_{\text{children}} - 1))^{0.7}$
- Other families: $ES = (N_{\text{adults}} + 0.5 * N_{\text{children}})^{0.7}$

We then rank each ACS and LIHTC household in the distribution of adjusted future income, based on the distribution of ACS renters in our 50 sample MSAs. To account for differences in earnings over the life-cycle, we rank each household within 5-year age bins based on the age of the head of household.

B.4 Move-out rates

We define move-in/move-out rates by following the head of household in both the market-rate and LIHTC samples. A move-in is defined based on the first year that the head of household is observed in a given building. A move-out is defined based on the last year that the head of household is observed in a given building *or* the first year they are observed filing taxes elsewhere (whichever comes first).[39] We use building-to-building moves, where we define a building based on the address string excluding the unit number. Using building-to-building moves helps account for measurement error in the MAFID-level addresses which can creates situations where a single individual matches to multiple MAFIDs that vary across years but are within the same building (e.g., one MAFID with a unit number and a second MAFID that either has no unit number or has the unit listed as the front desk).

LIHTC residents have substantially lower turnover than market-rate units (Table B.2). About 48% of LIHTC residents stay in the unit for at least three years, compared to 34% of market-rate tenants and 37% of LIHTC-eligible market-rate tenants. Among LIHTC households, those with vouchers, children, seniors, or joint-filers are more likely to be in the unit one or three years after move-in than the average household.

B.5 Housing quality

The American Housing Survey (AHS) is a panel survey of housing units that provides more details on housing quality than our baseline data, including various maintenance issues. We use data from the 2013 and 2015 waves. While usually the AHS is a stable sample units, the panel was re-sampled

[38] See here for additional details.

[39] Some non-tax sources of addresses may be slow to update, leading to 'stale' addresses for an individual.

Table B.2: Move-out heterogeneity

	Market-rate (MR)		LIHTC-eligible MR		LIHTC	
	1-year	3-year	1-year	3-year	1-year	3-year
Aggregate	0.7325	0.3411	0.7314	0.3664	0.7747	0.4779
White (non-Hispanic)	0.7249	0.3167	0.7273	0.3453	0.7592	0.4331
Black (non-Hispanic)	0.7604	0.3803	0.7524	0.3785	0.7734	0.4753
Hispanic	0.7611	0.3989	0.7658	0.4210	0.7789	0.4939
Any children	0.7383	0.3626	0.7301	0.3720	0.8091	0.4974
Joint filers	0.7407	0.3432	0.7712	0.4070	0.8491	0.5569
Any seniors	0.8151	0.5154	0.8195	0.5275	0.8445	0.6223
Has voucher	0.8308	0.5107	0.8346	0.5165	0.8736	0.6096
Household size: 1	0.7313	0.3466	0.7301	0.3697	0.7265	0.4500
Household size: 2	0.7207	0.3125	0.7161	0.3444	0.7641	0.4600
Household size: 3	0.7342	0.3440	0.7330	0.3653	0.7958	0.4814
Household size: 4 or more	0.7563	0.3827	0.7544	0.3915	0.8619	0.5437
Household income: non-filer	0.7238	0.4019	0.7184	0.4059	0.8008	0.5325
Household income: ($0, $10k]	0.7161	0.3215	0.7163	0.3316	0.7181	0.4169
Household income: ($10k, $20k]	0.7240	0.3280	0.7309	0.3484	0.7509	0.4467
Household income: ($20k, $30k]	0.7337	0.3414	0.7472	0.3766	0.7998	0.4921
Household income: ($30k, $40k]	0.7412	0.3407	0.7529	0.3800	0.8243	0.5192
Household income: >$40k	0.7395	0.3375	0.7372	0.3760	0.8416	0.5267

Notes: This table documents the fraction of households remaining in a unit one and three years after move-in for three different samples: market-rate, LIHTC-eligible market-rate, and LIHTC households. The sample covers the 50 MSAs in our sample and is restricted to move-ins between 2010-2017 so that we can observe at least three years after move-in.

for the 2015 AHS. Still, the sample is small. In the 50 MSAs in our main sample, we use data on 46,000 rental units, of which 1,400 are LIHTC units.

We regress a series of housing quality measures on indicators for whether the unit is market-rate, LIHTC, or public housing. We include fixed effects for the neighborhood (PUMA), year, and number of bedrooms. The results are presented in Table B.3. Relative to market-rate units in the same neighborhood, LIHTC units are smaller, but are newer and less likely to have various issues with maintenance, rodents, or barred windows.

Table B.3: Housing quality: market-rate, LIHTC, and public housing

	Market-rate mean	LIHTC coefficient	Public housing coefficient
Has maintenance issue	0.2127	-0.0223	0.0424
		(0.0151)	(0.0155)
Seen rodents last 3mo	0.1123	-0.0087	0.0523
		(0.0166)	(0.0213)
Seen roaches last 3mo	0.1536	-0.0298	0.0506
		(0.0179)	(0.0173)
Has barred windows	0.1837	-0.0883	-0.0739
		(0.0335)	(0.0228)
Unit square feet	1323	-378.4	-373.9
		(64.23)	(91.42)
Year built	1960	42.9	9.447
		(0.6901)	(0.7544)

Notes: This table documents housing quality differences using the 2013 and 2015 American Housing Survey, subset to units in the 50 sample MSAs. The coefficients are from regressions of housing characteristics on indicators for whether the unit is LIHTC or public housing (with market-rate being the holdout group) and fixed effects for the neighborhood (PUMA), year, and number of bedrooms. Market-rate means are weighted by the number of LIHTC units in the PUMA. Maintenance issues include peeling paint, broken toilets, broken heating, and leaks. Standard errors are presented in parentheses.

C Technical appendix

C.1 Instrumenting for market-rate rents

Our rent instrument consists of two components: 1) changes to the population demographics and industry composition over time and 2) a mapping of the population to the number of individuals selecting each housing option. These two components are similar to the 'shift' and 'share' of shift-share instruments.

We first describe how we construct the 'share' component. We characterize each individual by their industry, ten-year age bin, whether they are married, and whether they have children. For industry, we use the 3-digit NAICS code of their primary employer based on their highest-paying W-2. For marital status and the presence of children, we use the 1040 to identify spouses and dependents (under 18 years old). We index groups of individuals with the same (discrete) characteristics with b. We use individuals rather than households so that we can use the full population, rather than the annual 1% samples from the ACS. We then match each individual over the age of 21 living in the Chicago MSA—both homeowners and renters—to housing options using data on addresses sourced from the 1040s, W-2 forms, and the MAFARF between 2005 and 2009, prior to our main study period. For individuals observed at multiple addresses, we take the address they were observed at the longest. Each housing option j is a tuple of a neighborhood, number of bedrooms, and building type (single-family home, small apartment building, large apartment building, and other).

We use the observed housing choices to estimate a predictive model to characterize the relationship between individual attributes and housing option characteristics. For individual i of group b choosing option j, we define a scoring function:

$$\begin{aligned} v_{ibj} &= \gamma_b^{\text{beds}} + \gamma_b^{\text{building}} + \gamma_b^{\text{nbhd}} + \varepsilon_{ij} \\ &= v_{bj} + \varepsilon_{ij} \end{aligned}$$

where γ_b^{beds}, $\gamma_b^{\text{building}}$, and γ_b^{nbhd} are sets of fixed effects for unit size, building type, and neighborhood (PUMA) that vary by individual types and ε_{ij} are logit errors. Since groups b are multi-dimensional, we parameterize each set of fixed effects as the sum of the individual characteristics that compose each type b. For example:

$$\gamma_b^{\text{beds}} = \gamma_{industry}^{\text{beds}} + \gamma_{age}^{\text{beds}} + \gamma_{married}^{\text{beds}} + \gamma_{kids}^{\text{beds}}$$

where we again use vectors of indicators for each discrete individual characteristic. Given logit errors, the shares are given by the softmax function:

$$P_{jb} = \frac{\exp v_{bj}}{\sum_{j' \in \mathcal{J}} \exp v_{bj'}} \tag{C.1}$$

We estimate the parameters using Maximum Likelihood. In a simplified case where there was a one-dimensional individual type (e.g., group 1 and 2), the estimated shares $\widehat{P}_{bj}$ would just be the observed shares of individuals of each group in each housing option. While we could continue to define shares as just the observed shares of b in j, there are over 1000 individual types, and many of shares are zero. This alternative approach allows for some 'smoothing' such that no shares are exactly zero.

Importantly, v_{ij} should not be interpreted as a utility function, but as a latent score that determines the share of type b in option j. Although it shares a similar form to common discrete choice models of demand, the estimated parameters here have no structural interpretation.

The estimated model provides a mapping from the population in a city to the number of individuals who would select each housing option. Specifically, if there are N_b individuals with characteristics b in the market, we would estimate that $\sum_{b \in \mathcal{B}} \widehat{P}_{bj} N_b$ live in option j.

Next, we combine the estimated shares $\widehat{P}_{bj}$ with changes to the population (i.e. the 'shifts' component) to identify housing options that we expect are experiencing more or less 'rent pressure' in later periods relative to the pre-period. Figure C.1 plots the growth rates in the household characteristics used to form the instrument.[40] Define g_{bt} as the ratio of individuals with characteristics b in period t relative to the baseline, computed using the populations from all other cities in the sample besides Chicago. Excluding Chicago helps isolate changes due to broader, nationwide demographic and industry trends that are not unique to the Chicago market. We then construct the instrument as follows:

$$z_{jt} = \frac{\sum_b g_{bt} N_b \widehat{P}_{jb}}{\sum_b N_b \widehat{P}_{jb}}$$

and take the Z-score to standardize the magnitude prior to use in estimation.

Satisfying the exclusion restriction requires that $\mathbb{E}[z_{jt}\xi_{jt} \mid \mathbf{x}_{jt}, \psi_{g(j)}] = 0$, where $\mathbf{x}_{jt}$ are the observable characteristics of a housing option and $\psi_{g(j)}$ are neighborhood-level fixed effects. The primary threat to identification is if the estimated shares $\widehat{P}_{jb}$ are correlated with the unobservables ξ_{jt}, after conditioning on $\mathbf{x}_{jt}$ and $\psi_{g(j)}$. While persistent neighborhood unobservables are absorbed into the $\psi_{g(j)}$, changes over time may still be correlated with the baseline $\widehat{P}_{jb}$. This is similar to the argument in Goldsmith-Pinkham, Sorkin and Swift (2020) for shift-share ('Bartik') instruments, where identification hinges on the conditional exogeneity of the shares.

C.2 Market-rate model predictions

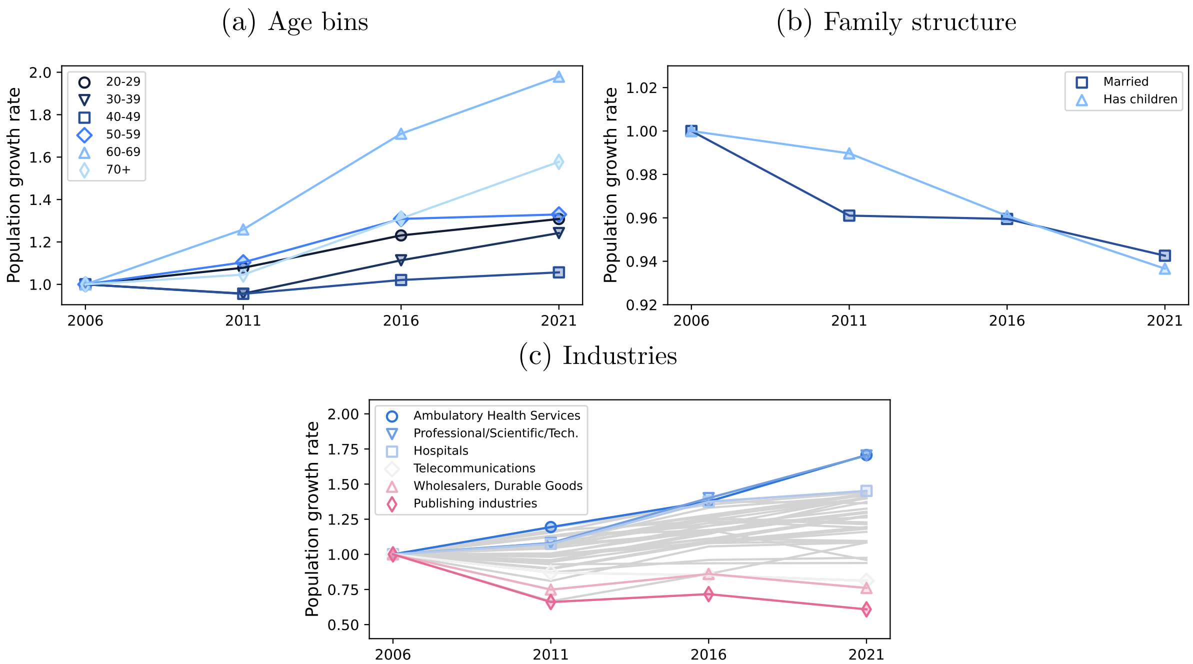
Table C.1 documents the true and predicted characteristics of those choosing market-rate housing options at different levels of neighborhood opportunity. Panel a) compares results for the full population of market-rate households. Across all levels of neighborhood opportunity, the true and predicted characteristics are closely aligned. Panel b) subsets to just those that are moving to compute the 'true' characteristics and uses just the choice probabilities for the non-endowed option to compute the model-predicted characteristics. For these 'movers', we also present results using a 'mini' model that estimates preferences using just race/ethnicity, log current income, and household size as household characteristics and just race/ethnicity shares, share with college, log median income, bedrooms, building type, and building age as housing and neighborhood characteristics. For movers, the main model continues to match the true characteristics of movers fairly well, while the model-predicted characteristics from the more limited model often deviate significantly from the true characteristics.

C.3 Moments used for estimation

We construct a set of moments $q \in \{1, 2, \ldots, Q\}$ for each period t, where $m_t^{(q)}$ denotes the sample moment observed in the data and $\widehat{m}_t^{(q)}$ denotes the model-predicted moment given a candidate parameter vector. The moment conditions take the form $\mathbb{E}[m_t^{(q)} - \widehat{m}_t^{(q)} \mid \boldsymbol{\theta}] = 0$.

[40] We document these using data available publicly (the 5-year ACS), although results look similar when constructed using the same sources that we use to construct the instrument internally.

Figure C.1: Growth rate in instrument components



Notes: This figure plots the growth rate for demographics and industries for individuals living in the 50 sample MSAs between 2006-2021. The underlying data for this figure is the ACS Public Use Microdata Sample, which is publicly available; for constructing our instrument in practice, we use a combination of IRS and Census records that cover the full population. Industry is based on 3-digit NAICS code and only industries with at least 500,000 workers in 2006 are included in the figure.

Move-in moments. We target the average characteristics of households moving into affordable housing and the covariance between those characteristics and the opportunity level of the neighborhood they end up in:

$$\text{Means:} \qquad \widehat{m}_t^{(q)} = \frac{\sum_{i \in \mathcal{I}_t} \left(w_i \times \sum_{j \in \mathcal{J}_t^{\text{AH}}} P_{ijt}^{\text{alloc}} \right)}{\sum_{i \in \mathcal{I}_t} \sum_{j \in \mathcal{J}_t^{\text{AH}}} P_{ijt}^{\text{alloc}}}$$

$$\text{Opportunity covariances:} \qquad \widehat{m}_t^{(q)} = \frac{\sum_{i \in \mathcal{I}_t} \sum_{j \in \mathcal{J}_t^{\text{AH}}} P_{ijt}^{\text{alloc}} \left(w_i - \overline{w}^{\text{AH}} \right) \left(\text{Opp}_{g(j)} - \overline{\text{Opp}}_t^{\text{AH}} \right)}{\sum_{i \in \mathcal{I}_t} \sum_{j \in \mathcal{J}_t^{\text{AH}}} P_{ijt}^{\text{alloc}}}$$

where w_i is an element of $\mathbf{w}_i$ (characteristics entering utility) and/or $\widetilde{\mathbf{w}}_i$ (characteristics observed by developers), $\overline{w}^{\text{AH}}$ and $\overline{\text{Opp}}_t^{\text{AH}}$ are the allocation-weighted means across affordable allocations in period t, and P_{ijt}^{alloc} are the equilibrium allocation probabilities from Equation 4. The sample analogues ($m_t^{(q)}$) are computed using the realized characteristics and neighborhoods of households moving into a LIHTC unit during period t.

The allocation probabilities depend on both who gets an offer and whether they accept. The probability of accepting is $\frac{1}{N}$ for a household with N offers (Assumption 2). This probability is challenging to compute directly, but, because offer probabilities are small and the number of options is large, we can approximate the distribution of the number of other offers (conditional on an offer at j) as a Poisson distribution with arrival rate $\rho_{ijt} = \sum_{j' \in \mathcal{J}_t^{\text{AH}}; j' \neq j} (P_{ij't}^{\text{apply}} \times P_{ij't}^{\text{offer}})$ by Le Cam

Table C.1: True and model-predicted characteristics (market-rate)

Nbhd opp. quartile	Estimates	Log AGI years [-3, 0)	White (non-Hispanic)	Black (non-Hispanic)	Has any children	Graduated college
Panel a) All						
	True	7.756	0.1453	0.612	0.4684	0.1662
Q1	Predicted (main)	7.730	0.1391	0.6172	0.4727	0.1654
	True	8.505	0.5046	0.2044	0.3658	0.3050
Q2	Predicted (main)	8.473	0.4995	0.2050	0.3705	0.3025
	True	9.283	0.6258	0.1337	0.3127	0.4342
Q3	Predicted (main)	9.254	0.6270	0.1348	0.3138	0.4296
	True	9.254	0.6303	0.1011	0.3840	0.4090
Q4	Predicted (main)	9.225	0.6266	0.1050	0.3858	0.4030
Panel b) Movers						
	True	8.308	0.1849	0.6193	0.4775	0.2024
Q1	Predicted (main)	8.335	0.1703	0.6290	0.4799	0.2008
	Predicted (mini)	8.622	0.2460	0.5669	0.3977	0.2762
	True	9.115	0.5623	0.1994	0.2961	0.3896
Q2	Predicted (main)	9.140	0.5428	0.1990	0.3325	0.3883
	Predicted (mini)	9.328	0.5457	0.2214	0.2989	0.4046
	True	9.687	0.6405	0.1346	0.2764	0.4990
Q3	Predicted (main)	9.622	0.6598	0.1296	0.2755	0.4872
	Predicted (mini)	9.589	0.6345	0.1721	0.2821	0.4473
	True	9.714	0.6497	0.1042	0.3389	0.4633
Q4	Predicted (main)	9.602	0.6613	0.0992	0.3217	0.4672
	Predicted (mini)	9.675	0.687	0.1224	0.2700	0.4565

Notes: This table compares the true and estimated characteristics those choosing market-rate housing options in different levels of neighborhood opportunity for either the full population or subset to those that do not choose their endowed options. The main model uses the full set of household characteristics while the 'mini' model is estimated using just a subset of both household and neighborhood characteristics. Note that neither model includes "graduated college" as a characteristic.

(1960). With this assumption:

$$P_{ijt}^{\text{accept}} \approx \sum_{n=0}^{|\mathcal{J}_t^{\text{AH}}|-1} \left(\frac{e^{-\rho_{ijt}}\rho_{ijt}^n}{n!}\right)\left(\frac{1}{1+n}\right)$$

Move-out moments. We target the mean probability that a household currently in affordable housing moves out, the covariance of that probability with household characteristics, and the covariance of that probability with the interaction between household characteristics and the opportunity level of the household's current neighborhood.[41] Let $j_i^0 \in \mathcal{J}^{\text{AH}}$ denote the affordable housing unit that household i is endowed with, and let $\text{Opp}_{g_{j_i^0}}$ denote the opportunity level of its neighborhood. The model-predicted moments are

$$\text{Mean:} \qquad \widehat{m}_t^{(q)} = \frac{1}{\left|\mathcal{I}_t^{\text{AH}}\right|} \sum_{i \in \mathcal{I}_t^{\text{AH}}} P_{it}^{\text{moveout}}$$

$$\text{Covariances:} \qquad \widehat{m}_t^{(q)} = \frac{1}{\left|\mathcal{I}_t^{\text{AH}}\right| - 1} \sum_{i \in \mathcal{I}_t^{\text{AH}}} (w_i - \overline{w}) \left(P_{it}^{\text{moveout}} - \overline{P}_t^{\text{moveout}}\right)$$

$$\text{Opportunity covariances:} \qquad \widehat{m}_t^{(q)} = \frac{1}{\left|\mathcal{I}_t^{\text{AH}}\right| - 1} \sum_{i \in \mathcal{I}_t^{\text{AH}}} \left(w_i \,\text{Opp}_{g(j_i^0)} - \overline{w_i \,\text{Opp}}\right) \left(P_{it}^{\text{moveout}} - \overline{P}_t^{\text{moveout}}\right)$$

where bars denote sample means across $i \in \mathcal{I}_t^{\text{AH}}$. Because move-out decisions depend only on household preferences and not on developer screening, these moments pin down $\boldsymbol{\alpha}^o$ separately from $\boldsymbol{\phi}_1$. With logit errors, the probability each household moves out is

$$P_{it}^{\text{moveout}} = \frac{\sum_{j \in \mathcal{J}_t^{\text{MR}}} \exp\left(\delta_{jt} + \lambda_{ijt}\right)}{\exp(\delta_{j_i^0 t} + \lambda_{ij_i^0 t}) + \sum_{j \in \mathcal{J}_t^{\text{MR}}} \exp\left(\delta_{jt} + \lambda_{ijt}\right)} \tag{C.2}$$

Evidence on move-ins and move-outs. Identification of the screening parameters and the preferences specific to affordable housing relies on differences between true move-ins/move-outs in LIHTC units and predicted move-in/move-outs based on preferences estimated in the market-rate sector.

For evidence on move-ins, Table C.2 presents the predicted and true values of various household characteristics for existing LIHTC developments in Chicago. The top two quartiles are combined because there are too few LIHTC developments in these neighborhoods to disclose their household characteristics separately. The predicted values are for $\boldsymbol{\alpha} = 0$, i.e. excluding any preferences specific to affordable housing. In all neighborhoods, preferences from the market-rate sector generate predicted LIHTC households that are less likely to have a Black household head, have fewer children, are more likely to include a married couple and seniors, and have lower incomes than the actual households that move in to LIHTC. Some of the gaps are large – the true share of households that include joint filers or a senior is half of the predicted shares. In cases where the predicted share is higher than the true share, either these households dislike affordable housing relatively more than observably similar market-rate units or are less likely to be selected in the screening process.

For move-outs, Table C.3 presents results from regressions of true and predicted move-outs for existing LIHTC tenants on a vector of characteristics for these households. The data are at the tenant-year level, with outcomes either the predicted probability of moving out or indicators of whether the household moved out that year. On average, LIHTC tenants move out more quickly than predicted based solely on the rent, housing, and neighborhood characteristics. This higher-than-predicted move-out rate helps explain why households are estimated to value a LIHTC unit less than an observably equivalent market-rate unit. Differences in the coefficients on household characteristics help explain the heterogeneity in $\boldsymbol{\alpha}_i$ across households. For example, voucher holders are predicted to move out at a faster rate than the average household but in practice are less likely

[41] Table B.2 documents that the move-out rates of LIHTC households are lower than the move-out rates of LIHTC-eligible households living in market-rate units, which can stem from both preferences for the observable characteristics (e.g., rent) as well as preferences for affordable housing specifically ($\boldsymbol{\alpha}$). We discuss move-out rates in more detail in Appendix Section B.4.

to move out each year; to rationalize this behavior, Table D.12 shows that voucher holders place *greater* value on an affordable housing unit relative to a comparable market-rate unit.

Table C.2: True and predicted affordable housing move-ins

	All		Q1		Q2		Q3 and Q4	
	Pred.	True	Pred.	True	Pred.	True	Pred.	True
White (non-Hispanic)	0.2709	0.1872	0.1168	0.0792	0.3571	0.2225	0.4339	0.3867
Black (non-Hispanic)	0.4947	0.6682	0.7331	0.8009	0.3289	0.6148	0.2945	0.4352
Hispanic	0.1472	0.1231	0.09844	0.1038	0.1942	0.1399	0.1671	0.1457
Log current income	5.77	6.382	5.274	6.028	6.065	6.545	6.267	6.978
Log income years [-3, 0)	6.634	7.205	6.295	6.943	6.776	7.296	7.069	7.683
Has current income	0.6185	0.6606	0.5636	0.6253	0.6529	0.6847	0.6706	0.7105
Has income years [-3, 0)	0.7161	0.7631	0.6782	0.7383	0.7371	0.778	0.7567	0.8007
Has any children	0.2778	0.4387	0.3004	0.4273	0.2572	0.4607	0.267	0.4371
Has married couple	0.07752	0.0395	0.05269	0.02437	0.08558	0.03801	0.1132	0.07534
Log household head age	3.66	3.648	3.729	3.671	3.577	3.624	3.656	3.625
Has any seniors	0.2139	0.09263	0.247	0.09942	0.1709	0.09174	0.2182	0.07846
Has voucher	0.123	0.2273	0.1714	0.2232	0.08955	0.1936	0.08222	0.2777
# of persons	1.653	2.023	1.647	1.972	1.668	2.076	1.643	2.072

Notes: This table compares the true and estimated characteristics of those choosing affordable housing options in different levels of neighborhood opportunity. The predicted characteristics use only the preference for housing and neighborhood characteristics estimated in the market-rate sector to estimate the average of different household characteristics among applicants to each development.

C.4 Estimating the cost of LIHTC

We estimate the potential costs of building a LIHTC development in different neighborhoods using two approaches. For our preferred approach, we abstract away from the supply-side details of LIHTC and instead estimate the 'implicit subsidy' for each unit based on the gap between the rent that a LIHTC household pays and an estimate of what the rent would be if it were a market-rate unit. This approximates the opportunity cost of setting aside units as LIHTC instead of renting them in the market-rate sector.

For our second approach, we combine historical data on LIHTC subsidies with a wide array of neighborhood and development characteristics likely to affect development costs. Then, we use machine learning to estimate a flexible mapping from characteristics to the number of tax credits awarded. This approach may underestimate the full cost to the government of a new development, as LIHTC developments often layer additional subsidies beyond just the tax credits, such as subsidized bonds, tax abatements, land grants, and expedited permitting (Cummings and DiPasquale, 1999).

C.4.1 Estimating 'implicit subsidies' for LIHTC

Our preferred approach for inferring the cost to the government is to compare the rent collected from a LIHTC unit to the rent the same unit could garner as a market-rate unit. We estimate how much each unit in a simulated development in Section 8.1 would rent for as market-rate units using a hedonic model trained on the sample of market-rate units, in the ACS. We estimate using OLS a model of gross rent regressed on neighborhood fixed effects and an array of unit characteristics, including fixed effects for the number of bedrooms, the ratio of total rooms to bedrooms, bins of

Table C.3: True and predicted affordable housing move-out rates

	Predicted move-out	True move-out
Intercept	0.5651	0.714
	(0.0121)	(0.0308)
White (non-Hispanic)	0.0564	0.0216
	(0.0054)	(0.0138)
Black (non-Hispanic)	0.0293	0.0084
	(0.0052)	(0.0132)
Hispanic	0.0222	0.0224
	(0.0056)	(0.0142)
Log current income	0.0092	-0.0067
	(0.0009)	(0.0022)
Log income years [-3, 0)	-0.0065	0.0093
	(0.0009)	(0.0022)
Has current income	0.0897	-0.0306
	(0.0078)	(0.0199)
Has income years [-3, 0)	-0.0824	0.0211
	(0.008)	(0.0204)
Has any children	-0.0106	-0.0031
	(0.0028)	(0.0072)
Has married couple	-0.062	0.0266
	(0.0033)	(0.0085)
Log household head age	-0.1444	-0.1451
	(0.0027)	(0.007)
Has seniors	-0.0381	0.0035
	(0.0024)	(0.0061)
Has voucher	0.0322	-0.0139
	(0.0018)	(0.0045)
# of persons	0.0353	-0.0135
	(0.0012)	(0.003)
Overall mean	0.1501	0.1595

Notes: This table compares the true and estimated move-out rates. The predicted move-outs rely only on preferences for housing and neighborhood characteristics from the market-rate sector to estimate the average move-out rate of current residents of existing LIHTC developments.

building age, and whether the building is a single-family residence, small apartment building, big apartment building, or other building type. We then predict the gross rent for each type of unit within the simulated LIHTC development and take the average. For LIHTC, the average rent ceiling for LIHTC units in Chicago between 2018 and 2019—the period we use for counterfactuals—was $1,011.

C.4.2 Data for estimating LIHTC award levels

We collect data on both LIHTC awards and a wide array of neighborhood characteristics to estimate the relationship between neighborhoods and the number of tax credits awarded.

LIHTC awards. We use publicly available data from HUD on each LIHTC development to observe the total subsidy allocated for a given development as well as the characteristics of the development (e.g., number of units). The subsidy allocation recorded is for a single year of tax credits, which is then doled out each year for the first ten years of operation. We use the CPI-U to denominate all values in 2019 dollars and compute the total upfront cost as the discounted sum of the face value of tax credits using a 3% annual discounting rate. We include only developments built between 2000 and 2010 that received 9% credits whose per-unit subsidy is within [$10000, $5000000]. The median per-unit subsidy in our sample MSAs is $147,653 and the interquartile range is [$93531, $210699].

Land use regulations. The Wharton Residential Land Use Regulatory Index (WRLURI) measures the stringency of local regulations for real estate using survey responses from 2,649 municipalities (Gyourko, Saiz and Summers, 2008). For the municipalities surveyed, we identify each tract contained within and assign it the corresponding WRLURI. The survey was conducted in 2005, but a follow-up survey in 2018 found that a municipality's regulatory stringency was highly persistent (Gyourko, Hartley and Krimmel, 2021). We use the 2005 survey for all years in our data. The municipalities surveyed cover 44% of the tracts in the 100 most populous metro areas.

Housing market characteristics and resident demographics. We use data from the 2000 and 2010 Census to measure characteristics of a neighborhood's residents and housing market, including the number of housing units, vacancy rate, population density, fraction below poverty, median household income, and resident demographics.

Number of offices and parks. We use data from Reference USA to measure the number of nearby office buildings in each year and data from OpenStreetMaps to measure the number of nearby parks.

Development intensity and land coverage. We use data from the National Land Cover Database (NLCDB) for 2001, 2006, 2011, and 2016. The data include four levels of development based on the percentage of land coverage: open (0-19%), low (20-49%), medium (50-79%), and high (80-100%). The raw data is at the level of 30m by 30m squares, but we use data aggregated to the tract level from Clarke and Melendez (2019). We construct a single measure of the average development in a tract using the midpoints of each land coverage category. The data also include the fraction of land that is water, forests, shrubs, and other land types. For each year in our neighborhoods data, we use the most recent level of development from the NLCDB (e.g., for 2008, we use the 2006 NLCDB aggregates).

Topography. For our main measure of topography, we follow Baum-Snow and Han (2024) and use the fraction of land defined as 'flat plains' in the Scientific Investigations Map 3085 (Cress et al., 2009), which is in turn derived from the US Geological Survey's National Elevation Database.[42] The underlying data include slope and elevation for each 30m by 30m square of land in the US. An area is a flat plain if the slope of at least half of the other squares in a 0.56km radius are under 8% and the total elevation change in that 0.56km radius is under 15 meters. The median tract in one of the 100 most populous metro areas contains 25% flat plains.

Land cost index. We use data on sales of land matched to the neighborhood characteristics described above to estimate the price of an acre of land in each tract-year. We treat this as an index—rather than the actual cost of land to developers—because we do not restrict to land sales that are suitable for multifamily construction, and properties can be built on bigger or smaller lots.

[42] The raw data are stored as raster files. Nate Baum-Snow kindly shared the tract-level aggregates they constructed for Baum-Snow and Han (2024).

We collect data on sales of plots of land in the 100 most populous metro areas between 2001 and 2019 from CoreLogic Deed records. We exclude any non-arms length transactions, transactions for plots of land smaller than 0.1 acres or larger than 20 acres, and transactions in the top and bottom 2.5% of the price-per-acre distribution within each MSA. The final sample includes 3.22 million transactions in the 100 most populous metro areas.

To train our model of land prices, we use the popular machine learning framework XGBoost (eXtreme Gradient Boosting), which uses a tree-based learning algorithm. (Chen and Guestrin, 2016). We tune the hyperparameters controlling the maximum tree depth, number of boosting rounds, and subsample size using a cross-validated grid search. For each state, we train the model on an 80% sample and evaluate the model accuracy on a 20% holdout. Our outcome is the log sale price of the parcel, adjusted for inflation. For features, we use the PUMA, year and month of sale, log acres, and characteristics of the Census tract, including the fraction flat plains, average level of development, WRLURI (with an indicator if missing), housing vacancy rate, log population density, log median household income, fraction white, fraction below poverty, log number of offices within 1 mile, and log number of parks within 1 mile. Averaging across states and weighting by the number of sales, the average R^2 is 0.57 on the holdout sample. The most important features are consistently the level of existing development, the housing vacancy rate, and the median household income. Given the estimated model, we predict the price of 1-acre, 5-acre, and 10-acre parcels of land sold in each tract-year and then take the average per-acre predicted price as our index.[43]

C.4.3 Estimating LIHTC award levels

We flexibly estimate the mapping from development characteristics and neighborhood characteristics to the number of tax credits awarded using the machine learning framework XGBoost. As with the estimation of land values, we tune the hyperparameters using a cross-validated grid search and train on an 80% sample of developments. For development characteristics, we include the number of units, whether entirely affordable, target population (if any), for vs. non-profit, target AMI, and indicators for receiving other sources of funding (e.g., a state bond). For neighborhood characteristics, we include the predicted land price, WRLURI (with an indicator if missing), housing vacancy rate, log population density, log median household income, fraction white, fraction with college, fraction below poverty, log number of offices within 1 mile, log number of parks within 1 mile, and whether the tract is a Qualified Census Tract or Difficult Development Area. The R^2 on the holdout group of developments is 0.54.

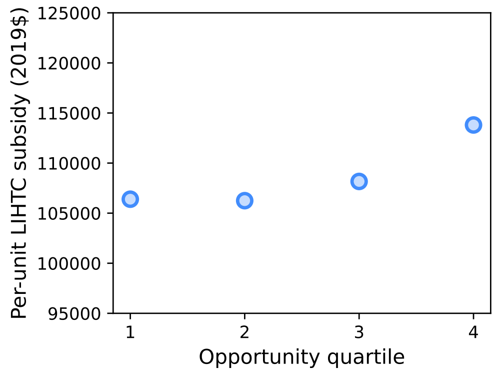
Figure C.2 plots the average estimated per-unit LIHTC subsidy by neighborhood opportunity quartile. From the bottom to the top quartile, the estimated LIHTC subsidy increases by 7%. A key limitation is that the data on LIHTC awards are selected; both developers' decisions to apply and the state's rationing process will be affected by the costs to develop and the potential tax credits at stake. The out-of-sample predictions of tax credits may not reflect the actual subsidy that would be awarded for typical development in a given neighborhood.

C.5 Effects on children and neighbors

In this section we describe the steps used to estimate the effects on the upward mobility of children and spillovers on neighbors documented in Section 8.3.

[43] We can observe a small sample of parcels that were sold specifically for purposes of building a LIHTC development using data from Costar, a commercial real estate company. The 25th, 50th, and 75th percentiles of acreage are, respectively, 0.82 acres, 3.49 acres, and 8.56 acres.

Figure C.2: Estimated tax credit subsidy



Notes: This figure documents estimates of the per-unit tax credit subsidy that would be awarded to a development for each quartile of neighborhood opportunity. The sample includes all 50 MSAs used for analyses.

Effects on children. Table C.4 details the complete set of steps to arrive at an estimate of the impact on children in the development. For a new development in the top quartile of neighborhood opportunity in Chicago, the average household moves from a neighborhood where the predicted individual earnings percentile in adulthood of children born to low-income families is 37.1 to a neighborhood where the predicted rank is 51.0. For developments in the bottom quartile, the average household still experiences a move 'up' in the distribution of expected future earnings for children, although the difference in income percentile ranks is smaller (from 32.5 to 36.3). A key difference across potential LIHTC neighborhoods is the share of tenants with children; for Chicago, we estimate that only 33.9% of households in developments in the top quartile would have at least one child at home, compared to 59.5% in the bottom quartile. One trade-off in choosing the location for a new LIHTC development, therefore, is providing a smaller treatment (+3.9 percentile ranks) to more children or a larger treatment (+13.9 percentile ranks) to fewer children.

We follow the methodology in Chetty et al. (2026) to translate the changes in income percentile ranks into an estimate of the causal effect on lifetime earnings for the individual. Chetty and Hendren (2018) estimate that 62% of the effect of changing neighborhoods on the predicted income rank is causal, so we scale down the 'treatment effect' on the percentile ranks accordingly. We then convert the treatment effect in ranks to the effect on discounted lifetime earnings, assuming a constant treatment effect over the lifetime. Finally, we multiply by the average number of children in a unit and divide by 18*12 to convert the estimates to be per unit-month of exposure, implicitly assuming that a month of exposure to a neighborhood has the same effect between birth and age 18 (then drops to zero).

Spillovers on neighbors. Diamond and McQuade (2019) provide estimates on neighbors' welfare for LIHTC developments built in eight classifications of Census block groups, which are based on whether the block group is over 50% Black/Hispanic ('high-minority') and quartiles of median household income in the 1990 Census. They define quartiles in the distribution of block groups with a LIHTC development.

We match each block group to our measure of neighborhood opportunity in Chicago, then use the per-household welfare effects estimated by Diamond and McQuade (2019) to compute the aggregate effect of a new development built in the block group based on the welfare of renters, homeowners, and landlords within 1.5 miles. We use the 2019 5-year ACS block group tabulations to estimate the number of each household type within a 1.5 mile radius of a block group, assuming

Table C.4: Steps for estimating the impact on lifetime earnings of children

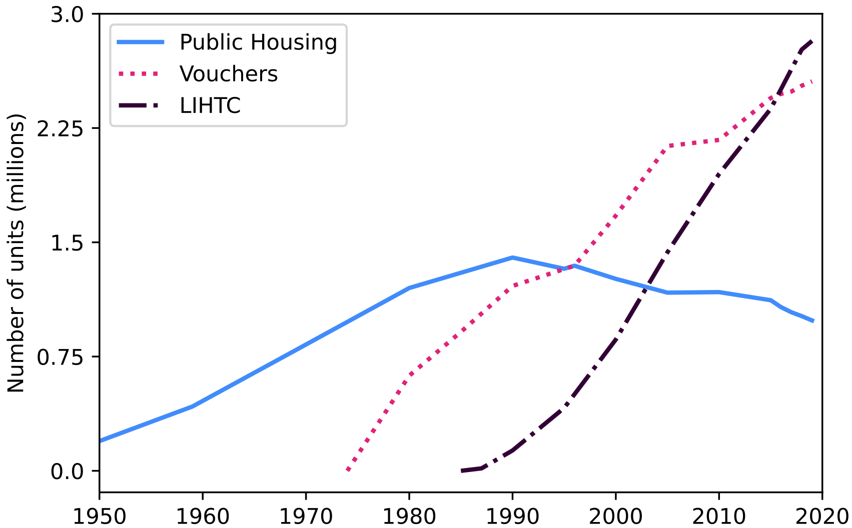
#	Step description	Q1	Q4
1	Average upward mobility rank in prior tract	32.5	37.1
2	[Translated to 2019$]	$10,741	$13,736
3	Change in tract-level upward mobility rank.	3.9	13.9
4	Estimated causal effect of move from birth (=62% of [3])	2.418	8.618
5	Expected upward mobility in ranks (=[1]+[4])	34.92	45.72
6	[Translated to 2019$]	$12,318	$19,160
7	Effect of move on yearly income at age 26 (=[6]-[2])	$1,578	$5,424
8	Average individual earnings at age 26 (ACS, 2019$)	$28,382	$28,382
9	Effect as % of average individual earnings (=[7]/[8])	5.56%	19.12%
10	Undiscounted lifetime income with 1% wage growth (ACS, 2019$)	$2,897,247	$2,897,247
11	Discounted (3%) lifetime income with 1% wage growth (ACS, 2019$)	$750,494	$750,494
12	Causal effect on undiscounted lifetime income (=[10]*[9])	$161,052	$553,633
13	Causal effect on discounted lifetime income (=[11]*[9])	$41,718	$143,411
14	Percent of households with children	59.5%	33.9
15	Average number of children conditional on at least 1	2	2
16	Average number of children in each household (=[14]*[15])	1.19	0.678
17	Effect on undiscounted lifetime inc. per unit-month (=([12]*[16])/(18*12))	$887.3	$1737.8
18	Effect on discounted lifetime inc. per unit-month (=([13]*[16])/(18*12))	$229.8	$450.1

Notes: This table presents the steps we take to approximate the causal effect on lifetime earnings of a change in neighborhood. The table structure mirrors that of Appendix Table 9 of Bergman et al. (2023), although we use the assumptions from Chetty et al. (2026) to estimate the effect on individual earnings. Row (1) and (2) take the average upward mobility in a household's previous tract and convert the percentile rank to dollars using data from the Opportunity Atlas, inflated to 2019$. Row (3) is the change in upward mobility in ranks, which is then deflated by the estimate of what share is causal from Chetty and Hendren (2018) (row 4). Row (5) is expected upward mobility in ranks for households using the causal effect, which is then converted to 2019$ in row (6) and reported as the difference in row (7). Row (8) is the average individual earnings of an individual at age 26 based on the 2019 5-year ACS. Row (10) is the undiscounted sum of individual earnings over the lifecycle, estimated by taking the average earnings for each age from the 2019 5-year ACS to expected lifetime earnings at birth, assuming 1% wage growth and mortality rates from the Social Security Administration's actuarial tables. Row (11) computes this same lifecycle earnings but now discounts future earnings at 3%. Rows (12) and (13) report the causal effects on lifetime earnings, assuming a constant treatment effect over the lifecycle (row 9). Row (14) is the percent of households with children in each quartile. Row (15) is the average number of children conditional on having 1, which we set at two by assumption (future versions will use the actual number; it was not disclosed for this draft). Row (16) is the average number of children in each unit. Rows (17) and (18) report the final causal effects on undiscounted and discounted lifetime earnings, where we divide by 18*12 to convert the number to per unit-month (implicitly assuming a constant effect by age of child).

households are distributed uniformly across the block group. We use the 1990 Census to categorize block groups according to Diamond and McQuade (2019), then match each to the corresponding PUMA used to define neighborhoods in our counterfactuals. To arrive at a single estimate, we assume constant effects within each of their eight block group categories. We find that developments built in the bottom and top quartiles of neighborhood opportunity reduce neighbors' welfare by $4.55 million and $8.30 million, respectively.

D Supplemental tables and figures

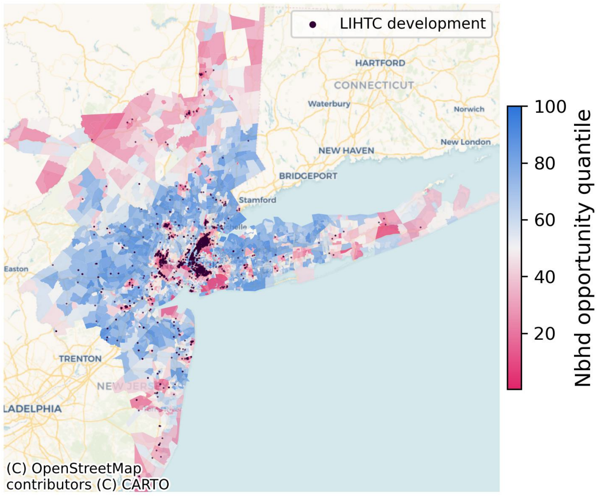
Figure D.1: Subsidized housing stock by year



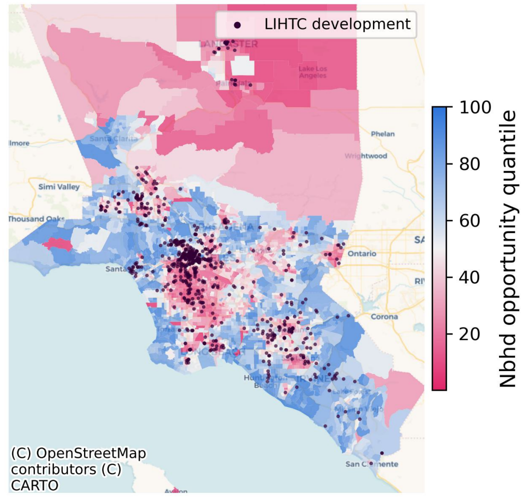
Notes: This figure documents the stock of public housing units, Section 8 housing vouchers, and LIHTC units by year. The underlying data are sourced from Schwartz (2021), HUD PICTRACs, and HUD's LIHTC database. LIHTC units include those funded by both 4% and 9% tax credits. The sample covers the full US.

Figure D.2: Neighborhood opportunity maps

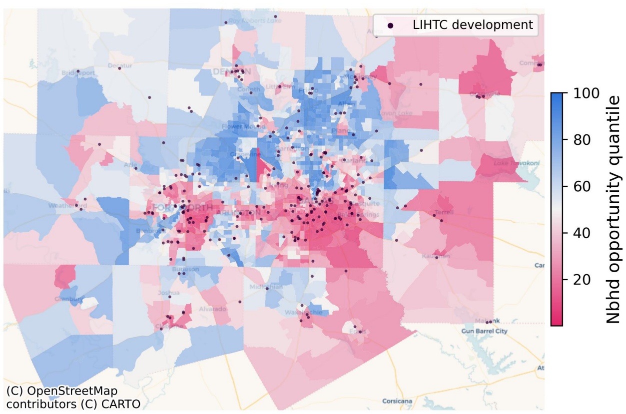
(a) New York City MSA



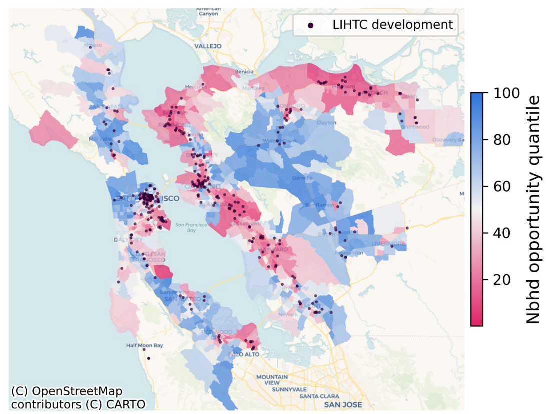
(b) Los Angeles MSA



(c) Dallas MSA

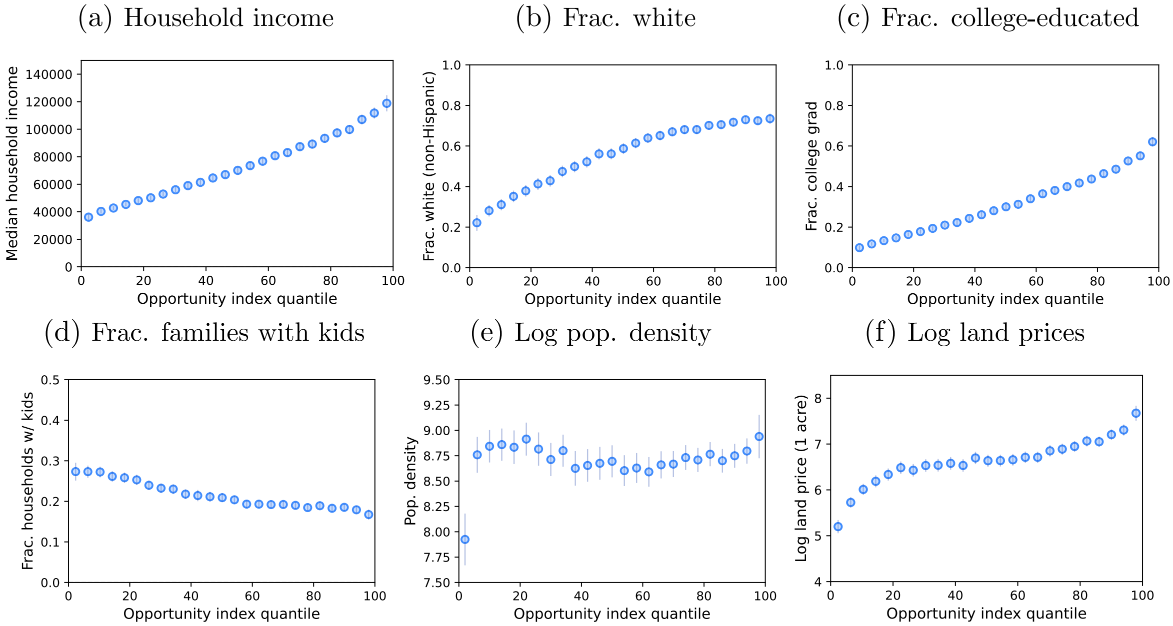


(d) San Francisco-Oakland MSA



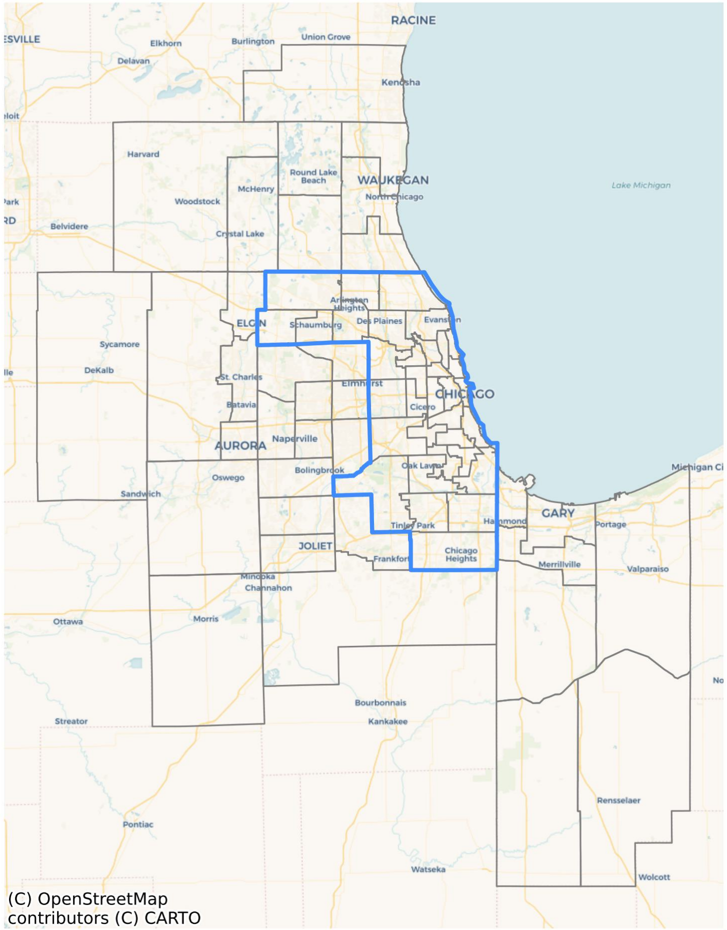
Notes: This figure plots spatial variation in our index of neighborhood opportunity and the location of LIHTC developments across four of the most populous metro areas in the US.

Figure D.3: Neighborhood opportunity measure



Notes: Each panel plots a binscatter between tract-level correlations between neighborhood opportunity and various neighborhood characteristics. The first five panels use characteristics from the 2015 5-year ACS. Income is inflated to 2019 dollars. The final panel uses an estimated index of land prices.

Figure D.4: Map of Chicago PUMAs



Notes: This figure maps the Public Use Microdata Areas (PUMAs) that make up the Chicago-Naperville-Elgin, IL-IN-WI MSA, which we use to define a 'neighborhood' for the purposes of the model estimation. The blue line corresponds to the City of Chicago boundaries.

Table D.1: Eligible population: market-rate v. LIHTC characteristics

	Avg. for LIHTC-eligible households in market-rate	Coefficient on is LIHTC
Financials and education		
Current Adjusted Gross Income (AGI)	15020.0	487
		(31.94)
Avg. AGI in years [-3, 0)	19230.0	-4320
		(41.07)
Avg. AGI in years (0, 3]	22600.0	-2628
		(51.73)
Predicted future income rank	0.3303	-0.0923
		(0.0029)
Filed taxes this year	0.6514	0.0506
		(0.001)
Childhood family income rank (household head)	0.4324	-0.1114
		(0.0009)
Graduated college (household head)	0.1853	-0.0791
		(0.0025)
Graduated high school (household head)	0.7981	-0.0205
		(0.0034)
Surveyed gross rent (ACS)	1025.0	-276.5
		(5.274)
Household structure		
Household has married couple	0.1377	-0.0359
		(0.0007)
Household has children (<18yo)	0.4209	0.052
		(0.0011)
Household has seniors (>64yo)	0.189	-0.0763
		(0.0007)
Race/ethnicity (household head)		
White (non-Hispanic)	0.4221	-0.1671
		(0.001)
Black (non-Hispanic)	0.2547	0.2098
		(0.001)
Hispanic	0.2259	0.0089
		(0.0009)
Previous tract chars. (household head)		
Miles from prev. tract	5.826	0.8878
		(0.0206)
<1mi from prev. tract	0.2449	-0.0929
		(0.001)
Prev. tract opportunity rank	0.4153	-0.0956
		(0.0006)
Prev. tract median household income	53110.0	-7214
		(52.6)
Prev. tract frac. white	0.5924	-0.0834
		(0.0006)

Notes: This table documents differences in the characteristics of households in LIHTC compared to eligible households living in a market-rate unit. The first column documents the average of a given characteristic for the market-rate sample and the second column documents the coefficient on whether a household is in LIHTC from a regression, which includes fixed effects for MSA interacted with year. The sample includes market-rate households in the ACS and LIHTC households constructed using the Census-IRS panel (2010-2019, 50 sample MSAs). Standard errors are reported in parentheses.

Table D.2: Alternative "eligible" populations: market-rate v. LIHTC characteristics

	Avg. for eligible households in market-rate	Coefficient on is LIHTC
Eligibility: AGI below 50% AMI		
Avg. AGI in years [-3, 0)	19230.0	-3628
		(41.67)
Childhood family income rank	0.4324	-0.1098
		(0.001)
Graduated college	0.1853	-0.076
		(0.0026)
Household has children (<18yo)	0.4209	0.0473
		(0.0011)
White (non-Hispanic)	0.4221	-0.1655
		(0.001)
Black (non-Hispanic)	0.2547	0.2136
		(0.0011)
Hispanic	0.2259	0.0074
		(0.0009)
Eligibility: average AGI in years [-3,0) below 50% AMI		
Avg. AGI in years [-3, 0)	19230.0	-173.9
		(26.87)
Childhood family income rank	0.4324	-0.1055
		(0.001)
Graduated college	0.1853	-0.0646
		(0.0026)
Household has children (<18yo)	0.4209	0.0409
		(0.0011)
White (non-Hispanic)	0.4221	-0.1545
		(0.001)
Black (non-Hispanic)	0.2547	0.2124
		(0.0011)
Hispanic	0.2259	0.0018
		(0.0009)

Notes: This table replicates a subset of results in Table D.1 using alternative measures of a household's eligibility for LIHTC. The first set use whether a household's current AGI is below 50% of the Area Median Income (AMI). The second set uses whether their average AGI for 3 prior years is below the same limit. The sample includes market-rate households in the ACS and LIHTC households constructed using the Census-IRS panel (2010-2019, 50 sample MSAs). Note that the average for eligible households in Column 1 corresponds to the standard eligible population. Standard errors are reported in parentheses.

Table D.3: Relationship between current AGI and other household characteristics

Household characteristic	All renters	All LIHTC-eligible renters
Correlations: current AGI		
Avg. AGI in years [-3, 0)	0.8577	0.5081
Avg. AGI in years (0, 3]	0.8740	0.5845
Childhood family income rank (household head)	0.2957	0.03235
Predicted future income rank	0.7342	0.3665
Average current AGI by char.		
Black (non-Hispanic)	32710	13860
White (non-Hispanic)	57950	13180
Hispanic	41780	16970
Graduated college (household head)	81120	16100
No college degree (household head)	34860	13880
Graduated high school (household head)	53890	15280
No high school degree (household head)	21470	10600
Household has children (<18yo)	51930	20370
Household does not have children	47280	9997
Household has seniors (>64yo)	30900	8030
Household does not have seniors	52740	15990
Household has married couple	86350	28600
Household has no married couple	37780	12130

Notes: This table documents the relationship between current Adjusted Gross Income (AGI) and other household characteristics for all renters and all LIHTC-eligible renters in the ACS. The first three rows are correlations, while the remainder are the average AGI for the group indicated in the left column.

Table D.4: LIHTC household chars. by neighborhood opportunity

	Q1 avg.	Quartile coefficients		
		Q2	Q3	Q4
Financials and education				
Current Adjusted Gross Income (AGI)	14590	553.7	1030	1727
		(199.8)	(238.4)	(318.6)
Avg. AGI in years [-3, 0)	14030	805.5	1666	2248
		(176.3)	(215)	(300)
Avg. AGI in years (0, 3]	18610	1132	2384	3281
		(280.3)	(326.7)	(461)
Predicted future income rank	0.2129	0.0454	0.0755	0.0833
		(0.0075)	(0.0089)	(0.0118)
Childhood family income rank (household head)	0.2845	0.045	0.0832	0.1101
		(0.004)	(0.0046)	(0.006)
Graduated college (household head)	0.0893	0.0197	0.0524	0.0838
		(0.0066)	(0.0084)	(0.0141)
Graduated high school (household head)	0.7512	0.0277	0.0642	0.0732
		(0.0089)	(0.0107)	(0.0133)
Household structure				
Household has married couple	0.0782	0.0249	0.0429	0.0561
		(0.0039)	(0.0041)	(0.0055)
Household has children (<18yo)	0.4743	-0.0278	-0.0308	-0.0492
		(0.0058)	(0.0069)	(0.0079)
Household has seniors (>64yo)	0.0977	0.0109	0.0278	0.033
		(0.0049)	(0.0074)	(0.0073)
Race/ethnicity of household head				
White (non-Hispanic)	0.1696	0.1182	0.1917	0.2454
		(0.0095)	(0.0123)	(0.0157)
Black (non-Hispanic)	0.5533	-0.1444	-0.213	-0.253
		(0.0118)	(0.0135)	(0.0159)
Hispanic	0.2426	0.0078	-0.003	-0.0274
		(0.0085)	(0.0096)	(0.0113)
Previous tract chars. (household head)				
Miles from prev. tract	6.256	0.5237	1.214	1.756
		(0.1175)	(0.1644)	(0.172)
Prev. tract opportunity rank	0.2452	0.0992	0.1888	0.2654
		(0.0046)	(0.0057)	(0.0073)
Prev. tract median household income	41690	5234	10240	16560
		(335)	(471.1)	(680.8)

Notes: This table documents how LIHTC household characteristics vary by the neighborhood opportunity of the development by regressing each characteristic on indicators for quartiles of within-MSA neighborhood opportunity. The specification includes controls for MSA interacted with year, the income limit, and the number of bedrooms. The holdout group is the first quartile; we report the average for this group in the first column. The sample includes all LIHTC households and characteristics are based on the household at move-in. Standard errors are reported in parentheses. A subset of these characteristics is used to construct Figure 3.

Table D.5: LIHTC household chars. by neighborhood opportunity (with income controls)

		Quartile coefficients		
	Q1 avg.	Q2	Q3	Q4
Financials and education				
Avg. AGI in years [-3, 0)	14030	441.2	998.7	1110
		(95.42)	(114.5)	(178.1)
Avg. AGI in years (0, 3]	18610	592.3	1399	1630
		(115.8)	(132.9)	(193.1)
Predicted future income rank	0.2129	0.0404	0.057	0.0715
		(0.0066)	(0.0081)	(0.0109)
Childhood family income rank (household head)	0.2845	0.0439	0.0810	0.1070
		(0.0039)	(0.0045)	(0.0059)
Graduated college (household head)	0.0893	0.0185	0.0496	0.0800
		(0.0066)	(0.0083)	(0.014)
Graduated high school (household head)	0.7512	0.0245	0.0582	0.0630
		(0.0088)	(0.0105)	(0.013)
Household structure				
Household has married couple	0.0782	0.0217	0.0369	0.0462
		(0.0036)	(0.0039)	(0.005)
Household has children (<18yo)	0.4743	-0.0352	-0.0443	-0.0711
		(0.0045)	(0.0051)	(0.007)
Household has seniors (>64yo)	0.0977	0.0131	0.0316	0.0386
		(0.0044)	(0.0066)	(0.0065)
Race/ethnicity of household head				
White (non-Hispanic)	0.1696	0.1185	0.1924	0.2469
		(0.0095)	(0.0123)	(0.0156)
Black (non-Hispanic)	0.5533	-0.1436	-0.2114	-0.2507
		(0.0117)	(0.0135)	(0.0159)
Hispanic	0.2426	0.0068	-0.0051	-0.0308
		(0.0084)	(0.0096)	(0.0112)
Previous tract chars. (household head)				
Miles from prev. tract	6.256	0.5364	1.240	1.797
		(0.1172)	(0.1646)	(0.1718)
Prev. tract opportunity rank	0.2452	0.0990	0.1884	0.2648
		(0.0045)	(0.0057)	(0.0073)
Prev. tract median household income	41690	5202	10180	16470
		(332)	(468.1)	(678.8)

Notes: This table replicates Table D.4, but adds controls for bins of household income. The income bins are constructed using a household's current adjusted gross income. Standard errors are reported in parentheses.

Table D.6: LIHTC household chars. by neighborhood opportunity (with neighborhood controls)

		Quartile coefficients		
	Q1 avg.	Q2	Q3	Q4
Controls: nbhd frac. white (non-Hispanic) decile				
Avg. AGI in years [-3, 0)	14030	550.8	1310	1893
		(189.2)	(241.4)	(320.1)
Childhood family income rank (household head)	0.2845	0.021	0.0449	0.0666
		(0.0038)	(0.0051)	(0.0062)
Graduated college (household head)	0.0893	0.0189	0.055	0.0878
		(0.0072)	(0.0094)	(0.0157)
Prev. tract opportunity rank	0.2452	0.0733	0.1491	0.2221
		(0.0046)	(0.0059)	(0.0076)
White (non-Hispanic)	0.1696	0.0268	0.0356	0.0651
		(0.0082)	(0.0117)	(0.0149)
Black (non-Hispanic)	0.5533	-0.0397	-0.0503	-0.0746
		(0.0109)	(0.0129)	(0.0158)
Hispanic	0.2426	-0.0193	-0.0323	-0.051
		(0.0089)	(0.0104)	(0.0124)
Controls: nbhd median income decile				
Avg. AGI in years [-3, 0)	14030	257.1	550.2	521.6
		(185.1)	(231)	(337.2)
Childhood family income rank (household head)	0.2845	0.034	0.0628	0.0812
		(0.0042)	(0.0054)	(0.0073)
Graduated college (household head)	0.0893	0.0174	0.0493	0.0759
		(0.007)	(0.0095)	(0.0151)
Prev. tract opportunity rank	0.2452	0.0861	0.1658	0.2282
		(0.0046)	(0.0063)	(0.0086)
White (non-Hispanic)	0.1696	0.0929	0.1477	0.1855
		(0.0096)	(0.0128)	(0.0191)
Black (non-Hispanic)	0.5533	-0.1245	-0.1813	-0.2196
		(0.0122)	(0.0156)	(0.0198)
Hispanic	0.2426	0.0106	0.006	-0.002
		(0.0091)	(0.0114)	(0.0134)

Notes: This table replicates Table D.4, but adds controls for either deciles of neighborhood fraction white (non-Hispanic) or of neighborhood median income in 2010. Standard errors are reported in parentheses.

Table D.7: Market-rate household chars. by neighborhood opportunity

		Quartile coefficients		
	Q1 avg.	Q2	Q3	Q4
Avg. AGI in years [-3, 0)	30580	11560	21740	34020
		(132.8)	(151.8)	(174.4)
Current Adjusted Gross Income (AGI)	35990	13730	25900	40660
		(153.5)	(173.7)	(197.1)
White (non-Hispanic)	0.3165	0.1883	0.2877	0.345
		(0.0017)	(0.0017)	(0.0017)
Black (non-Hispanic)	0.3523	-0.1666	-0.2239	-0.2649
		(0.0016)	(0.0015)	(0.0014)
Hispanic	0.255	-0.0403	-0.0951	-0.1317
		(0.0015)	(0.0014)	(0.0014)
Graduated college (household head)	0.2082	0.118	0.226	0.349
		(0.0015)	(0.0016)	(0.0016)
Predicted future income rank	0.3969	0.1057	0.1853	0.2615
		(0.001)	(0.001)	(0.001)
Household has children (<18yo)	0.4894	-0.0709	-0.1163	-0.1371
		(0.0017)	(0.0017)	(0.0017)
Childhood family income rank (household head)	0.4211	0.1017	0.1657	0.217
		(0.0015)	(0.0015)	(0.0015)
Prev. tract opportunity rank	0.3035	0.1491	0.2613	0.358
		(0.001)	(0.001)	(0.001)
Miles from prev. tract	5.909	0.8334	1.229	1.18
		(0.0364)	(0.0382)	(0.0382)

Notes: This table documents how market-rate household characteristics vary by the neighborhood opportunity of the development by regressing each characteristic on indicators for quartiles of within-MSA neighborhood opportunity. The specification includes controls for MSA interacted with year, the income limit, and the number of bedrooms. The holdout group is the first quartile; we report the average for this group in the first column. The sample is cross-sections of market-rate households (including those who are ineligible for LIHTC) in the ACS (2010-2019). Standard errors are reported in parentheses.

Table D.8: Market-rate household chars. by neighborhood opportunity (with income controls)

		Quartile coefficients		
	Q1 avg.	Q2	Q3	Q4
Avg. AGI in years [-3, 0)	30580	2718	5102	8840
		(89.52)	(105.2)	(125.1)
Current Adjusted Gross Income (AGI)	35990	457.9	1147	3554
		(51.42)	(61.06)	(72.6)
White (non-Hispanic)	0.3165	0.1719	0.2576	0.3008
		(0.0017)	(0.0017)	(0.0018)
Black (non-Hispanic)	0.3523	-0.1547	-0.202	-0.2332
		(0.0016)	(0.0015)	(0.0015)
Hispanic	0.255	-0.0345	-0.083	-0.1113
		(0.0015)	(0.0015)	(0.0014)
Graduated college (household head)	0.2082	0.073	0.1428	0.2266
		(0.0014)	(0.0016)	(0.0017)
Predicted future income rank	0.3969	0.0435	0.0743	0.1045
		(0.0006)	(0.0006)	(0.0006)
Household has children (<18yo)	0.4894	-0.0686	-0.1098	-0.1238
		(0.0016)	(0.0017)	(0.0017)
Childhood family income rank (household head)	0.4211	0.0832	0.1339	0.1732
		(0.0015)	(0.0015)	(0.0016)
Prev. tract opportunity rank	0.3035	0.1381	0.241	0.3281
		(0.001)	(0.001)	(0.0011)
Miles from prev. tract	5.909	0.7883	1.152	1.083
		(0.0368)	(0.0393)	(0.04)

Notes: This table replicates Table D.8, but adds controls for bins of household income. The income bins are constructed using a household's current adjusted gross income. Standard errors are reported in parentheses.

Table D.9: Gap in neighborhood chars. of future-LIHTC vs LIHTC-eligible market-rate households

	Chicago MSA		50 Sample MSAs	
	(1)	(2)	(1)	(2)
Share non-Hispanic Black (2010)	0.1179	-0.0436	0.0681	0.0023
	(0.0241)	(0.0214)	(0.0028)	(0.0026)
Share Hispanic (2010)	-0.0405	0.0246	0.0100	0.0110
	(0.0146)	(0.0132)	(0.0023)	(0.0022)
Share non-Hispanic white (2010)	-0.0666	0.0151	-0.0695	-0.0127
	(0.0198)	(0.0183)	(0.003)	(0.0027)
Share w/ college (2010)	-0.0428	-0.0112	-0.0477	-0.0178
	(0.0137)	(0.0134)	(0.0024)	(0.0024)
Neighborhood opportunity percentile	-0.0841	-0.0154	-0.0754	-0.0238
	(0.0153)	(0.0127)	(0.0033)	(0.0031)
HUD jobs index	-2.562	-0.8358	-1.139	0.2741
	(1.207)	(1.186)	(0.2637)	(0.2606)
Upward mobility index	-9.601	-0.0683	-6.692	-1.740
	(1.934)	(1.79)	(0.3037)	(0.2893)
HUD school index	-6.673	-1.015	-6.381	-1.933
	(1.799)	(1.669)	(0.313)	(0.2973)
HUD transit index	-0.1232	-0.7673	1.441	0.6080
	(0.8513)	(0.8923)	(0.1552)	(0.1515)
Log median household income	-0.0996	0.0150	-0.1139	-0.0487
	(0.0287)	(0.0262)	(0.005)	(0.0049)
Log pop. density (2010)	-0.0517	-0.0971	0.1075	0.0305
	(0.0744)	(0.0754)	(0.0127)	(0.0124)
Controls				
Year FE	✓	✓	✓	✓
CBSA FE			✓	✓
CBSA × year FE			✓	✓
Household chars. used in model		✓		✓

Notes: This table presents a series of regressions of neighborhood characteristics on an indicator for whether the head of household moves into a LIHTC unit in the next two years. The sample includes ACS households who are eligible for LIHTC in their city at the time surveyed but are not currently living in affordable housing. The second specification adds controls for all household characteristics that are used in the demand model, including indicators for race, whether the household has children, whether there are joint filers, whether the household has any seniors, whether the head of household has a voucher, bins of household income, and indicators for the number of individuals in the household. The upward mobility index comes from Chetty et al. (2026) and measures the upward mobility of households born in the tract to parents at the 25th percentile of the income distribution (normalized to match the scaling of other opportunity indices). All opportunity indices are scaled 0 to 100 (except for the percentiles, which are scaled 0 to 1). Standard errors are presented in parentheses.

Table D.10: Relationship between instrument and neighborhood amenities

Outcome	Outcome mean	Coef. on instrument
# restaurants	2.051	0.008562
		(0.0044)
# personal services	1.178	0.009641
		(0.005)
# grocery stores	1.008	-0.01620
		(0.0038)
# general retail	0.4508	-0.01064
		(0.0048)
# entertainment	0.2946	-0.002269
		(0.0035)
Frac. White (non-Hispanic)	0.5607	0.003697
		(0.0017)
Frac. Hispanic	0.1971	-0.002002
		(0.0015)
Frac Black (non-Hispanic)	0.1665	-0.002546
		(0.0008)
Frac with college degree	0.4250	0.005678
		(0.0033)
Frac housing vacant	0.0891	-0.001284
		(0.0008)
Log median household income	11.16	0.01193
		(0.0052)
Log population density	8.487	0.0004986
		(0.0033)

Notes: Establishment counts are based on the Business Register. We categorize establishments based on their 4-digit NAICS code: restaurants (7224, 7225); grocery stores (4451, 4452); general retail (4522, 4528, 4523); and entertainment places (7111, 7112, 7121). Other neighborhood characteristics are based on the ACS. The first column is the mean across Chicago MSA neighborhoods. The second column regresses the outcome on the z-score of our instrument for market-rate rents with fixed effects for neighborhood and year. Standard errors are presented in parentheses.

Table D.11: Instrument first-stage

Covariate	Coefficient on rent
Exposure instrument	0.3099
	(0.0524)
2 bedrooms	2.736
	(0.0973)
3+ bedrooms	5.762
	(0.1346)
Building <25yo	2.323
	(0.095)
Big apartment building	0.3375
	(0.1425)
Small apartment building	-1.543
	(0.0883)

Notes: This table documents the first-stage of Equation 10, which regresses rent on our instrument. Standard errors in parentheses are clustered at the PUMA-level.

Table D.12: Preference heterogeneity: housing characteristics

Household char.	Avg. of char. in population	Gross rent (00s)	Is prev. option	Dist. prev. option	2 bedrooms	3+ bedrooms	Small apt. building	Big apt. building	Building <25yo	Is AH	(Is AH) x (opp)
Avg. household	-	-0.1673	6.152	-0.1382	0.6844	1.253	0.2889	0.6939	0.7725	-0.1315	-
		(0.0494)	(0.0024)	(0.0002)	(0.1381)	(0.277)	(0.0805)	(0.0403)	(0.1145)	(0.032)	
White (non-Hispanic)	0.4492	0.0467	-0.3892	0.0101	-0.1418	-0.3665	-0.4114	-0.1596	-0.2891	-0.0703	-0.0365
		(0.0016)	(0.0084)	(0.0006)	(0.0099)	(0.0144)	(0.0114)	(0.0096)	(0.0093)	(0.0223)	(0.0254)
Black (non-Hispanic)	0.2917	0.0084	-0.5476	-0.0084	-0.1276	-0.2093	0.0376	0.0478	-0.0691	0.3	-0.0752
		(0.0019)	(0.009)	(0.0007)	(0.0113)	(0.0159)	(0.013)	(0.0106)	(0.0106)	(0.0175)	(0.0238)
Hispanic	0.1641	-0.0234	-0.295	-0.0312	-0.0549	-0.141	-0.56	-0.1295	-0.1576	-0.034	-0.046
		(0.0019)	(0.0093)	(0.0007)	(0.0114)	(0.0161)	(0.0134)	(0.0104)	(0.0108)	(0.0157)	(0.0164)
Has voucher	0.0639	-0.0043	-0.2364	-0.005	0.183	0.4827	-0.3199	-0.2846	0.1558	0.2554	-0.2686
		(0.0022)	(0.0092)	(0.0008)	(0.0129)	(0.0168)	(0.015)	(0.0102)	(0.0108)	(0.0178)	(0.037)
Any children	0.3786	0.0007	0.0011	-0.0219	0.3148	0.2737	-0.11	-0.0278	-0.0352	0.2407	-0.1912
		(0.0012)	(0.006)	(0.0004)	(0.0074)	(0.0103)	(0.0088)	(0.0066)	(0.007)	(0.0164)	(0.0537)
Has married couple	0.1983	-0.0076	0.2029	-0.0013	-0.0441	-0.1351	0.0907	-0.1053	0.044	-0.1926	0.1245
		(0.0012)	(0.0059)	(0.0004)	(0.0074)	(0.0103)	(0.0085)	(0.0066)	(0.0068)	(0.0188)	(0.0122)
Any seniors	0.1572	0.0101	0.4562	-0.0108	0.0307	0.1883	0.9873	0.0372	0.1989	-0.314	0.4956
		(0.0016)	(0.0088)	(0.0006)	(0.0103)	(0.0143)	(0.0118)	(0.0097)	(0.0096)	(0.0255)	(0.0431)
Has current income	0.7769	-0.2238	0.0554	-0.062	0.1312	0.5229	0.4346	0.509	-0.0066	-0.0097	0.0474
		(0.0059)	(0.0285)	(0.002)	(0.034)	(0.0483)	(0.0414)	(0.0327)	(0.0326)	(0.0129)	(0.0157)
Has income years [-3, 0)	0.8317	-0.1096	-0.7557	0.0595	-0.5041	-0.1918	0.0993	0.5304	-0.1255	0.029	-0.0704
		(0.0052)	(0.026)	(0.0017)	(0.0308)	(0.0435)	(0.0376)	(0.0296)	(0.0298)	(0.0103)	(0.017)
Household size: 2	0.2754	0.0317	-0.0311	-0.0022	0.5674	0.5791	-0.3407	-0.0122	-0.0365	-0.0536	0.0273
		(0.0011)	(0.0053)	(0.0004)	(0.0063)	(0.0094)	(0.0077)	(0.0061)	(0.0063)	(0.0154)	(0.0264)
Household size: 3	0.1382	0.0226	-0.0024	0.0008	0.9686	1.565	-0.3917	0.0058	-0.0044	0.0305	-0.0712
		(0.0016)	(0.0076)	(0.0005)	(0.0102)	(0.0135)	(0.0117)	(0.0085)	(0.0092)	(0.0124)	(0.0154)
Household size: 4 or more	0.1511	0.0294	-0.127	-0.0001	1.196	2.093	-0.729	-0.2509	-0.0947	0.2694	-0.4023
		(0.0018)	(0.0084)	(0.0006)	(0.0126)	(0.0159)	(0.0139)	(0.0094)	(0.0104)	(0.0126)	(0.0236)
Log household head age	3.71	0.0164	0.8703	-0.029	0.0236	0.0732	0.2885	-0.0156	-0.0504	-0.1807	0.2213
		(0.0013)	(0.0062)	(0.0004)	(0.0075)	(0.0108)	(0.0092)	(0.0067)	(0.0074)	(0.0262)	(0.0417)
Log current income	8.232	0.0214	-0.0252	0.0066	-0.0192	-0.0436	-0.0111	-0.0166	-0.0039	0.0548	-0.0522
		(0.0006)	(0.0028)	(0.0002)	(0.0034)	(0.0048)	(0.0041)	(0.0032)	(0.0032)	(0.0109)	(0.0442)
Log income years [-3, 0)	8.611	0.0142	0.0372	-0.0053	0.0446	-0.0107	-0.0389	-0.0579	0.014	0.0076	-0.0612
		(0.0005)	(0.0027)	(0.0002)	(0.0031)	(0.0044)	(0.0038)	(0.003)	(0.003)	(0.022)	(0.0594)

Notes: This table documents the estimated preference parameters for neighborhood characteristics. Because we recenter household characteristics to have mean zero, the common component of utility corresponds to the average household. The coefficients listed here report the marginal effect of the associated characteristic on the preference parameter. See Table D.14 for a more easily interpreted version of the preference estimates for binary household variables. Standard errors are reported in parentheses.

Table D.13: Preference heterogeneity: neighborhood characteristics

Household char.	Avg. of char. in population	Share white	Share Black	Share Hispanic	Share w/ college	Log pop. density	Log med. income	HUD school index	HUD jobs index	HUD transit index	HUD poverty index
Avg. household				——— Absorbed by neighborhood fixed effects ———							
Black (non-Hispanic)	0.2917	0.5809	1.089	0.2303	-0.3142	0.4611	0.0262	-0.1178	0.0289	-0.5654	0.3654
		(0.0269)	(0.0227)	(0.0189)	(0.013)	(0.0196)	(0.0117)	(0.0148)	(0.0056)	(0.0218)	(0.017)
Hispanic	0.1641	0.6591	0.7241	0.481	-0.2823	0.5945	0.1807	0.1194	0.0436	-0.8226	0.0402
		(0.0264)	(0.0219)	(0.0183)	(0.013)	(0.0205)	(0.0116)	(0.0149)	(0.0057)	(0.0226)	(0.0174)
White (non-Hispanic)	0.4492	0.7514	0.3697	0.1253	-0.2224	0.5883	0.1094	-0.106	0.0149	-0.7158	-0.0043
		(0.0226)	(0.0191)	(0.0159)	(0.0112)	(0.0177)	(0.0099)	(0.0133)	(0.0048)	(0.0194)	(0.0149)
Has voucher	0.0639	-0.209	0.0869	0.0329	0.1092	0.0705	0.0069	-0.0695	-0.0141	-0.0136	0.2381
		(0.0356)	(0.03)	(0.0243)	(0.0153)	(0.0209)	(0.0146)	(0.0165)	(0.0066)	(0.0242)	(0.0205)
Any children	0.3786	-0.3892	-0.1618	-0.2547	-0.4085	-0.1606	0.1686	0.0449	-0.0169	0.08	0.2009
		(0.0184)	(0.0156)	(0.0129)	(0.0086)	(0.0124)	(0.0078)	(0.0098)	(0.0039)	(0.0132)	(0.0114)
Has married couple	0.1983	-0.3188	-0.3271	-0.2458	-0.1366	-0.0881	0.0246	0.1669	0.0225	0.1494	-0.1236
		(0.017)	(0.0145)	(0.0119)	(0.0081)	(0.0123)	(0.0074)	(0.0097)	(0.0036)	(0.0132)	(0.0109)
Any seniors	0.1572	-0.2224	-0.1886	-0.1467	-0.1494	-0.1897	0.1701	-0.0501	-0.1049	0.0034	0.0075
		(0.0271)	(0.0232)	(0.0191)	(0.0124)	(0.0181)	(0.0115)	(0.0143)	(0.0057)	(0.0194)	(0.0164)
Log household head age	3.71	-0.2057	-0.1774	-0.2364	-0.426	-0.0418	0.2291	0.0564	-0.0668	-0.0569	0.0186
		(0.0185)	(0.0156)	(0.0129)	(0.0086)	(0.0127)	(0.008)	(0.0098)	(0.0038)	(0.0139)	(0.0115)
Household size: 2	0.2754	0.0404	-0.0895	-0.0331	0.0283	-0.127	-0.0252	-0.1147	-0.0165	0.1402	-0.0494
		(0.0157)	(0.0133)	(0.0109)	(0.0073)	(0.011)	(0.0069)	(0.0089)	(0.0032)	(0.0121)	(0.0098)
Household size: 3	0.1382	0.3356	0.0744	0.105	0.1605	-0.1567	-0.0096	-0.0798	-0.0757	-0.0104	-0.2654
		(0.0233)	(0.0198)	(0.0163)	(0.011)	(0.0161)	(0.0101)	(0.0127)	(0.0049)	(0.0174)	(0.0147)
Household size: 4 or more	0.1511	0.1335	-0.1358	-0.0889	0.022	-0.0647	0.0711	-0.0778	-0.0567	-0.0659	-0.3721
		(0.0266)	(0.0226)	(0.0186)	(0.0126)	(0.0182)	(0.0114)	(0.0142)	(0.0057)	(0.0194)	(0.0167)
Has current income	0.7769	1.102	0.5613	0.0813	-0.788	0.3886	0.5299	0.6729	0.1556	-0.3274	-1.261
		(0.0898)	(0.0762)	(0.0629)	(0.0409)	(0.0603)	(0.0385)	(0.0479)	(0.018)	(0.0663)	(0.0533)
Has income years [-3, 0)	0.8317	1.275	0.7459	0.4525	0.4628	0.0805	-0.0721	0.1547	-0.1613	-0.1627	-0.8998
		(0.0793)	(0.0674)	(0.0557)	(0.0364)	(0.053)	(0.034)	(0.0426)	(0.0162)	(0.0577)	(0.0476)
Log current income	8.232	-0.0965	-0.0422	0.0118	0.0971	-0.0424	-0.0711	-0.0494	-0.0152	0.0417	0.1339
		(0.0088)	(0.0075)	(0.0062)	(0.004)	(0.006)	(0.0038)	(0.0048)	(0.0018)	(0.0066)	(0.0053)
Log income years [-3, 0)	8.611	-0.1355	-0.0882	-0.0624	-0.059	-0.0013	0.0094	-0.0266	0.0222	0.0131	0.0942
		(0.008)	(0.0068)	(0.0057)	(0.0037)	(0.0054)	(0.0035)	(0.0044)	(0.0016)	(0.0059)	(0.0049)

Notes: This table documents the estimated preference parameters for neighborhood characteristics. Because we recenter household characteristics to have mean zero, the common component of utility corresponds to the average household. The coefficients listed here report the marginal effect of the associated characteristic on the preference parameter. See Table D.14 for a more easily interpreted version of the preference estimates for binary household variables. Standard errors are reported in parentheses.

Table D.14: Preference heterogeneity with un-centered household variables

Housing characteristics	Gross rent (00s)	Is prev. option	Dist. prev. option	2 bedrooms	3+ bedrooms	Small apt. building	Big apt. building	Building <25yo	Is AH	(Is AH) x (opp)
White (non-Hispanic)	0.0233	-0.0546	0.008	-0.0409	-0.1408	-0.2376	-0.1019	-0.1391	-0.1262	0.0018
Black (non-Hispanic)	-0.0045	-0.3633	-0.0095	-0.072	-0.085	0.1334	0.0796	0.0136	0.2692	-0.0541
Hispanic	-0.0196	-0.2466	-0.0261	-0.0459	-0.1179	-0.4681	-0.1082	-0.1317	-0.0284	-0.0385
Has voucher	-0.004	-0.2213	-0.0046	0.1713	0.4519	-0.2995	-0.2664	0.1459	0.2391	-0.2514
Any children	0.0004	0.0007	-0.0136	0.1956	0.1701	-0.0684	-0.0173	-0.0219	0.1496	-0.1188
Has married couple	-0.0061	0.1627	-0.0011	-0.0354	-0.1083	0.0727	-0.0844	0.0352	-0.1544	0.0998
Any seniors	0.0085	0.3845	-0.0091	0.0259	0.1587	0.8321	0.0313	0.1676	-0.2646	0.4177
Household size: 2	0.0154	-0.003	-0.0017	0.0966	-0.1129	-0.0826	0.0283	-0.0115	-0.0837	0.0904
Household size: 3	0.0108	0.0179	0.0012	0.6274	1.0636	-0.2047	0.0351	0.0137	0.0087	-0.0254
Household size: 4 or more	0.0192	-0.1095	0.0002	0.902	1.6609	-0.5678	-0.2256	-0.0791	0.2506	-0.3629
Has current income	-0.0499	0.0124	-0.0138	0.0293	0.1167	0.097	0.1136	-0.0015	-0.0022	0.0106
Has income years [-3, 0)	-0.0184	-0.1272	0.01	-0.0848	-0.0323	0.0167	0.0893	-0.0211	0.0049	-0.0119
Neighborhood characteristics	Share white	Share Black	Share Hispanic	Share w/ college	Log pop. density	Log med. income	HUD school index	HUD jobs index	HUD transit index	HUD poverty index
White (non-Hispanic)	0.2444	-0.114	0.0018	-0.0308	0.1895	0.0526	-0.024	-0.0002	-0.2293	-0.109
Black (non-Hispanic)	0.3017	0.8226	0.1623	-0.2087	0.2415	-0.0051	-0.0726	0.0206	-0.2975	0.3078
Hispanic	0.5509	0.6053	0.4021	-0.236	0.4969	0.151	0.0998	0.0365	-0.6876	0.0336
Has voucher	-0.1957	0.0814	0.0308	0.1022	0.066	0.0065	-0.065	-0.0132	-0.0127	0.2229
Any children	-0.2418	-0.1005	-0.1583	-0.2538	-0.0998	0.1048	0.0279	-0.0105	0.0497	0.1248
Has married couple	-0.2556	-0.2622	-0.1971	-0.1095	-0.0706	0.0197	0.1338	0.018	0.1198	-0.0991
Any seniors	-0.1874	-0.159	-0.1236	-0.1259	-0.1599	0.1434	-0.0422	-0.0884	0.0028	0.0063
Household size: 2	-0.0373	-0.0546	-0.0251	-0.005	-0.0606	-0.0276	-0.0603	0.007	0.113	0.0571
Household size: 3	0.2793	0.0997	0.1108	0.1364	-0.1086	-0.0114	-0.0404	-0.0586	-0.0302	-0.1882
Household size: 4 or more	0.085	-0.114	-0.0839	0.0012	-0.0232	0.0695	-0.0439	-0.042	-0.0829	-0.3056
Has current income	0.2459	0.1252	0.0181	-0.1758	0.0867	0.1182	0.1501	0.0347	-0.073	-0.2813
Has income years [-3, 0)	0.2146	0.1255	0.0762	0.0779	0.0135	-0.0121	0.026	-0.0271	-0.0274	-0.1514

Notes: To ease interpretation of the preference estimates, this table documents the heterogeneity in the parameters presented in Table D.12 and D.13 after un-centering the indicator variables for household characteristics. The primary estimates use household characteristics centered to be mean-zero in the population, so that the baseline estimates correspond to the average household. However, this can make the interpretation of indicator variables more difficult; it requires accounting for differences from the average household (e.g., for a household with a married couple, the re-centered value for that characteristic is one minus the population average). We do not include the continuous household characteristics (e.g., income) as those parameter estimates are unaffected by the centering.

Table D.15: Screening parameters

Household char.	Baseline (ϕ_0)	By nbhd opportunity (ϕ_1)
White (non-Hispanic)	-0.0874	-0.0047
	(0.0131)	(0.0124)
Black (non-Hispanic)	0.3253	-0.2460
	(0.0163)	(0.0167)
Hispanic	-0.0443	0.0091
	(0.0134)	(0.0113)
Has voucher	0.1924	-0.2143
	(0.0171)	(0.0291)
Any children	0.1576	-0.0694
	(0.0225)	(0.0240)
Has married couple	-0.1523	0.0986
	(0.0145)	(0.0088)
Any seniors	-0.2044	0.2562
	(0.0147)	(0.0188)
Log household head age	0.0050	-0.3198
	(0.0217)	(0.0428)
Household size: 2	-0.0503	0.0394
	(0.0142)	(0.0171)
Household size: 3	0.0188	-0.0389
	(0.0122)	(0.0131)
Household size: 4 or more	0.2069	-0.3101
	(0.0156)	(0.0249)
Has current income	-0.0180	0.0456
	(0.0091)	(0.0118)
Has income years [3, 0)	0.0213	-0.0526
	(0.0059)	(0.0124)
Log current income	-0.0435	0.1480
	(0.0151)	(0.0624)
Log income years [3, 0)	-0.0056	0.0894
	(0.0232)	(0.0417)

Notes: This table documents the estimated screening parameters for neighborhood characteristics. Note that the household characteristics in $\mathbf{w}$ are not re-centered to be mean-zero for this table. The neighborhood opportunity index is set to range from $[-0.5, 0.5]$ such that the baseline estimates correspond to a median opportunity neighborhood. Standard errors are reported in parentheses.

Table D.16: Value of affordable housing (α_i/β_i)

	Neighborhood opportunity idx		
Population	p25	p50	p75
All eligible	-99.65	-67.46	-35.28
	(2.38)	(1.624)	(1.332)
White (non-Hispanic)	-263.7	-206.5	-149.3
	(3.729)	(2.144)	(2.003)
Black (non-Hispanic)	35.27	56.3	77.32
	(3.315)	(1.772)	(1.171)
Hispanic	-86.91	-82.3	-77.7
	(3.651)	(2.054)	(1.765)
Any children	76.04	29.68	-16.68
	(2.816)	(2.134)	(2.072)
Has married couple	-103.7	-130	-156.3
	(6.494)	(4.698)	(3.979)
Any seniors	-315.7	-163.6	-11.52
	(3.82)	(2.996)	(2.878)
Has voucher	58.69	67.72	76.74
	(6.313)	(3.508)	(2.289)
1 person	-178.7	-99.5	-20.32
	(2.932)	(2.03)	(1.786)
2 persons	-143.1	-105.4	-67.78
	(5.381)	(4.075)	(3.529)
3 persons	16.3	-6.395	-29.09
	(4.771)	(3.751)	(3.53)
4+ persons	137.3	47.0	-43.31
	(4.152)	(3.588)	(3.52)
High-need	-66.47	-29.11	8.261
	(3.308)	(2.103)	(1.742)
Moderate-need	-128.6	-100.9	-73.23
	(3.271)	(2.303)	(2.008)
Black or Hispanic	-2.475	13.48	29.43
	(2.646)	(1.614)	(1.352)
White or other	-234.2	-179.5	-124.8
	(3.435)	(2.061)	(1.9)

Notes: This table reports the average α_i/β_i at different levels of neighborhood opportunity for different populations of households. 'High-need' refers to households whose predicted future income is in the bottom quartile of the nationwide distribution of renters, adjusted for household size and age. Bootstrapped standard errors are reported in parentheses.