Where to Build Affordable Housing? Evaluating the Tradeoffs of Location*

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Abstract

How does the location of affordable housing affect household welfare, the distribution of assistance, and broader societal objectives such as racial integration? Using administrative data on affordable housing tenants, we first show that, despite fixed eligibility requirements, developments in higher-opportunity neighborhoods disproportionally house tenants who are higher income, more educated, less likely to have children, and less likely to be Black or Hispanic. To quantify the welfare implications, we build a model in which households choose from both market-rate and affordable housing options, where the latter are rationed by private developers. Building in higher-opportunity neighborhoods costs more, but increases household welfare and reduces racial and economic segregation. However, the welfare gains accrue to more moderate-need and white (non-Hispanic) households at the expense of other households. Using the estimated model, we show that the shift in the distribution of assistance is primarily due to a 'crowding out' effect: households that only apply for assistance in higher-opportunity neighborhoods crowd out those willing to apply regardless of location. Relative to the initial choice of location, policy levers available post-construction—such as lowering the income limits used for means-testing—have only limited effects.

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1 Introduction

Central to many affordable housing programs is a 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, greater economic opportunity, and less racial segregation. Initiatives in this vein include local 'inclusionary zoning' policies requiring that new market-rate developments set aside units for low-income households, state policies requiring that municipalities build their 'fair share' of affordable housing, and a federal rule that cities must "take meaningful actions to overcome patterns of segregation and foster inclusive communities."[2]

What are the tradeoffs of shifting affordable housing towards more opportunity-rich neighborhoods? While providing housing in such neighborhoods can be more expensive, tenants may value the improved access to good schools, jobs, and local amenities. Affordable housing in these neighborhoods also has the potential to increase the long-run earnings of children in the development (Chetty and Hendren, 2018) and reduce city-wide racial and economic segregation, but may have negative spillovers on the surrounding neighbors (Diamond and McQuade, 2019). One tradeoff that has received less attention is that *where* affordable housing is built determines *who* applies for assistance if households have heterogeneous preferences for neighborhoods. Policy goals such as targeting those with the greatest need or reducing segregation rely on take-up by households with characteristics that are difficult to observe (e.g., long-term need) or illegal to screen on (e.g., race).

In this paper, we evaluate the tradeoffs of providing affordable housing in different types of neighborhoods. We focus on units built through the Low-Income Housing Tax Credit (LIHTC) program, 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 with market-rate and affordable housing options, where the latter are priced below-market and must be rationed among applicants. Because units are rationed, both household preferences and the mechanism used to ration units affect which households receive a unit. We use the estimated model to disentangle these two factors and to quantify the effects of adding affordable housing to different neighborhoods on tenant welfare, city-wide integration, and other common policy considerations. Finally, we compare the effects of the choice of location to other policy levers, such as lowering the income limits used for means-testing.

We combine data from individual-level tax records, residential address histories, and Census survey responses to build a panel of households living in LIHTC and market-rate rental units. For

[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." The effects on racial segregation have also been the topic of numerous court cases, summarized in Appendix Section A.3.

[2] This quote was taken from the Department of Housing and Urban Development (HUD) page on Affirmatively Furthering Fair Housing (source). In 2023, then-secretary of HUD, Marcia Fudge described the department's top priority as "[making] sure people in this country have decent, affordable, safe housing. [...] We want people to live in communities of opportunity" (Kimura, 2023).

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. While we do not observe applications for LIHTC units, we observe the population of eligible households and which households receive a unit. Our primary sample covers households in the 50 most populous metro areas between 2010 and 2018.

We first show that the characteristics of affordable housing tenants vary widely across neighborhoods, despite fixed within-city rent and income limits. While the average household living in a LIHTC unit exhibits greater need and is far more likely to be Black than other eligible households, 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] Relative to LIHTC households living in the bottom quartile of neighborhood opportunity, households living in the top quartile have higher long-run income, are twice as likely to have a college-educated household head, grew up in higher-income families, and are three times as likely to be white (non-Hispanic). The differences across neighborhoods persist even conditional on income at move-in—the characteristic used for means-testing—in part because current income is far less correlated with race/ethnicity and various proxies for need within the population of low-income renters than in the overall population.

Motivated by the descriptive evidence, we build a structural model of household and developer behavior, which we estimate for the Chicago metro area. Our model builds on existing residential choice models by adding an affordable housing sector, where units must be rationed. Households in the model first decide whether to apply for each affordable housing option, then developers allocate units to applicants. LIHTC developers have substantial discretion in allocating units, including the option to require tenants to meet some minimum income threshold. To incorporate the role of developers, we model the rationing process as a weighted lottery in which developers can favor households based on observable characteristics such as current income. Households not allocated an affordable housing unit must select from among the market-rate options.

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 a shifter that captures 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 follow the approach in Bayer, Ferreira and McMillan (2007) to estimate household preferences—excluding this shifter—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 for different types of housing stemming from trends in

[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.

the demographic and industry composition of cities. The instrument is similar in spirit to Waldfogel instruments from the industrial organization literature: the preferences of other participants in a market affect the prices that a given individual faces (Waldfogel, 2003; Berry and Haile, 2016).

With estimates of preferences for housing and neighborhood characteristics in hand, in the second step we use the Generalized Method of Moments (GMM) to estimate household preferences specific to affordable housing and the weights developers place on different household characteristics. Preferences estimated in the first step inform which households would want to live in a given development, up to any preferences specific to affordable housing. To separate the role of developer discretion from heterogeneity in household preferences for affordable housing, we use moments based on who moves into a LIHTC development and how long they remain. While developers in the model only affect move-ins, household preferences affect both move-in and move-out decisions.

Using the estimated model, we quantify the effects of location by simulating adding new LIHTC units and varying the neighborhood in which they are placed. We find that total household surplus is $151 more per month for a new unit built in the top instead of bottom quartile of neighborhood opportunity. However, the increase in the costs exceeds the increase in household surplus. To measure costs, we predict the market-rate rent of 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 $213 per month in the bottom quartile of neighborhood opportunity (18% discount off of market-rate) to $671 per month in the top quartile (41% discount).

The benefits to tenants of building in higher-opportunity neighborhoods do not accrue evenly across households. Instead, providing affordable housing in higher-opportunity neighborhoods transfers surplus, especially across racial/ethnic lines. Household surplus for Black and Hispanic households is $273 *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 share of moderate-need and white (non-Hispanic) households who apply for assistance is increasing in 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 low-income households face when searching for housing (DeLuca, Wood and Rosenblatt, 2019; Bergman et al., 2023). 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), we show that changing the location of affordable housing alone is unlikely to 'pull' many households out of lower-opportunity neighborhoods, partly because of this crowding out.[4]

Turning to other considerations that may enter the social planner's objective, we evaluate

[4] The policy shift towards providing affordable housing in higher-opportunity neighborhoods stems in part from evidence on the benefits for households, including improvements in the physical and mental health of adults (Kling, Liebman and Katz, 2007) and better economic outcomes for children (Chetty, Hendren and Katz, 2016; Chetty and Hendren, 2018). For more on neighborhood effects, see, also, Brooks-Gunn et al. (1993); Rosenbaum (1995); Currie and Yelowitz (2000); Katz, Kling and Liebman (2001); Oreopoulos (2003); van Dijk (2019); Chyn (2018).

the effects of location on segregation, lifetime earnings of children, and spillovers on neighbors. First, we show that affordable housing in higher-opportunity neighborhoods reduces racial/ethnic and economic segregation. However, relative to a benchmark in which a development *and its tenants* are moved from the bottom to top quartile of neighborhood opportunity, there is substantial 'leakage' when we allow the composition of tenants to adjust, reducing the effects on racial/ethnic integration by over half.[5] This creates a nuanced tradeoff 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. (2022) to assess the impact on lifetime earnings for children. On net, we calculate that a LIHTC unit in the top quartile of neighborhood opportunity increases the discounted lifetime earnings of children by +\$266 per month more than a unit in the bottom quartile (+132,000 per child). Finally, we use estimates from Diamond and McQuade (2019) to show that the impact on neighbors' welfare goes in the other direction. We estimate a net effect on neighbors' welfare of −\$46,000 for a unit built in the top instead of bottom quartile (−\$203 per month if amortized over 15 years at a 3% discount rate).

Finally, we conduct two sets of counterfactual exercises to quantify the role of developers versus household preferences and to evaluate the potential effects of additional policy changes. First, while we estimate that developers prefer to allocate to higher-income households, allocating units with a fair lottery has only marginal effects on the composition of tenants by race/ethnicity and predicted future income. In contrast, shutting down heterogeneity in household preferences specific to affordable housing leads to fewer Black/Hispanic tenants and, consistent with 'self-targeting' (Nichols and Zeckhauser, 1982), tenants with higher predicted future incomes across all levels of neighborhood opportunity. Second, we show that many policy levers available post-construction have only modest effects on outcomes relative to the choice of location. Lowering the income limits or using income-based rents selects for lower-income households, but has little impact on other margins, such as the composition of tenants by race/ethnicity and education. Giving priority to current neighborhood residents—as is common in New York City and San Francisco—generates more household surplus by selecting households that value the neighborhood more, but amplifies the effects of location on the composition of tenants, reducing the potential to promote integration.

Our results contribute to work in the public, urban, and empirical market design literatures. A large body of work studies the tradeoffs associated with place-based affordable housing programs, including the potential effects on the surrounding neighborhood (Baum-Snow and Marion, 2009; Diamond and McQuade, 2019; Almagro, Chyn and Stuart, 2024), spillovers onto the market-rate sector and crowding out of other new construction (Sinai and Waldfogel, 2005; Eriksen and Rosenthal, 2010; Soltas, 2024; Lee, Ferdowsian and Yap, 2024), and the potential for affordable housing to perpetuate segregation (Ellen, O'Regan and Voicu, 2009; Freedman and McGavock, 2015; Ellen, Horn and O'Regan, 2016; Ellen, Horn and Kuai, 2018). We build on this work by showing that the choice of location is also implicitly a choice of tenants, which in turn affects aggregate welfare, the

[5] While outside the scope of this paper, general equilibrium re-sorting after a new development enters may amplify these partial equilibrium effects (Davis, Gregory and Hartley, 2023).

distribution of assistance, and policy goals such as reducing segregation.

While the mechanisms to ration housing are often studied in theory,[6] few empirical applications exist. One notable exception is Waldinger (2021), which uses applications for public housing in Cambridge to show that changes to the mechanism that improve allocative efficiency also reduce targeting on need. In contrast, we focus on changes to the *product* being allocated (i.e. the housing) and the ensuing effects on efficiency, targeting, and other policy considerations. In other common empirical market design settings, such as school choice (Abdulkadiroğlu, Pathak and Roth, 2005; Agarwal and Somaini, 2020) and kidney exchanges (Agarwal et al., 2021), researchers directly observe applications and the mechanism used to map applications to allocations. For decentralized affordable housing programs such as LIHTC, data on applications are scarce, and even the exact mechanism developers use is unknown. We develop an approach to overcome these limitations, which relies on two ingredients: a parallel market-rate sector where we can estimate demand for the characteristics of the rationed good and a flexible approximation of the allocation mechanism that allows for developer discretion. To separately identify developer discretion and any household preferences specific to affordable housing, we incorporate additional information from moves *out* of affordable housing.

The intuition for the link between location and who applies for assistance builds on a broader literature studying how the take-up of in-kind transfers depends on demand for the offered good.[7] In most empirical applications, the transferred good is homogeneous (e.g., food stamps), and receipt depends only on an eligible household's decision to take up assistance (Alatas et al., 2016; 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 process for rationing units. Moreover, while the government sets income limits, the residual rights of control when allocating LIHTC units lie with private developers (Wilson, 1989; Hart, Shleifer and Vishny, 1997). Using intermediaries whose incentives align with the social planner's can improve outcomes if they have informational advantages (Alderman, 2002; Alatas et al., 2012), but may lead to 'slippage' of resources if the incentives misaligned (Olken, 2006, 2007; Basurto, Dupas and Robinson, 2020). In our case, we find that developers favor higher-income applicants, although their effect is small relative to the role of household preferences.

Finally, our model builds on previous work using structural models to estimate preferences for housing and neighborhoods (Bayer, Ferreira and McMillan, 2007; Geyer and Sieg, 2013; Wong, 2013; Galiani, Murphy and Pantano, 2015; Diamond, 2016; Bayer et al., 2016). We add to this literature by developing a new instrument for market-rate rents and extending the model in Bayer, Ferreira and McMillan (2007) to incorporate an affordable housing sector.

[6] See, e.g., Thakral (2016); Bloch and Cantala (2017); Arnosti and Shi (2020); Leshno (2022); Kang (2022); Ferdowsian, Lee and Yap (2024).

[7] In-kind transfers can improve targeting if demand is positively correlated with unobserved need (Nichols and Zeckhauser, 1982; Besley and Coate, 1991; Kleven and Kopczuk, 2011), but may *worsen* targeting if the ordeals disproportionately deter those with greater need (Bertrand, Mullainathan and Shafir, 2004).

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).

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). In California, for example, incentives for building in 'higher-resource areas' (as defined by the state government) increased the share of LIHTC developments in such areas from 15% to 30% (Owens and Smith, 2023). We describe the supply-side details of LIHTC in greater detail in Appendix Section A.1, which are also studied in depth by Soltas (2024).

2.2 Screening and rationing of LIHTC units

In exchange for tax credits, 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 fixed 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). Other 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 wait lists, first-come-first-serve, and referrals from current tenants are all common methods for filling vacancies. Even in cities with lotteries to allocate new units, developers can legally set minimum incomes, favor applicants with higher credit scores, or require that applicants have no past evictions. Under the Fair Housing Act, however, they cannot screen on characteristics such as race, age, disability status, or the presence of children.

3 Data

We combine administrative data from the US 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 US 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 US 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.

[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).

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.

LIHTC units. 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 MSA, 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, were placed in service after 1995, and for which Census staff were able to match the unit-level addresses to MAFIDs.[10]

3.2 Sample definitions

Our primary unit of analysis will be a renter household living in one of the 50 of the most populous Metropolitan Statistical Areas (MSAs) between 2010 and 2018.[11] 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 for 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.

[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.

[10] While the earliest LIHTC properties date back to 1987, many of these properties were no longer in service as an affordable development by 2018. Other 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.

[11] A handful of MSAs have insufficient coverage of LIHTC unit addresses, so we use the 50 most populous MSAs with sufficient coverage. The excluded MSAs are Tampa-St. Petersburg-Clearwater, FL, Orlando-Kissimme-Sanford, FL, and Birmingham-Hoover, AL. The least populous MSA in the sample is Salt Lake City, UT.

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 household members. For non-filers who do not have AGI, 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.[12] 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 1994-1995 or 1998-2005, we measure their childhood family income (CFI) as the average household income of their parents when they were under 18 years old. 1994 is the first year we can observe claimer-dependent relationships, so the earliest birth cohort for which we can measure CFI is 1978. We follow Chetty et al. (2022) 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 (and above). 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

[12] For the average household, past work has found that tax records provide similar estimates of household income as other administrative sources (Chetty et al., 2020). However, tax records often understate household income for low-income households because many earn below the threshold required to file taxes or may earn income in the informal labor market. While we use AGI as our primary measure of household income throughout, we supplement analyses using surveyed income from the ACS as a separate measure where possible.

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 their income, household structure, race, and neighborhood characteristics. We use households sampled by the ACS as training data and then predict average household income in the three subsequent years for both ACS and LIHTC households, which we then adjust for household size using an equivalence scale. We then 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).

Migration. For both the market-rate and LIHTC samples, we follow the household head to define when a household moved in/out of a unit and where they lived before moving in. When address sources disagree on where an individual lived in a given year, we select a single address in order of 1040 tax returns, W-2 forms, and the MAF-ARF.

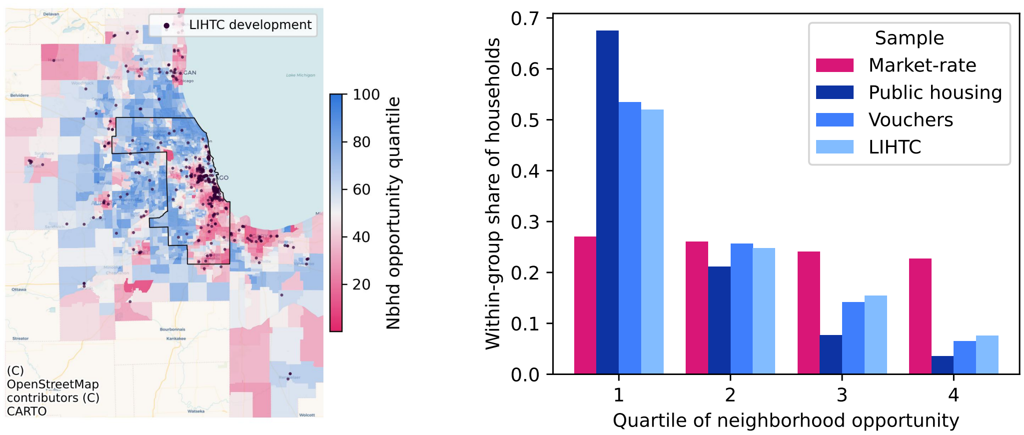
Rent. For each LIHTC unit, we compute the rent based on the unit's income limit and number of bedrooms. The regulated rent ceiling for LIHTC units includes the estimated cost of utilities. In rare cases, developers may price a vacant unit below the rent ceiling if they cannot fill the unit. For market-rate 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., 2022), 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 1973-1983 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 US 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, a greater share of LIHTC households live in each of the top two quartiles of opportunity than public housing residents or even households with vouchers. The pattern looks similar—as do the results throughout the paper—if we instead divide neighborhoods by their median household income, share college educated, or the share white (non-Hispanic) residents.

Figure 1: Neighborhood opportunity

(a) Map of the Chicago MSA (b) Distribution of households (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, 2010-2018. 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 512,000 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 opportunity, lower median income, and fewer white (non-Hispanic) residents.[13] The gaps are magnified if we compare LIHTC households at the time of move-in to other recently moved households.

[13]Households living in LIHTC are disproportionately likely to receive assistance from housing vouchers, food stamps, Supplemental Security Income, and other government assistance programs (Table D.1).

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)	$57,770	$15,610	$16,560	$14,870
Avg. AGI in years [-3, 0)	$51,120	$18,880	$19,320	$14,490
Avg. AGI in years (0, 3]	$63,210	$22,320	$25,710	$19,180
Predicted future income rank	0.517	0.323	0.321	0.245
Filed taxes this year	0.822	0.669	0.720	0.698
Childhood family income rank*	0.518	0.431	0.469	0.320
Graduated college*	0.330	0.180	0.215	0.106
Graduated high school*	0.875	0.799	0.837	0.770
Surveyed gross rent (ACS)	$1,182	$1,001	$1,091	$716
Household structure				
# of persons	2.209	2.157	2.163	2.151
Household has married couple	0.245	0.141	0.139	0.089
Household has children (<18yo)	0.386	0.402	0.425	0.424
Household has seniors (>64yo)	0.150	0.211	0.111	0.164
Race/ethnicity				
White (non-Hispanic)*	0.509	0.440	0.449	0.275
Black (non-Hispanic)*	0.223	0.272	0.265	0.438
Hispanic*	0.196	0.229	0.218	0.213
Other*	0.072	0.059	0.068	0.074
Previous tract chars.				
Miles from prev. tract*	6.234	5.797	6.290	6.955
Prev. tract opportunity ptile*	0.473	0.409	0.425	0.329
Prev. tract median HH income*	$58,160	$53,150	$54,310	$46,990
Prev. tract frac. white*	0.628	0.586	0.601	0.512
N	2,495,000	1,014,000	357,000	512,000

Notes: This table documents household characteristics for market-rate and LIHTC households. Characteristics with an asterisk (*) are defined for the household head. The sample includes cross-sections of market-rate households from the ACS and the full sample of LIHTC households from the Census-IRS panel. LIHTC eligibility is based on a household's current AGI compared to the 60% Area Median Income threshold. 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.

4 Who lives in affordable housing?

In this section, we describe the characteristics of affordable housing tenants along two dimensions: average differences between LIHTC households and eligible households living in market-rate units and differences across neighborhoods within the population of LIHTC households. On average, households living in LIHTC developments exhibit greater levels of need and are less likely to be white (non-Hispanic). Across neighborhoods, however, developments in higher-opportunity neighborhoods house tenants who exhibit lower levels of need and are 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.[14] 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.2 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). While the difference in income at the time of move-in is only 8%, larger differences arise in characteristics not used for means-testing. Compared to eligible households living in market-rate units, the average LIHTC household earned 25% less in the three years prior to move-in, is 38% less likely to have a college-educated household head, has a household head that grew up in a family 11 percentiles (26%) lower in the parental income distribution for their birth cohort, and is 3% more likely to include a child. Similar gaps arise in other characteristics; LIHTC households are also less likely to include a married couple and move from lower-opportunity tracts (Table D.2). 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 8 percentiles (26%) lower in the distribution of predicted future income than other eligible households.

The average LIHTC household is also 69% 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 by race echo the disproportionate representation of Black households in public housing in earlier decades (Massey and Denton, 1998).

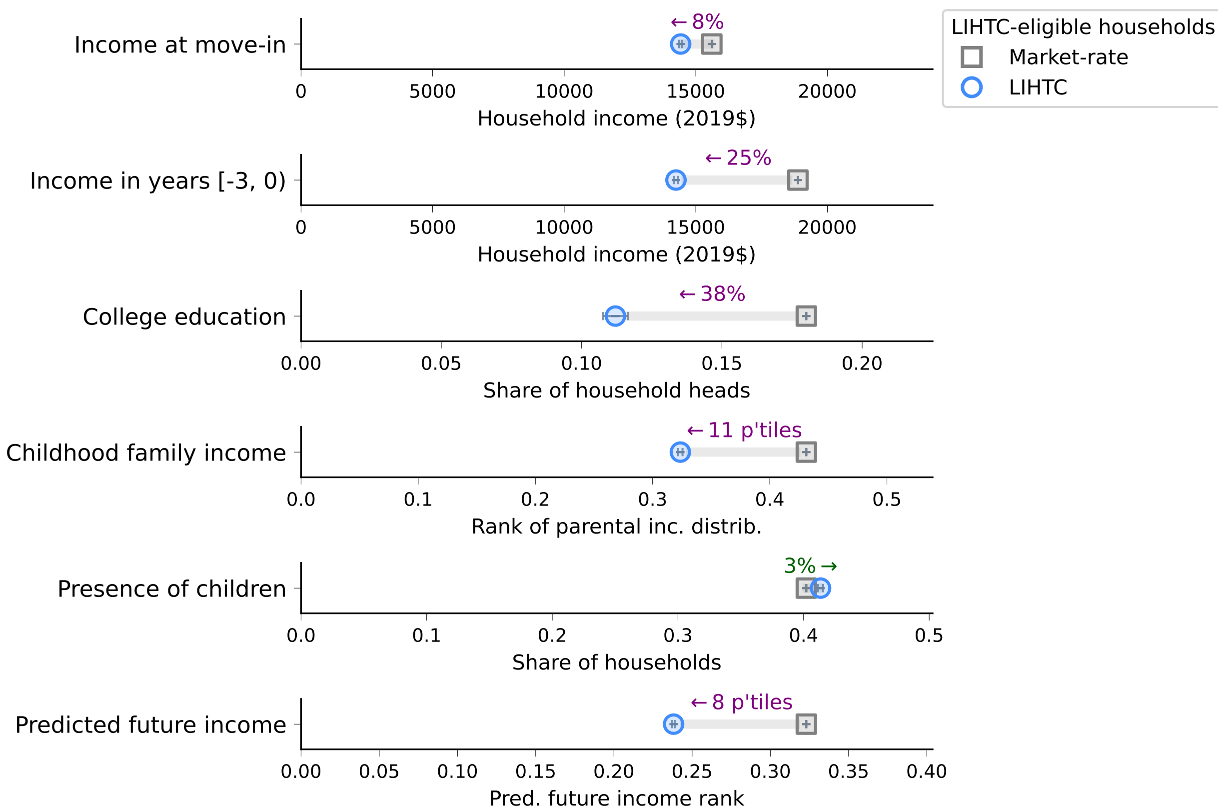
4.2 Differences in LIHTC household characteristics across neighborhoods

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 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 in Tables D.4-D.8.

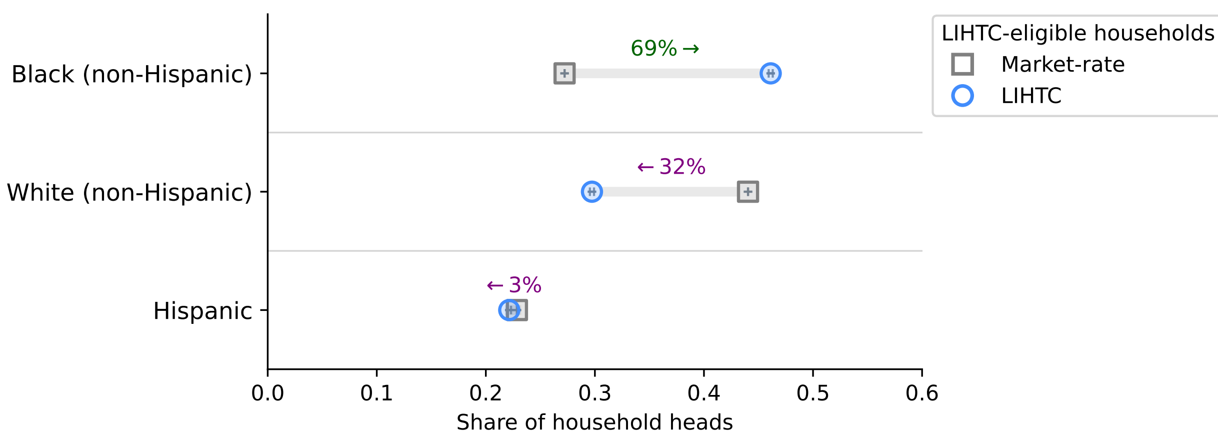
[14] We classify a household in the ACS as eligible for LIHTC if their adjusted gross income in the year surveyed is below the 60% AMI income limit for their city. While households close to the limit may be ineligible for units that use lower income limits (e.g., 50% AMI), the results are similar if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

Figure 2: LIHTC recipients v. 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 (2010-2018, 50 sample MSAs). 95% confidence intervals are represented by gray bars.

Proxies for a household's level of need are decreasing in neighborhood opportunity, despite fixed rent and income limits across neighborhoods within a city.[15] Relative to LIHTC developments in the bottom quartile of opportunity, developments in the top quartile house tenants who earned 14% higher income prior to move-in, grew up in families 13 percentiles (45%) higher in the parental income distribution, are twice as likely to have a college-educated head, and are 9 percentiles (39%) higher in the distribution of 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 19% fewer families with children than those in the bottom quartile. Movers to developments in higher-opportunity neighborhoods also come from neighborhoods that are higher-opportunity (Table D.4).[16]

There are also large differences across neighborhoods in the racial and ethnic composition of LIHTC developments. 77% of LIHTC households in the bottom quartile of neighborhood opportunity are Black or Hispanic, compared to just 39% in the top quartile. Non-Hispanic white households go from making up only 18% of LIHTC units in the bottom quartile to 51% of LIHTC units 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 compared to households in the top quartile (Table D.7). On net, LIHTC households in the top quartile of neighborhood opportunity are *less* likely to be Black or Hispanic than the average eligible household.

Adding controls for narrow bins of current household income does little to explain the sorting patterns by other household characteristics. Even comparing households with similar income, LIHTC developments in the top quartile of neighborhood opportunity house tenants who had higher income in previous years, grew up in more affluent families, are more educated, have higher expected future income, and are less likely to have a Black household head. Why does household income explain so little of the patterns 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, is that changing the income limits used for means-testing has limited impact on the composition of the development by other characteristics.

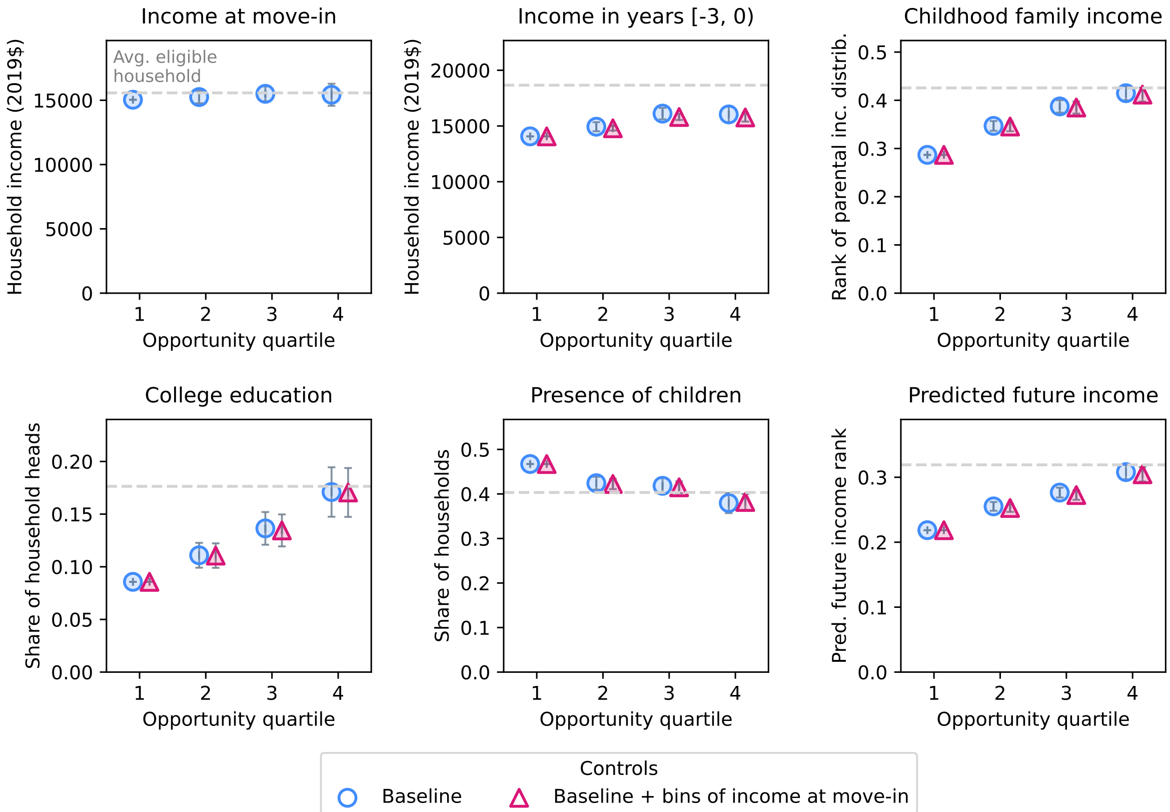
Differences in the LIHTC population across neighborhoods can stem from both household preferences (i.e., who applies for assistance) as well as the process used to ration units among applicants. To help disentangle the role of these two forces, we next build a structural residential choice model with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

[15] Developers may price below the rent limit if there is insufficient demand. Figure D.4 shows that the rent reported to the ACS by LIHTC households is slightly increasing in opportunity, although this could be due to misreporting. Adding controls for surveyed rent has little effect on the patterns across neighborhoods (Figure D.4).

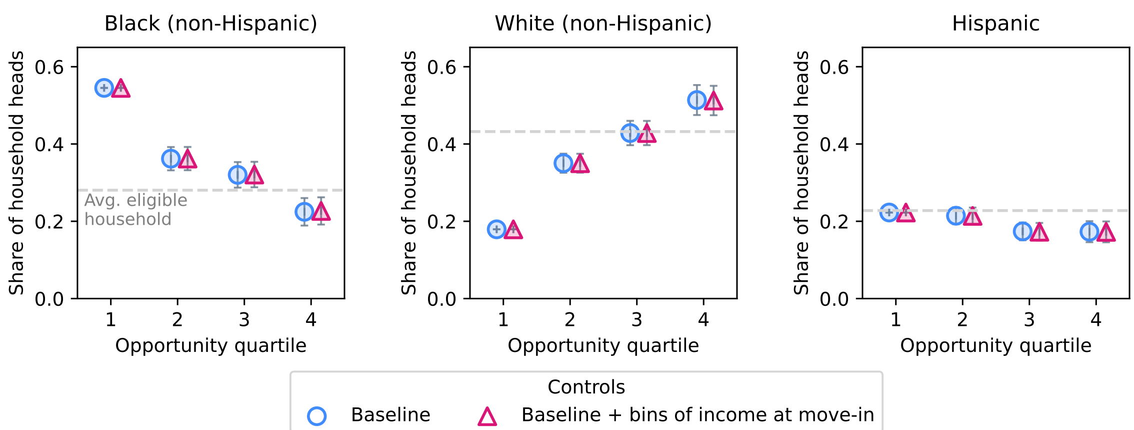
[16] In Table D.6, we explore whether these patterns across levels of neighborhood opportunity can be explained by specific characteristics of the neighborhood. Adding controls for bins of the share white (non-Hispanic) has the largest effect, attenuating the relationship between opportunity and race/ethnicity by about two-thirds and the relationship between opportunity and proxies for need by up to 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 (2010-2018, 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 with two stages. In the first stage, eligible households decide whether to apply to different affordable housing units, which developers then ration. In the second stage, households not allocated an affordable unit select among market-rate units. While rents adjust to clear the market for market-rate units, affordable housing units are priced below-market and must be rationed by private developers, who may favor certain types of households.

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, which can be 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, 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:

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

where $\mathbf{x}_j$ is a vector of housing and neighborhood characteristics,[17] r_j is the unit's rent, $\mathbb{1}_{j \neq j_i^0}$ is an indicator for whether j is the household's endowed housing option, $\mathbb{1}_{j \in \mathcal{J}^{AH}}$ 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 a parameter that captures the difference in utility associated with affordable housing (α_i), conditional on other characteristics. 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 (κ_i) incurred by households that select any option other than their endowed choice. This allows the model to generate realistic move-out rates, which will be an important empirical moment.[18]

[17] We treat neighborhood characteristics as exogenous. For racial/ethnic shares, this assumption implies that preferences for same-race/ethnicity shares are due to correlated preferences for neighborhood unobservables proxied for by the racial/ethnic shares rather than homophily. Recent empirical evidence on same-race/ethnicity preferences is mixed, with some papers finding that they primarily reflect unobserved neighborhood characteristics (Caetano and Maheshri, 2021) and others contending that they are due to homophily (Bayer et al., 2022; Davis, Gregory and Hartley, 2023).

[18] In principle, we could also let move-out costs vary by the distance moved. However, Galiani, Murphy and Pantano (2015) estimate that, for within-city moves, the marginal cost of distance is small relative to the fixed cost of moving. By their estimate, each additional mile increases the moving cost by less than 1% of the fixed cost.

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

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

5.2 Allocation of affordable housing units

We model the allocation process as consisting of three steps: 1) households decide to apply to each affordable housing option, 2) developers make offers to applicants, and 3) households accept a single offer. Without a price mechanism to equilibrate supply and demand, the offer probabilities must adjust to clear the market.

Households decide whether to apply for each affordable housing option based on their preferences for its housing and neighborhood characteristics compared to their preferences for other options in the city. Households can apply to multiple affordable housing options, and each application decision is made independently. We assume households can apply for affordable housing developments without cost—beyond any captured by α_i—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.[19] With logit errors, the probability household i applies to option j is

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

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

Estimating the utility specific to affordable housing (α_i) requires taking a stance on the mechanism used to ration units among interested households. We approximate the allocation mechanism as a weighted lottery, with weights that vary by a set of household characteristics $\widetilde{\mathbf{w}}$.

Assumption 1 (mechanism). *Applicant i with characteristics $\widetilde{\mathbf{w}}_i$ receives an offer with probability $\pi_{ij} = \min\{\pi_j \phi_i, 1\}$, where weights $\phi_i = \phi_0 + \sum_k \phi_k \widetilde{w}_{ik}$ are common across options but vary by household characteristic (indexed by k), and π_j is the baseline offer probability for development j.*

While we refer to the mechanism as a lottery, the assumption would hold for any mechanism where the probability of receiving an offer *conditional on* $\widetilde{\mathbf{w}}$ is constant across households. For

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).

[19] Assuming zero application costs also allows us to abstract away from applicant beliefs about the probability they receive an offer.

example, this mechanism nests a waitlist in which households are randomly ordered and are offered a unit with some probability that varies only by their observables $\widetilde{\mathbf{w}}$ upon reaching the top of the queue. In Table D.14, we provide supporting evidence for the simplifying assumption of common weights $\boldsymbol{\phi}$ by comparing the characteristics of tenants in units managed by for-profit and non-profit developers.[20] Despite having different incentive structures, for-profit and non-profit developers house tenants with similar incomes, race/ethnicity, and predicted future income.

In the absence of a price mechanism, the baseline offer probabilities at each development (π_j) adjust to satisfy the market-clearing condition:

$$s_j = \sum_{i \in \mathcal{I}} \overbrace{P_{ij}^{\text{apply}} \times \pi_{ij} \times P_i^{\text{accept}}}^{\text{Probability } i \text{ is allocated to } j} \tag{4}$$

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

Estimation of the residential choice model is comprised of 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 lottery weights ($\boldsymbol{\phi}$) using the Generalized Method of Moments (GMM) to match moments based on both move-in and move-out decisions.

We estimate the model using repeated cross-sections of household decisions for the Chicago MSA, the third-largest metro area.[21] We aggregate observations into 3-year periods between 2010

[20] Approximately 24% of developments and 19% of units in our full sample are managed by non-profits as of 2019. The numbers are similar in Chicago. In 2021, the private equity firm Blackstone became one of the largest for-profit owners of LIHTC developments after purchasing over 650 developments (Kimura, 2021).

[21] Chicago is also a convenient setting as its rental market consists of mostly market-rate and LIHTC units.

and 2018, 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 (π_{ijt}), and sets of households ($\mathcal{I}_t$) and housing options ($\mathcal{J}_t$). To define housing options, we use Public Use Microdata Areas (PUMAs) as neighborhoods,[22] discretize bedrooms as 0-1, 2, and 3+, and define building types as single-family, small apartment building (<10 units), or large apartment building. The housing and neighborhood characteristics in $\mathbf{x}$ include the number of bedrooms, building type, indices of school quality, transit access, jobs access, and poverty from HUD, race/ethnicity shares and population density from the 2010 Census, and the number of nearby parks from OpenStreetMaps.

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

$$\boldsymbol{\gamma}_i = \boldsymbol{\gamma}_0 + \sum_\ell \boldsymbol{\gamma}_\ell w_{i\ell} \qquad \beta_i = \beta_0 + \sum_\ell \beta_\ell w_{i\ell}$$
$$\alpha_i = \alpha_0 + \sum_\ell \alpha_\ell w_{i\ell} \qquad \kappa_i = \kappa_0 + \sum_\ell \kappa_\ell w_{i\ell}$$

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 include in $\mathbf{w}$ bins of average income in the three years prior, household size, race/ethnicity, presence of children, presence of seniors, presence of a married couple, and whether the household has a housing voucher. The non-idiosyncratic components of u_{ijt} can be rewritten as

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

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

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 for our estimation strategy and allows us to recover the preferences of households living in affordable housing units based on 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 are instead observed making 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 evi-

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.

[22] PUMAs are geographically larger than the Census tracts used in prior sections (see Figure D.5). The ACS is only a 1% annual sample, so defining housing options using tracts leads to many options with zero observed shares. Moreover, for households that move we can only observe the rent of their previous option (j_i^0) if some another household is sampled there in the current period. Aggregating to PUMAs solves many of these issues. This is also the motivation for aggregating to 3-year periods instead of using the annual ACS data.

dence that these observed household characteristics explain much of the differences in the housing choices of LIHTC households and other eligible households. Unconditional on household observables, eligible households that move into a LIHTC unit within the next two years live in poorer, less white, less dense, and lower opportunity neighborhoods than other eligible households. Conditional on the observables used in the demand model, however, these differences in neighborhood characteristics become statistically indistinguishable from zero. This suggests that persistent unobservables play a limited role in the housing choices of LIHTC households versus other households. While transient unobserved shocks may still affect housing choices, Table 1 shows that *observable* income is similar at move-in to LIHTC as in the three prior years, suggesting that moving into affordable housing is not preceded by a negative income shock for the average household.

6.1 Preferences for housing & neighborhood characteristics

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 $\widetilde{\boldsymbol{\theta}}^{\mathrm{MR}} = \left\{\widetilde{\boldsymbol{\delta}}, \widetilde{\gamma}_\ell, \widetilde{\beta}_\ell, \widetilde{\boldsymbol{\kappa}}\right\}$, the pseudo log-likelihood of the observed choices is given by

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

where $\mathbb{1}_{j_i=j}$ is an indicator for household i choosing option j and $\mathcal{I}_t^{\mathrm{MR}}$ is the set of renters in the market-rate sample. Conditional on selecting a market-rate option, preferences for affordable housing ($\boldsymbol{\alpha}$) have no impact on 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:

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

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.[23] 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

[23]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.

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 $j \in \mathcal{J}^{\mathrm{MR}}$. 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.[24] 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}). To exclude variation specific to Chicago, we use only data from the other cities in our sample to compute g_{bt}. During our sample period, cities became substantially older, experienced large changes in the composition of industries, and contained fewer married couples and fewer households with kids (Figure C.1).

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.[25] 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}.

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. Unobserved characteristics of a housing option may respond endogenously to changes in demand over time. In Table D.10, we show that our instrument is associated with small and often insignifi-

[24] 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.

[25] While neighborhood fixed effects absorb average preferences for time-invariant components of $\mathbf{x}_{jt}$, we still estimate how preferences for these characteristics vary by household observables.

cant changes in the counts of various types of establishments (e.g., restaurants and grocery stores) and other neighborhood characteristics. Even holding fixed the unobserved characteristics of each option, changes to the renter population may affect the value that the average household places on these unobserved characteristics (i.e., the ξ_{jt}) by changing the identity of the average household. If the true demand shocks are common across all households, as in the current specification, then such changes would not affect the estimated demand shocks. If the true demand shocks systematically vary across households, then an increase in the number of households of a given group will skew the estimated demand shocks towards the underlying demand shocks for this group.[26]

Table 2 compares the parameter estimates using OLS versus IV. In the first stage, a one standard deviation increase in our instrument increases rents by \$30 (F-statistic of 16.3). When ignoring the rent endogeneity, we estimate that households prefer housing options with higher rent. Once we incorporate the instruments, we find the expected result: households dislike paying higher rents.[27]

Comparison to alternative instruments. A common approach in the residential choice literature is to instrument for rent using characteristics of nearby neighborhoods. 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.[28] A potential concern with using such instruments for residential choice models is that unobserved demand shocks may be spatially correlated, and, if the neighborhood features used to form an instrument are also spatially correlated, this can violate the exclusion restriction.[29]

The difference in threats to exogeneity between BFM instruments and our own make them complementary. BFM instruments rely on *cross-sectional* variation in housing and neighborhood characteristics included in the demand specification (i.e. the $\mathbf{x}$), which may be endogenous if unobservables are spatially correlated.[30] In contrast, our instrument uses external, within-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 ($\widehat{P}_{jb}$). The final column of Table 2 presents estimates using BFM instruments. Despite the differences in threats to identification, the two instruments lead to broadly similar estimates. The implied willingness to pay for

[26]This assumption could be weakened by allowing the demand shocks ξ_{jt} to vary by household characteristics. However, this introduces an additional complication as many options have zero observed shares for some demographics.

[27]The willingness to pay estimates are similar to those for New York City renters presented in Calder-Wang (2021). Both sets of estimates find that households are willing to pay about \$500 more for apartments with multiple bedrooms and about \$100 less for units in large buildings.

[28]Recent examples include Anagol, Ferreira and Rexer (2023); Barwick et al. (2024) and Calder-Wang (2021). Variants of the instrument include using changes in plausibly exogenous characteristics over time (e.g., Almagro and Domınguez-Iino, 2024), combining the BFM instruments with other sources of variation (e.g., Carneiro, Das and Reis, 2022), or using the average rents in observably similar neighborhoods directly (e.g., Geyer and Sieg, 2013; Galiani, Murphy and Pantano, 2015).

[29]In Appendix Section C.2, we show that many commonly used characteristics for forming BFM instruments exhibit significant spatial correlation in Chicago.

[30]Using transformations of variables included in the demand specification as instruments can also make the estimates especially sensitive to model misspecification (Andrews et al., 2023).

units with more bedrooms or in buildings of different sizes are not statistically different between the two sets of estimates.

Heterogeneity in household preferences. We present the estimated preference parameters in Tables D.12 and D.13. Our estimates broadly match patterns found in other work on residential preferences. Each racial/ethnic group exhibits strong preferences for living in neighborhoods with a high share of same-race/ethnicity residents. Higher-income households tend to put more weight on amenities like school quality and job access, and larger households naturally prefer larger units. All households face substantial moving costs for leaving their endowed housing option. Lower-income, Black, and Hispanic households are more sensitive to rents and, as a result, will be more responsive to the below-market rents offered by affordable housing.

Table 2: Estimated preferences for average household

		Alternatives	
Covariate	IV	OLS	BFM
Gross rent ($00s)	-0.2577	0.0309	-0.1970
	(0.1173)	(0.009)	(0.1031)
2 bedrooms	1.254	0.4368	1.082
	(0.3371)	(0.0574)	(0.3004)
3+ bedrooms	1.181	-0.2814	0.8815
	(0.6009)	(0.0701)	(0.5327)
Small apartment building (2-10 units)	0.1029	0.5061	0.1906
	(0.1718)	(0.0529)	(0.1569)
Big apartment building (>10 units)	-0.4348	-0.4886	-0.4364
	(0.0778)	(0.0532)	(0.0734)
Neighborhood (PUMA) fixed effects	✓	✓	
F-statistic (first-stage)	16.33		20.30
N	1800	1800	1800

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 variation in neighborhood characteristics over time. The BFM instruments use cross-sectional variation, so we do not include neighborhood fixed effects. For the BFM instruments we use four 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 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.

6.2 Lottery weights & preferences for affordable housing

To estimate preferences for affordable housing ($\boldsymbol{\alpha}$) and the lottery weights developers use ($\boldsymbol{\phi}$), we use the Generalized Method of Moments (GMM) to match three sets of moments each period: the average characteristics of households moving into affordable housing, the average rate at which households move out of affordable housing, and the covariance between moving out and household characteristics. The intuition for separating the role of developers from that of households is that developers only affect move-ins, while household preferences affect both move-in and move-out decisions.[31]

We construct a set of moments $q \in \{1, 2, \ldots, Q\}$ for each period t, where we use $m_t^{(q)}$ to denote the sample moment observed in the data and $\widehat{m}_t^{(q)}$ to denote the model-predicted moment given a candidate vector of parameters. The moment conditions take the form of $\mathbb{E}[m_t^{(q)} - \widehat{m}_t^{(q)} \mid \boldsymbol{\theta}] = 0$. We compute standard errors using 250 bootstrap samples of households.

Move-in moments. We compute the model-predicted average characteristics of households moving into affordable housing in period t as

$$\widehat{m}_t^{(q)} = \frac{\sum_{i \in \mathcal{I}_t} \left(w_i \times \sum_{j \in \mathcal{J}_t^{\text{AH}}} P_{ijt}^{\text{alloc}} \right)}{\sum_{i \in \mathcal{I}_t} \sum_{j \in \mathcal{J}_t^{\text{AH}}} P_{ijt}^{\text{alloc}}} \tag{11}$$

where w_i is an element of either $\mathbf{w}_i$ (characteristics entering utility) and/or $\widetilde{\mathbf{w}}_i$ (characteristics observed by developers). The weights P_{ijt}^{alloc} are the equilibrium probabilities that household i is allocated option j in period t given by Equation 4.[32] We then compute the sample analogues ($m_t^{(q)}$) as the average of each characteristic among households who move into a LIHTC unit during a given period.

Move-out moments. Next, we target the mean probability that a household currently in affordable housing moves out and the covariance of that probability with household characteristics.[33] Let $j_i^0 \in \mathcal{J}^{\text{AH}}$ denote the affordable housing unit that household i is endowed with. The model-predicted moments are

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

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

In practice, moves to other affordable housing options are rare, so for simplicity we model the move-out decision as a decision to move to a market-rate option.[34] With logit errors, the probability

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

[32] The probability of accepting an offer 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 $\rho_{ijt} = \sum_{j' \in \mathcal{J}_t^{\text{AH}}; j' \neq j} (P_{ij't}^{\text{apply}} \times \pi_{ij't})$ (Le Cam, 1960). With this assumption, $P_{ijt}^{\text{accept}} \approx \sum_{n=0}^{|\mathcal{J}_t^{\text{AH}}|-1} \left(\frac{e^{-\rho_{ijt}} \rho_{ijt}^n}{n!} \right) \left(\frac{1}{1+n} \right)$

[33] 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.

[34] In Chicago, only 2.6% of moves into a LIHTC building are from another LIHTC building.

each household moves out is

$$P_{it}^{\text{moveout}} = \frac{\sum_{j \in \mathcal{J}_t^{\text{MR}}} \exp\left(\delta_{jt} + \lambda_{ijt}\right)}{\exp(\delta_{j_i^0 t} + \lambda_{ij_i^0 t}) + \sum_{j \in \mathcal{J}_t^{\text{MR}}} \exp\left(\delta_{jt} + \lambda_{ijt}\right)} \tag{12}$$

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 year before being surveyed. For the sample analogues, we take the households observed in LIHTC each year within a period and compute the average annual move-out rate and the covariance between moving out each year and household characteristics. For $\widetilde{\mathbf{w}}$, we include bins of *current* income (to reflect that developers often only observe current income) and whether or not a household has a voucher. While for household preferences we include eight bins of household income in $\mathbf{w}$, with the highest being for households earning over \$100,000, for $\widetilde{\mathbf{w}}$ we combine the top four bins into a single bin of >\$40,000.

Estimated parameters. The average LIHTC-eligible household values an affordable housing unit at \$218/mo more than an observably similar market-rate unit, suggesting that any stigma or hassle costs are smaller than other unobserved quality differences. To investigate potential differences in unobserved quality, we compare LIHTC units sampled by the American Housing Survey (AHS) to other units in the neighborhood (see Appendix Section C.5 for details). Unlike public housing units, LIHTC units are newer, have fewer maintenance issues, and are less likely to have roaches or barred windows than market-rate units in the same neighborhood. The perhaps surprising result that households place *positive* value on living in LIHTC is echoed in surveys conducted by Reid (2018), in which current tenants highlighted other, less tangible benefits of living in LIHTC, including reliable property managers, protection from unexpected rent increases, a greater sense of community, and feeling like the development was a 'safe-haven' in their neighborhood.[35]

The value of affordable housing is especially high for non-Hispanic Black households (\$352 per month), families with children (\$278) or seniors (\$328), and is decreasing in household income (Figure 4 Panel a). Households that are smaller, do not have children, have a non-Hispanic white household head, or are higher-income are all less likely to apply for an affordable housing development regardless of its location.

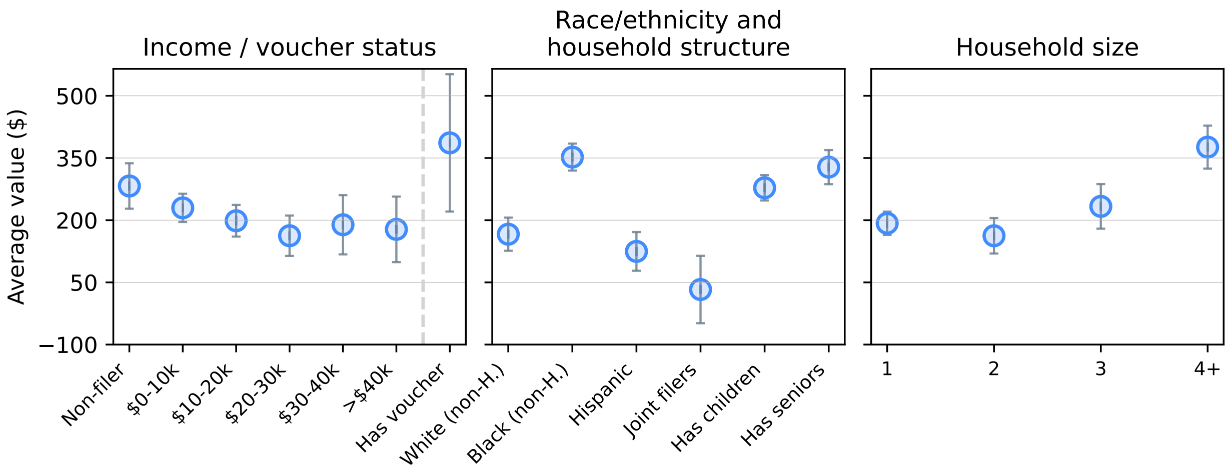
While lower-income households have relatively stronger preferences for affordable housing, developers prefer higher-income households. Developers put the lowest weight on households with zero income and the highest weight on households whose annual income exceeded \$40,000 a year (Figure 4 Panel b). Households with vouchers, however, both prefer living in a LIHTC development more than other household types and are favored by developers in the selection process.[36]

[35] LIHTC units have also experienced less rent growth historically than market-rate units. If households' value for LIHTC is partly based on expectations of future rent growth, this will load onto the $\boldsymbol{\alpha}$ parameters in our model.

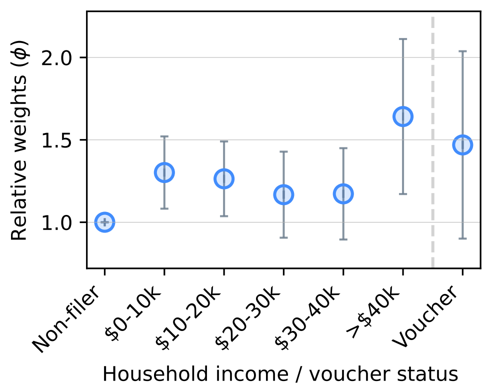
[36] The large estimated value of affordable housing for voucher holders may partly reflect the discrimination they face in the market-rate. In an audit study, Phillips (2017) found that landlords are half as likely to respond to prospective renters in the market-rate sector who expressed a desire to use a voucher.

Figure 4: Estimated value of affordable housing & lottery weights

(a) Average value of affordable housing (α_i/β_i)



(b) Lottery weights (ϕ)



Notes: Panel (a) documents the average value of affordable housing per month relative to an observably similar market-rate unit for different household types. The sample is restricted to LIHTC-eligible households (Chicago MSA, 2010-2018). Each reported value of affordable housing is the average for all households with the indicated characteristic. The value is converted into units of monthly rent using each household's rent disutility. Panel (b) reports the estimated weights developers place on applicants when allocating units, relative to a baseline of households that do not file taxes or have a housing voucher. The weights are cumulative; an applicant with a voucher will have the sum of weights for their income bin and having a voucher. Gray bars represent 95% confidence intervals from bootstrapped standard errors.

6.3 Discussion

Estimating demand under rationing is challenging as the observed allocations do not reflect solely the underlying preferences of applicants, but also the supply of goods and the mechanism used to ration. Moreover, unlike for rationed goods in other common empirical market design settings (e.g., school choice), in our setting we cannot observe applications or even the exact rules of the rationing mechanism. We show how these limitations can be overcome using a parallel market in which we can estimate demand for many characteristics of the rationed good and a flexible approximation of the rationing mechanism. Our approach may be useful in other settings where the researcher does not observe applications, but cannot use observed allocations to estimate revealed preferences without accounting for the rationing mechanism.

Our approach comes with important caveats. First, while we treat observed market-rate choices as reflective of true preferences, external factors constrain residential choices for many households. 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), and other frictions may constrain lower-income households' choices regardless of their race/ethnicity (Bergman et al., 2023). Similarly, although we assume full information about the choice set, households may be uninformed about options far from their existing home. To the extent that some households are disproportionately discriminated against or are less informed about options in higher-opportunity neighborhoods, our estimates 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 $\widetilde{\mathbf{w}}$, in practice, developers may screen on characteristics beyond what we include in $\widetilde{\mathbf{w}}$, and mechanisms such as waitlists have additional dynamic considerations (e.g., heterogeneity in attrition). If developers affect allocations beyond what the weights $\boldsymbol{\phi}$ capture, our estimates of preferences for affordable housing ($\boldsymbol{\alpha}$) will be biased towards overstating the value of affordable housing for household types that developers favor.

7 The tradeoffs of location

7.1 Tenant welfare, the distribution of assistance, and costs

To evaluate the effects of where affordable housing is built, we simulate adding a new LIHTC development to households' choice sets and vary in which neighborhood it is placed.[37] We then simulate which households receive affordable housing and how much they value it, holding fixed market-rate supply, rents, and neighborhood characteristics. This exercise, therefore, measures the partial equilibrium response to a marginal development.

For exposition, we divide tenants into four types by race/ethnicity (Black/Hispanic and white/other) and by whether their predicted future income—adjusted for household size and age—is in the bottom quartile of the nationwide distribution of households ('high-need') or in the top three quartiles ('moderate-need'). In the Chicago MSA, 58% of LIHTC-eligible renters are Black or Hispanic and 45% are high-need.

[37] 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.

Composition of LIHTC developments. Consistent with the descriptive evidence, which households receive a unit depends on the location (Figure 5 Panel a). For developments in the top quartile of neighborhood opportunity, 29% of households are Black/Hispanic households and 38% are high-need. In contrast, for developments in the bottom quartile, 72% of households are Black/Hispanic and 50% are high-need. Much like in the descriptives, the simulated fraction of household heads with a college degree also increases by 51% from the bottom to the top quartile, and the fraction of households with children decreases by 22% (Table D.15).

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 5 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 four 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 76% of the decline in the share of Black/Hispanic households between the bottom and top quartiles of neighborhood opportunity.[38] 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. While budgetary restrictions may lead to similar dynamics in these programs in the long run, the crowding-out effect for affordable housing units is immediate: take-up of a LIHTC unit by one household necessarily excludes another household interested in the unit.

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.[39] 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.

[38]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).

[39]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.

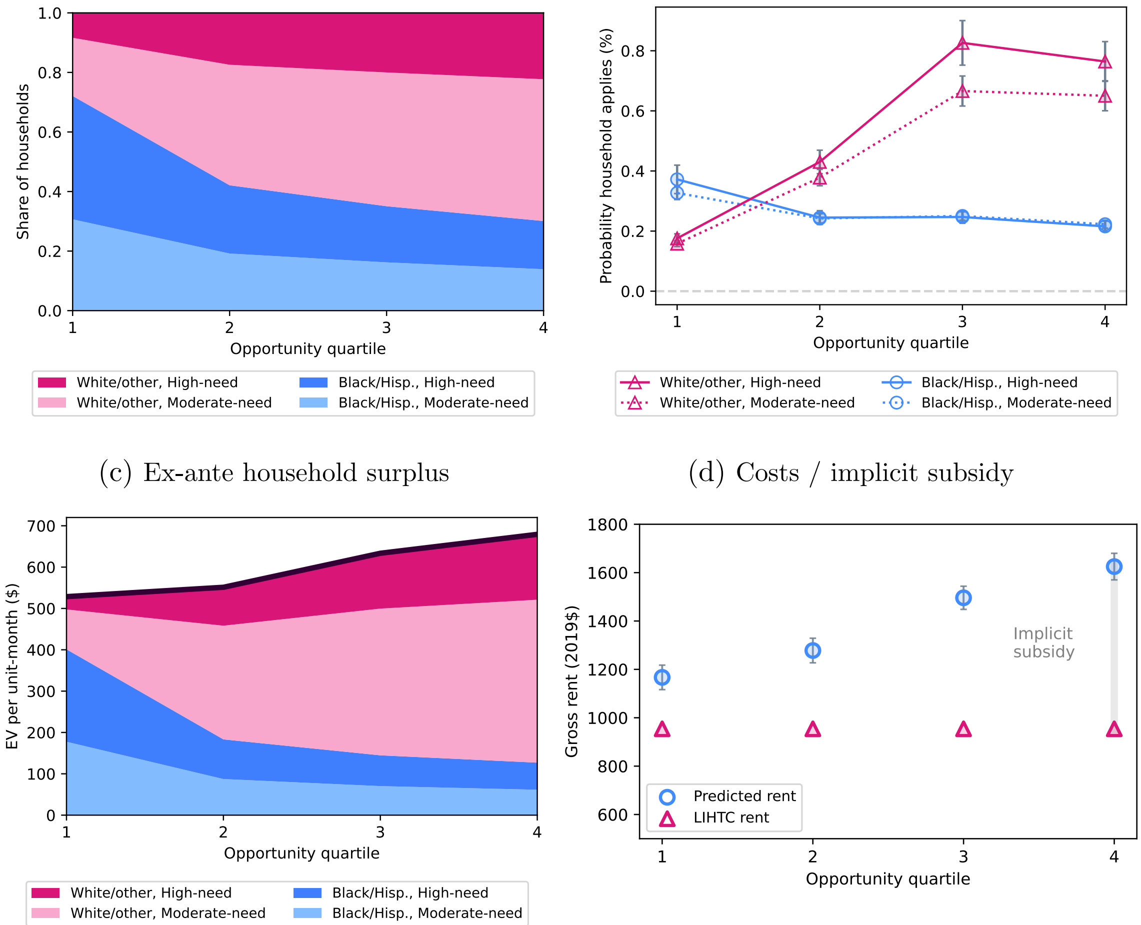
Figure 5: Composition, value, and costs of a new LIHTC unit

(a) Distribution of household types

(b) Probability household *applies*

(c) Ex-ante household surplus

(d) Costs / implicit subsidy



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 \$151 per unit-month (from \$529 to \$680) for a development built in the top instead of bottom quartile of neighborhood opportunity (Figure 5 Panel c). However, the gains do not accrue evenly across households. While white/other households value a new unit in the top quartile \$424 more per month than a unit in the bottom quartile, Black/Hispanic households value the unit \$273 *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 (+\$181) than high-need households (-\$33).

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.3). The monthly implicit subsidy for a typical unit increases from \$213 (18% discount off of market-rate) in the bottom quartile to \$671 (41% discount) in the top quartile (Figure 5 panel d).[40]

Net effects of location. Figure 6 summarizes the tradeoffs 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 $-\$327$ 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. As we show next, building in a higher-opportunity neighborhood promotes both racial/ethnic and economic integration and offers greater upward mobility for children. However, it can also reduce targeting on proxies for need and have negative spillovers on neighbors' welfare.

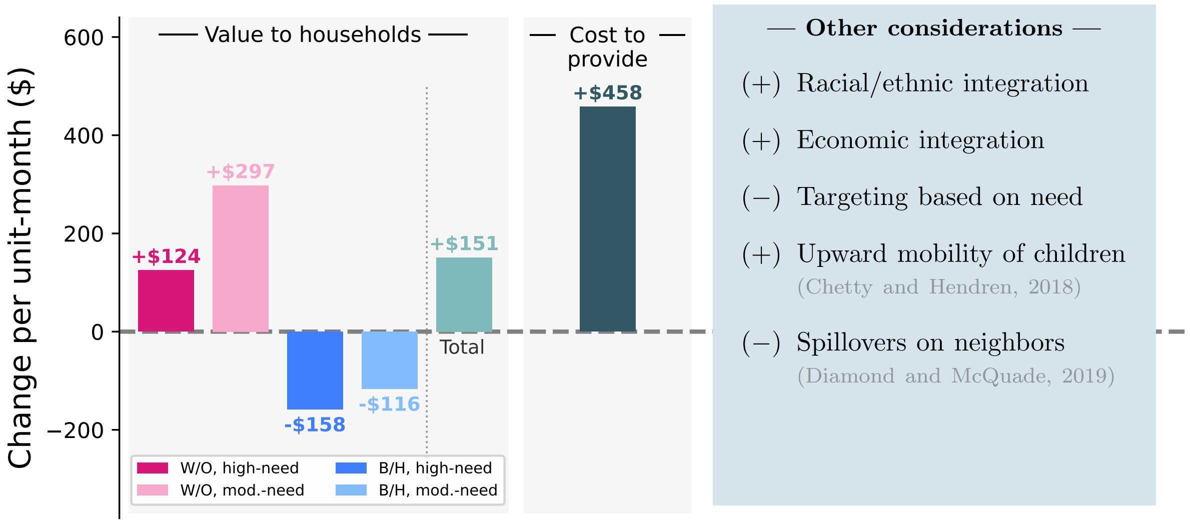
7.2 Racial/ethnic and economic integration

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).[41] On appeals, 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

[40] An alternative measure of costs is the number of tax credits awarded per unit. In Appendix C.3, 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.

[41] This case shares similarities with earlier cases on the location of public housing, dating back to soon after the passage of the Fair Housing Act in 1968; we provide an overview of relevant cases in Appendix Section A.3.

Figure 6: Effects of building in top v. 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.

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 neighborhood and where tenants would otherwise live. We use the following index of residential isolation[42] between groups A and B (in our case, Black/Hispanic and white/other or high-need and moderate-need):

$$\text{Isolation} = \overbrace{\frac{1}{|\text{A}|}\sum_{i\in \text{A}} \underbrace{\text{fracA}_{g(i)}}_{\substack{\text{Home nbhd} \\ \text{frac. A}}}}^{\text{Avg. exposure to A by A}} - \overbrace{\frac{1}{|\text{B}|}\sum_{i\in \text{B}} \text{fracA}_{g(i)}}^{\text{Avg exposure to A by B}} \tag{13}$$

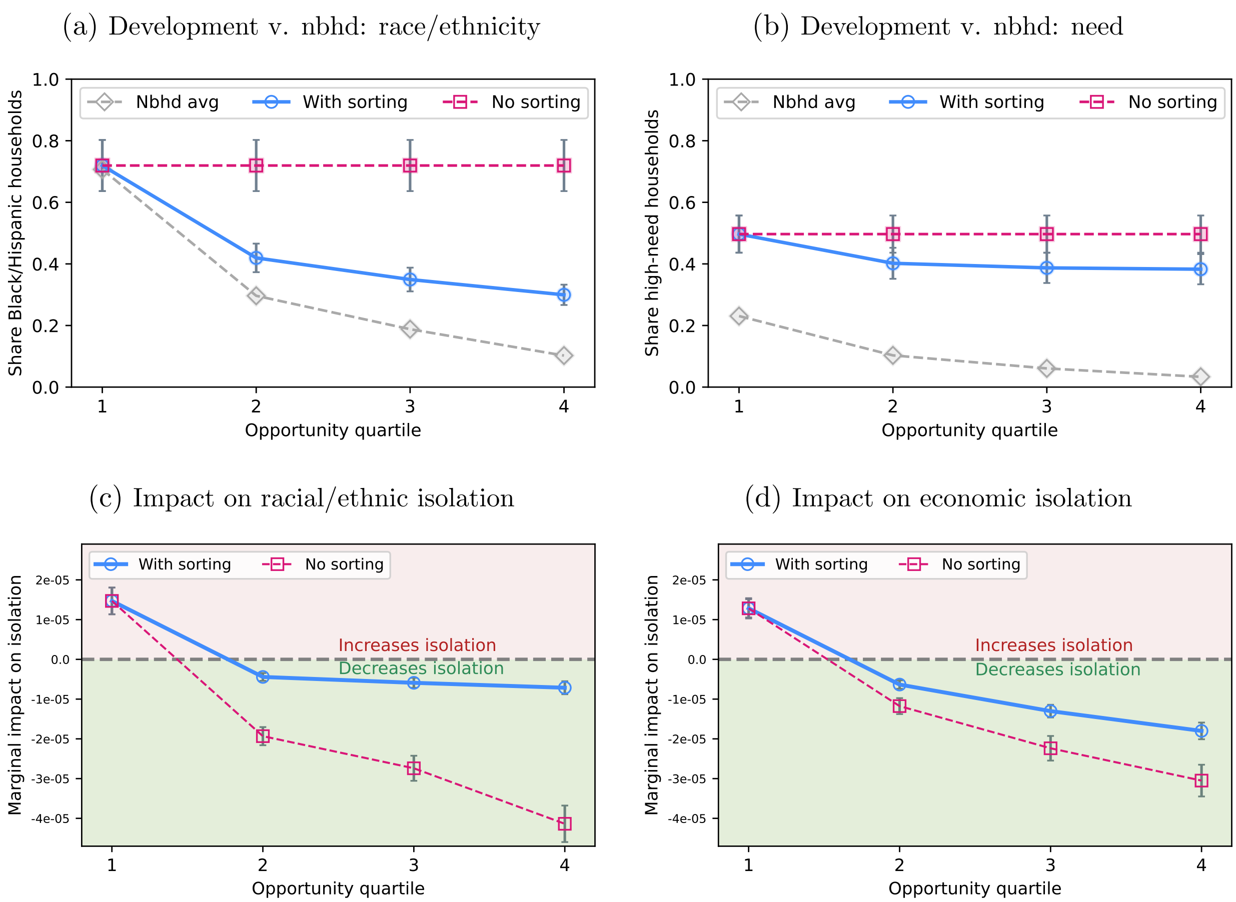
where $g(i)$ indexes the neighborhood of resident i and frac$A_{g(i)}$ is the fraction of neighborhood g's population that belong to group A. In the Chicago MSA, the average white/other household lives in a neighborhood with 78% white/other residents, while the average Black/Hispanic household lives in a neighborhood with 49% white/other residents (i.e. an isolation index of 0.29). For economic isolation, the average high-need household lives in a neighborhood with 83% of residents are moderate-need, while the average moderate-need household lives in a neighborhood in which 91% 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 devel-

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

opment *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 isolation on the margin, while moving these developments (with their tenants) to higher opportunity neighborhoods would steadily decrease both isolation measures (Figure 7). 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 7). 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 (61%). For economic integration, the income limits restrict the extent of tenant sorting by income; allowing tenants to re-sort dampens the effect on economic integration by just 29%.

Figure 7: Effect of location on residential isolation



Notes: This figure documents how a new development affects city-wide economic and racial/ethnic integration on the margin. 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 first two panels report the share of a given type 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. Bootstrapped 95% confidence intervals are represented with gray bars.

7.3 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. (2022) 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.4.

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., 2022), which is based on the upward mobility of the 1978-1983 birth cohorts.[43] 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. On net, we estimate that a development in the top quartile of neighborhood opportunity increases the discounted lifetime earnings of children in the development by +\$449 per unit-month, compared to +\$183 per unit-month for a development in the bottom quartile (i.e. a difference of +\$266 of 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 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 −\$203 per unit-month if we amortize the effects over the first 15 years of the development.

8 Counterfactuals

In this section, we explore two sets of counterfactuals. The first aims to disentangle the role of developer discretion from household preferences specific to affordable housing in determining who receives a unit. The second evaluates the impact of potential post-construction policy changes, such as changing the income limits or giving priority to nearby residents. We measure the effects of each counterfactual on household surplus, the distribution of assistance, and residential segregation. Table 3 presents the results on tenants for simulated developments in the bottom quartile of

[43]While Chetty et al. (2022) 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).

neighborhood opportunity (Q1) and the change from the bottom to top quartile of neighborhood opportunity (Q1→Q4). Table D.16 documents similar results for additional characteristics, including income at move-in. Figure 8 illustrates the effects on racial/ethnic and economic segregation.

8.1 Developer discretion and household preferences

To separate the role of developer discretion from household preferences specific to affordable housing, we shut down heterogeneity in either developer weights on households ($\boldsymbol{\phi} \equiv \mathbf{0}$)—i.e. allocate units with a fair lottery—or heterogeneity in preferences for affordable housing ($\boldsymbol{\alpha} \equiv \mathbf{0}$).

Removing heterogeneity in household preferences for affordable housing ($\boldsymbol{\alpha}$)—documented in Figure 4—leads to fewer Black/Hispanic households across all levels of neighborhood opportunity and increases the average tenant's predicted future income rank and likelihood of having a college-educated head of household. The share of Black/Hispanic households, for example, decreases from 72% to 64% in the bottom quartile of neighborhood opportunity and from 30% to 25% in the top quartile. Absent this heterogeneity in preferences for affordable housing, building in higher-opportunity neighborhoods would also have a smaller impact on racial/ethnic integration. Of course, if we were further removed *all* heterogeneity in preferences for housing and neighborhood characteristics, then tenant characteristics would just match those of the eligible population, where 58% of households are led by a Black or Hispanic head of household.

In contrast, heterogeneity in lottery weights has little impact on the development composition by race/ethnicity or need. While we estimate that developers prefer to make offers to higher-income applicants, effects on the composition are second-order to the changes across neighborhoods in which households apply. Relative to the baseline, allocating units with a fair lottery leads to housing residents that are less likely to be Black/Hispanic, have marginally higher predicted future income, and are lower income at move-in (Table D.16); however, the differences are not statistically distinguishable from the baseline allocations.

8.2 Alternative policies for managing units

Beyond fair lotteries, we evaluate three counterfactual changes to the LIHTC program that, depending on the social planner's objective, may complement the choice of location.[44]

1. **Lower income limit.** Lower 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. **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

[44]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.

Table 3: Comparison of counterfactuals

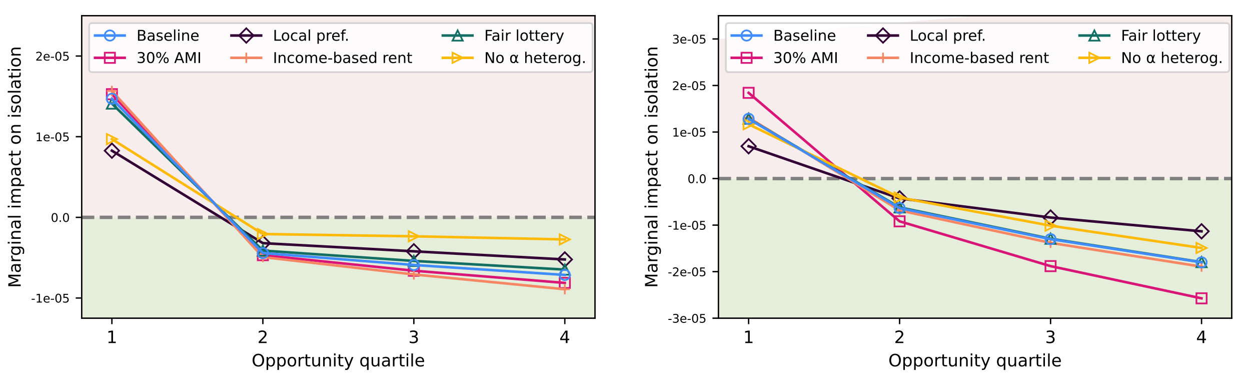
	Frac. Black/Hisp.		Future inc. rank		Frac. w/ college		WTP ($/unit-mo.)	
	Q1	Q1→Q4	Q1	Q1→Q4	Q1	Q1→Q4	Q1	Q1→Q4
Baseline								
60% AMI	0.7201	-0.4201	0.2857	+0.0508	0.1455	+0.0742	528.6	+150.7
	(0.0202)	(0.0279)	(0.0166)	(0.0045)	(0.0159)	(0.0078)	(185.6)	(17.73)
HHs and developers								
No $\boldsymbol{\alpha}$ heterog. ($\boldsymbol{\alpha} \equiv \mathbf{0}$)	0.6423	-0.3965	0.3072	+0.0414	0.1746	+0.0748	402.7	+262.1
	(0.0158)	(0.0265)	(0.0156)	(0.0041)	(0.0145)	(0.0078)	(183.3)	(13.14)
Fair lottery ($\boldsymbol{\phi} \equiv \mathbf{0}$)	0.7099	-0.4183	0.2863	+0.0502	0.1478	+0.0739	540.5	+149.2
	(0.0206)	(0.0276)	(0.0172)	(0.0049)	(0.0159)	(0.0078)	(186.1)	(21.89)
Alternative policies								
30% AMI	0.7326	-0.4137	0.2390	+0.0480	0.1286	+0.0670	865.0	+160.1
	(0.0206)	(0.0275)	(0.0193)	(0.0049)	(0.0172)	(0.0081)	(188.1)	(20.70)
Income-based rents	0.7363	-0.4092	0.2813	+0.0507	0.1437	+0.0728	789.0	+160.5
	(0.0211)	(0.0273)	(0.0168)	(0.0045)	(0.0161)	(0.0077)	(187.0)	(18.93)
Local preferences	0.7714	-0.4926	0.2682	+0.0864	0.1290	+0.1055	776.2	+258.3
	(0.0228)	(0.0330)	(0.0177)	(0.0075)	(0.017)	(0.0130)	(187.8)	(22.71)

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 at least 50% of new tenants come from the surrounding neighborhood. Bootstrapped standard errors are reported in parentheses.

Figure 8: 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' imposes that developers run a fair lottery, while 'no α heterogeneity' sets the preferences for affordable housing equal to the population average. Each panel computes the marginal impact on an isolation index under counterfactual processes or structural parameters.

The first policy lowers the income limits to 30% of AMI. The lower limits naturally disqualify many households with higher incomes, leading to more economic integration and housing tenants with lower predicted future income. However, the effects of lowering the income limits are much larger on average household income at the time of move-in (Table D.16) than on other proxies for need, likely because current income is a poor predictor of these other household characteristics once subset to the left tail of the income distribution (Table D.3). Lowering the income limits alone also does not affect the share of households by race/ethnicity. Because rents are set as a function of the income limit, the lower income limits increase the value of assistance to households by approximately $300 a month. Similarly, using income-based rents generates more household surplus by charging lower average rents, but has no statistically significant effect on household characteristics.

Prioritizing households who live in the same neighborhood as the development increases the differences in tenant characteristics across neighborhoods. Developments in the bottom quartile of neighborhood opportunity house even more Black/Hispanic residents with even lower predicted future income, while the reverse occurs for developments in the top quartile. New York City was recently sued over whether its policy of prioritizing local residents perpetuates racial segregation in the city.[45] 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. However, prioritizing local residents generates greater household surplus by selecting households who value the characteristics of the neighborhood more. It may also accomplish other policy goals not captured by our framework, such as reducing the displacement of long-time neighborhood residents (Pennington, 2021) or increasing community support for new developments.

9 Conclusion

This paper evaluates the tradeoffs that policymakers face when choosing where to provide affordable housing. Using a newly constructed panel of households, we show that the choice of location is implicitly a choice of tenants, too, because of how heterogeneity in household demand for neighborhoods interacts with the process for rationing units. This link between location and tenants has broader consequences for potential policy goals such as targeting assistance based on need or promoting racial/ethnic and economic integration.

We show that providing affordable housing in opportunity-rich neighborhoods with better schools, jobs, and other amenities can be more costly, but provides greater value to tenants. The social planner must then weigh the direct costs and benefits against other considerations, including the distribution of assistance, effects on other policy goals, and any externalities that the tenants of the development do not internalize. On net, we find building in higher-opportunity neighborhoods reduces city-wide racial/ethnic and economic segregation and provides some low-income households

[45] The case was settled in 2024, with NYC agreeing to reduce the number of units set aside for local residents from 50% to 15%.

with pathways to higher-opportunity neighborhoods that they may not be able to afford otherwise. However, some of the potential effects are offset by changes in the composition of tenants. The effects on integration are likely of particular policy interest, given evidence on the pernicious effects of segregation on minority family outcomes (Ananat, 2011; Chetty et al., 2020; Chyn, Collinson and Sandler, 2024) and court cases on whether affordable housing developments in high-minority areas perpetuate racial segregation.

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

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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.[46] 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.[47]

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 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.[48] 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 Action 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 transit, neighbor-

[46] 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.

[47] 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).

[48] 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.

hood 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 (2007) 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 with DDAs as tracts on both sides of the threshold will receive the basis boost in DDAs.[49] 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.

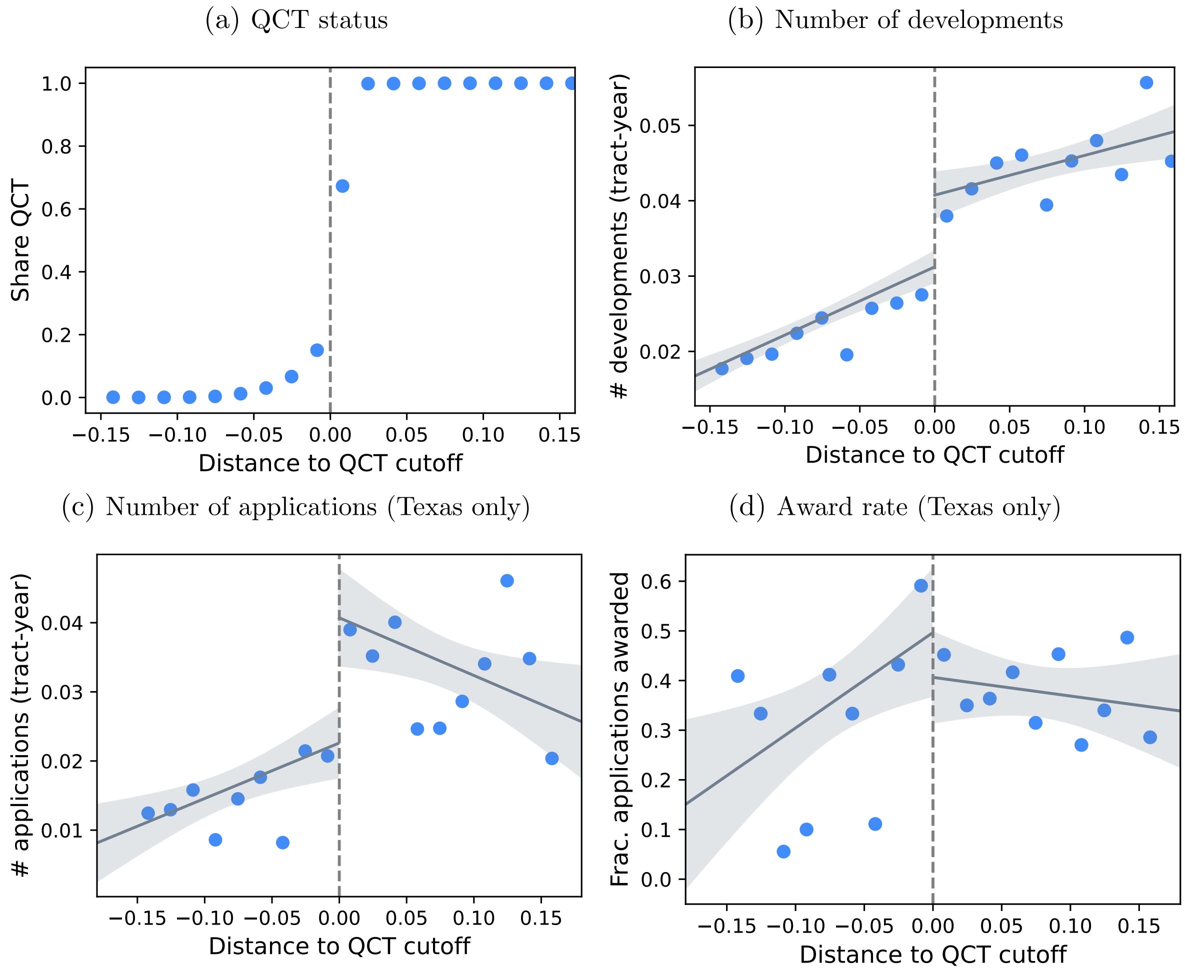
The effect on whether a tract has a development could be due to either an increase in the number of applications for tax credits or an increase in the probability an application is accepted. We collect data on applications for tax credits in Texas metro areas between 2000-2015. We geocode the address 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.

A.3 Affordable housing judicial cases

Affordable housing has been the subject of numerous judicial cases over the years, often focused on whether developments' locations or rationing processes violate the Fair Housing Act of 1968. We provide a summary of a few particularly relevant cases here.

[49]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.

Gautreaux v. Chicago Housing Authority (1969). Gautreaux was the nation's first lawsuit on public housing segregation shortly after the passage of the Civil Rights Act of 1964. In 1966, Dorothy Gautreaux, a Chicago public housing resident, partnered with the American Civil Liberties Union (ACLU) and three other residents to file a lawsuit alleging that the Chicago Housing Authority (CHA) violated Title VI of the Civil Rights Act, which prohibits racial/ethnic discrimination in federally funded activities. The judge sided with Gautreaux and ruled that the agency had perpetuated residential segregation through its choice of where to build public housing and its tenant selection processes. As part of the remedy, the judge ordered CHA to build at least three out of four future units outside of minority neighborhoods, defined as tracts at least a mile away from any tract with 30% Black residents. In response, CHA stopped building units; no new units were built in the five years following the ruling.

A follow-up case was brought against HUD in 1969 for its responsibility overseeing CHA. The case was first dismissed, with the judge acknowledging the tension inherent in choosing where to build housing: "HUD had to continue funding the discriminatory program or deprive low-income families of much-needed housing" (Goetz, 2018). On appeals, the case eventually reached the Supreme Court in *Hills v. Gautreaux*, which ruled in 1976 that HUD was indeed responsible for the segregation that HUD-funded CHA programs had perpetuated. As part of the remedy, public housing residents in Chicago were provided with housing vouchers to resettle in other, less segregated neighborhoods.

Otero v. New York City Housing Authority (1973). In *Otero v. New York City Housing Authority (NYCHA)*, the court considered whether NYCHA had to honor an agreement it had made to give displaced residents from a redevelopment project priority access to a new public housing development on the site. While NYCHA had initially intended to rehouse the displaced families, take-up among displaced residents—who were majority Black or Hispanic—was higher than NYCHA had anticipated, and, to avoid re-segregating the neighborhood, NYCHA began admitting mostly white residents from the waitlist instead of rehousing the displaced families.

While the district court initially sided with the plaintiffs and ruled that NYCHA had to honor its original agreement even if it meant increasing segregation, an appeals court overturned the decision. It held that NYCHA could defend its practice if it could argue that its original agreement would trigger a 'tipping point' that would re-segregate the surrounding, majority-white neighborhood. In its ruling, the court recognized the societal goal of integration, stating that the duty "to act affirmatively to promote the policy of fair, integrated housing is not to be put aside whenever racial minorities are willing to accept segregated housing." (Otero v. NYCHA, 1973).

Otero v. NYCHA established a precedent for pursuing integration even when it amounts to favoring non-minority residents in the allocation of public housing units. Subsequent court rulings retreated from this stance, however. For example, the court ruled in *U.S. v. Charlottesville Redevelopment and Housing Authority (1989)* that a tenant assignment program violated the Fair Housing Act by favoring certain racial/ethnic groups in pursuit of integration (Hartman and Squires, 2009).

ICP v. Texas DHCA (2015). In Section 7.2, we provided a brief description of the case between the Inclusive Communities Project (ICP) and the Texas Department of Housing and Community Affairs (DHCA). We provide a more comprehensive description here.

- 2008: ICP submits its initial complaint.
  - To support its case, the ICP complaint leaned on statistics regarding the spatial distribution of LIHTC developments: "While 19% of all renter-occupied units in the City of Dallas are located in 70% to 100% white census tracts, only 2.9% of DHCA's LIHTC units in the City are in those [...] tracts." The district court sided with ICP and mandated a remedial plan for DHCA, which required DHCA to include measures of neighborhood opportunity in its QAP for awarding future LIHTC subsidies (ICP v. DHCA, 2012).
- 2012: Texas district court rules in ICP's favor and mandates that DHCA must take remedial steps, including using an opportunity index in its selection process for developers.
- 2014: On appeal, the 5th Circuit agrees that 'disparate impact' (even without discriminatory intent) was cognizable under the Fair Housing Act and established legal standards for evaluating disparate impact claims.
  - The 5th Circuit adopted HUD's 2013 disparate impact guidelines, which consist of 'burden-shifting' procedures for such cases:
    1. Burden initially on the plaintiff to show a government program or practice *caused* discriminatory effects

2. Burden shifts to the defendant to argue that there were no other means of accomplishing another nondiscriminatory goal
3. Burden shifts back to the plaintiff to prove that the defendant's nondiscriminatory interests could be served by some other program or practice that has a less discriminatory effect

- 2015: Supreme Court affirms the 5th Circuit ruling; disparate impact claims allowed under the Fair Housing Act. The case is remanded to the district court.
  - In oral arguments, Chief Justice Roberts recognized the tension associated with building in different neighborhoods: "Which is the bad thing to do, not promote better housing in the low-income area or not promote housing integration?" (ICP v. DHCA, 2015).
  - "A disparate impact claim that relies on a statistical disparity must fail if the plaintiff cannot point to a defendant's policy or policies causing that disparity" (Opinion of the court, delivered by Justice Kennedy)
- 2016: District court reverses and now rules in DHCA's favor, stating that ICP's case does not meet the barrier of proof established by the Supreme Court's ruling

Although ICP's specific case was eventually overturned, the Supreme Court ruling is generally seen as a win for fair housing activists. It established clear procedures for bringing lawsuits on the grounds of disparate impact, even in cases without disparate treatment or intention.

Winfield v. City of NY (2016). Shortly after the Supreme Court ruling in *ICP v. Texas DHCA*, a disparate impact case was filed in NYC, alleging that the locations of affordable housing and the processes for rationing units helped cement racial/ethnic segregation in the city. New affordable housing units in NYC are allocated via a lottery that gives explicit priority for 50% of the units to residents of the community district in which the development is constructed. The plaintiffs argue that such a restriction perpetuates segregation by prioritizing white applicants for developments built in majority-white neighborhoods. In the initial complaint, the plaintiffs further asserted that community preferences restrict the potential for moving to opportunity: "Access to [neighborhoods of opportunity] is effectively prioritized for white residents who already live there and limited for African-American and Latino New Yorkers who do not" (Winfield v. City of New York, 2015). The case was settled in 2024. As part of the settlement, NYC agreed to reduce the share of units set aside for local residents to 15%.

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

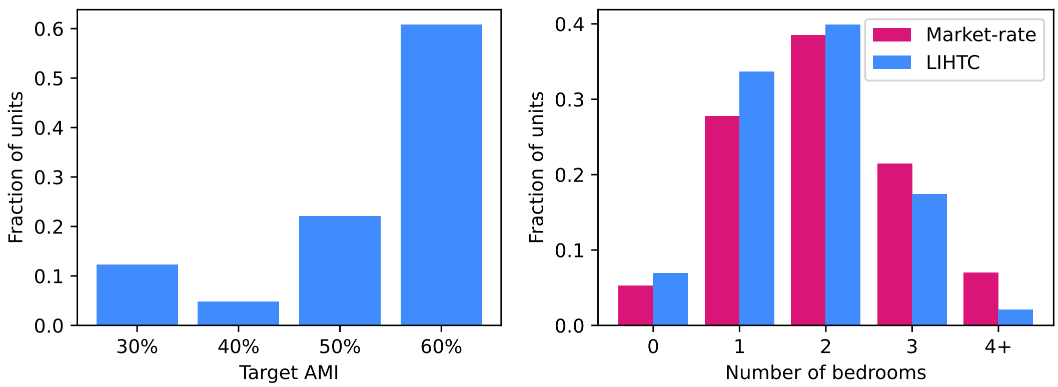
Characteristic	In-sample	Out-of-sample	Normalized diff.	T-statistic
Development characteristics				
MAFID match rate	0.8558	0.07969	3.037	141.4
Year placed in service	2007	2006	0.1971	9.191
# LIHTC units	105.4	94.89	0.1055	4.912
# total units	107.7	96.38	0.1091	5.077
Nonprofit developer	0.1915	0.2143	-0.05632	-2.624
Neighborhood characteristics				
Median household income (2010)	43720	44450	-0.0303	-1.412
Frac. white (2010)	0.4927	0.4609	0.1093	5.099
Frac. Black (2010)	0.3082	0.3413	-0.1031	-4.811
Population per sq. mile (2010)	13850	14130	-0.01177	-0.5501
Upward mobility (p25 parents)	0.3876	0.3831	0.06551	3.053
HUD jobs index	56.36	52.28	0.1845	8.595
HUD school index	35.86	35.59	0.01044	0.4864
HUD transit index	72.68	71.67	0.04431	2.066
HUD poverty index	30.78	31.05	-0.009886	-0.4608
Overall opportunity index (average)	45.83	44.5	0.0897	4.181

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. (2022) 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.

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.

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[50] 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')
- 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.

[50]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.

We then define households as the simply 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 householder 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 an additional 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:[51]

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

[51] See here for additional details.

comes first).[52] 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 49% of LIHTC residents stay in the unit for at least three years, compared to 34% of market-rate tenants and 36% 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.

Table B.2: Move-out rate heterogeneity

	Market-rate (MR)		LIHTC-eligible MR		LIHTC	
	1-year	3-year	1-year	3-year	1-year	3-year
Aggregate	0.7135	0.3390	0.7212	0.3597	0.7939	0.4855
White (non-Hisp.)	0.7062	0.3145	0.7237	0.3397	0.7961	0.4773
Black (non-Hisp.)	0.7518	0.3798	0.7511	0.3775	0.7860	0.4742
Hispanic	0.7577	0.4051	0.7680	0.4266	0.7972	0.4926
Any children	0.7124	0.3554	0.7075	0.3596	0.8095	0.4850
Joint filers	0.7136	0.3421	0.7598	0.4042	0.8299	0.5393
Any seniors	0.7994	0.5130	0.8044	0.5234	0.8677	0.6508
Has voucher	0.8167	0.5058	0.8197	0.5102	0.8395	0.5618
HH size: 1	0.7159	0.3484	0.7251	0.3679	0.7672	0.4745
HH size: 2	0.6981	0.3103	0.7035	0.3366	0.7987	0.4790
HH size: 3	0.7153	0.3439	0.7207	0.3597	0.8260	0.5034
HH size: 4 or more	0.7375	0.3702	0.7398	0.3760	0.8358	0.5079
HH income: non-filer	0.6935	0.3991	0.6904	0.4058	0.8056	0.5507
HH income: ($0, $10k]	0.7104	0.3170	0.7159	0.3270	0.7667	0.4384
HH income: ($10k, $20k]	0.7094	0.3132	0.7230	0.3342	0.7907	0.4676
HH income: ($20k, $30k]	0.7215	0.3316	0.7406	0.3643	0.8120	0.4963
HH income: ($30k, $40k]	0.7323	0.3450	0.7553	0.3791	0.8197	0.5092
HH income: >$40k	0.7155	0.3386	0.7376	0.3753	0.8115	0.4900

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 2010-2016 so that we can observe at least three years after move-in.

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

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, and, if it were a utility function, we would want to acknowledge some unobservables ξ_{jb} that enter into utility (e.g., price). Instead, this is a classification problem, where the goal is to model the relationship between individual and housing characteristics and to predict the probability an individual is observed in a given housing option.

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.[53] 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 BLP-style instruments for rent

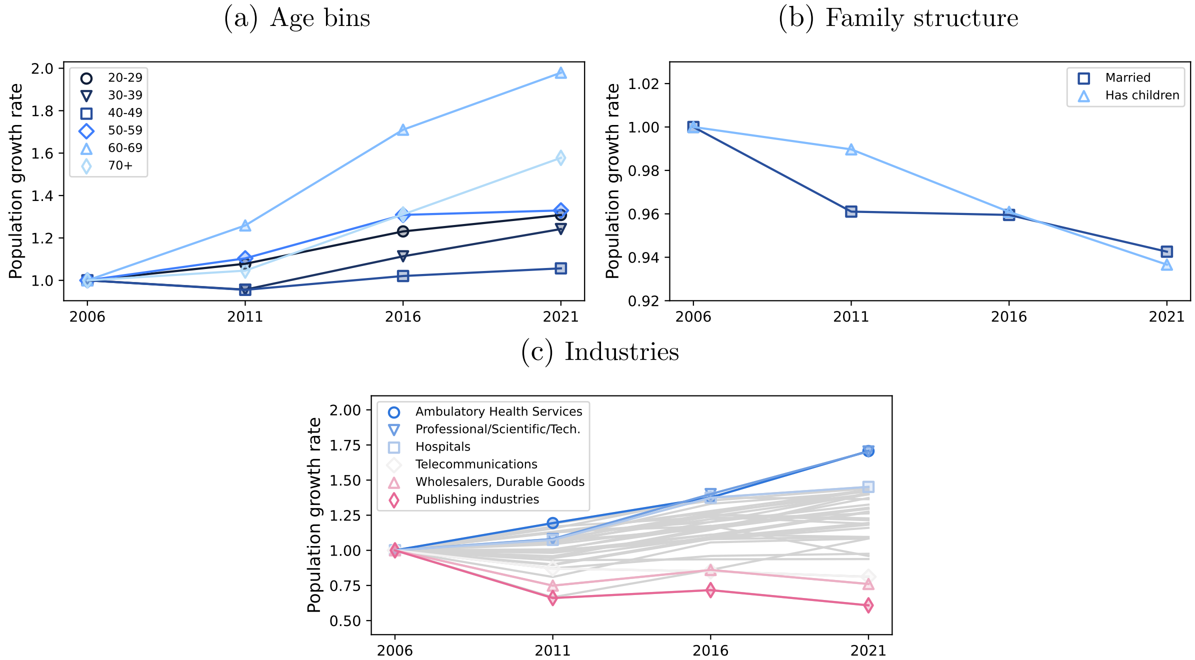
BLP-style rent instruments introduced in Bayer and Timmins (2007) may fail to recover the true parameters if there is spatial correlation in both unobserved quality and in the housing characteristics used to form instruments. Many characteristics commonly used to form these instruments exhibit strong spatial correlation. Figure C.2 shows that the median year of construction, fraction of single-family residences, and fraction of land undeveloped are all positively correlated with distance from the city center in Chicago. If unobserved quality is also correlated with distance from the city center, then using these characteristics—or transformations of them, such as the average in a ring of tracts around the focal tract—will lead to biased estimates as the exclusion restriction will no longer hold.

C.3 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

[53] 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.

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).

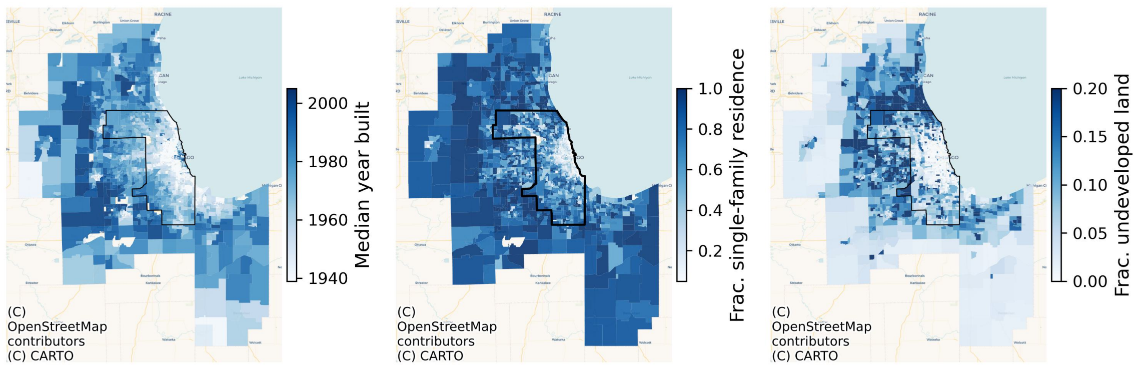
C.3.1 Estimating 'implicit subsidies' for LIHTC

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 7.1 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 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.

Note that the average rent ceiling for LIHTC units in Chicago between 2016 and 2018—the

Figure C.2: Spatial correlation in common instruments

(a) Median year built (b) Frac. single-family (c) Frac. undeveloped land



Notes: This figure maps neighborhood characteristics that are commonly used to form instruments for rent. Median year built and fraction single-family residences are sourced from the 2019 5-year ACS. The fraction of undeveloped land is sourced from the National Land Cover Database (NLCDB).

period we use for counterfactuals—was \$954, which is greater than the average rent that tenants report to the ACS in the same period (\$742). However, it is unclear the extent to which developers are actually charging below the rent limit for a few reasons. First, we infer the rent limits based on 30% of the unit's current income limit; however, there are cases where the rent limit may be even lower, which we cannot directly observe (Stagg, 2018). Second, the ACS rents are surveyed, and households may occasionally misreport their rent, e.g., if they do not report all utilities (which are included in the LIHTC maximums) or if multiple individuals contribute to the rent/utilities but the respondent only reports their share.

C.3.2 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 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, 2005, 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.[54] 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. 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

[54] 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).

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.[55]

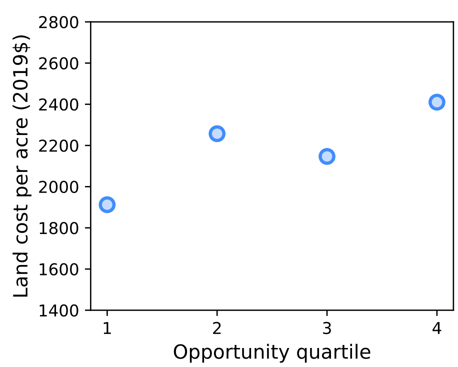
C.3.3 Estimating LIHTC award levels

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.

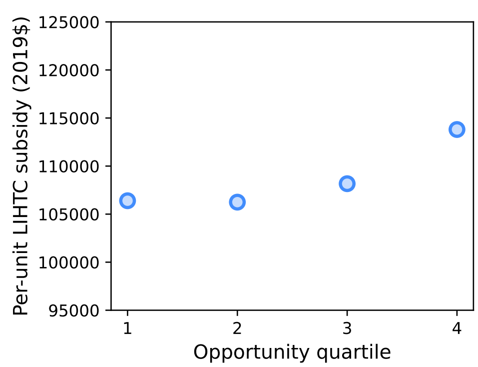
Figure C.3 plots the average estimated per-unit LIHTC subsidy by neighborhood opportunity quartile and the estimated cost of an acre of land. From the bottom to the top quartile, the estimated LIHTC subsidy increases by only 7% while the estimated land cost increases by 26%. A key limitation is that 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.

Figure C.3: LIHTC costs

(a) Land value



(b) Tax credit subsidy



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

C.4 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 7.3.

[55]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.

Effects on children. Table C.1 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 33.7 (roughly $12,500 in 2019-equivalent dollars) to a neighborhood where the predicted rank is 50.9 ($19,800). 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 31.2 to 36.5). A key difference across potential LIHTC neighborhoods is the share of tenants with children; we estimate that only 25% of households in developments in the top quartile would have at least one child at home, compared to 32% in the bottom quartile. One tradeoff in choosing the location for a new LIHTC development, therefore, is providing a smaller treatment (+5.3 percentile ranks) to more children or a larger treatment (+17.2 percentile ranks) to fewer children.

We follow the methodology in Chetty et al. (2022) 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).

Among the assumptions used to reach the final numbers, the final result is particularly sensitive to the discount rate. Discounting future earnings by more than 3% will lower the estimated effect, while the effect on *undiscounted* earnings is much larger (+$705 and +$1733 in the bottom and top quartiles, respectively).

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) estimates 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 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.

C.5 Housing quality

The American Housing Survey (AHS) is a panel survey of housing units that provides more far details on housing quality than our baseline data, including data on various maintenance issue. We

Table C.1: Steps for estimating the impact on lifetime earnings of children

#	Step description	Q1	Q4
1	Average upward mobility rank in prior tract	31.2	33.7
2	[Translated to 2019$]	$10675	$12457
3	Change in tract-level upward mobility rank.	5.3	17.2
4	Estimated causal effect of move from birth (=62% of [3])	3.29	10.66
5	Expected upward mobility in ranks (=[1]+[4])	34.49	44.36
6	[Translated to 2019$]	$13013	$19796
7	Effect of move on yearly income at age 26 (=[6]-[2])	$2338	$7339
8	Average individual earnings at age 26 (ACS, 2019%)	$28382	$28382
9	Effect as % of average individual earnings (=[7]/[8])	8.24%	25.86%
10	Undiscounted lifetime income with 1% wage growth (ACS, 2019$)	$2897247	$2897247
11	Discounted (3%) lifetime income with 1% wage growth (ACS, 2019$)	$750494	$750494
12	Causal effect on undiscounted lifetime income (=[10]*[9])	$238618	$749150
13	Causal effect on discounted lifetime income (=[11]*[9])	$61811	$194058
14	Percent of households with children	31.9%	25.0
15	Average number of children conditional on at least 1	2	2
16	Average number of children in each household (=[14]*[15])	0.638	0.5
17	Effect on undiscounted lifetime inc. per unit-month (=([13]*[16])/(18*12))	$704.8	$1732.8
18	Effect on discounted lifetime inc. per unit-month (=([13]*[16])/(18*12))	$182.6	$448.8

Notes: This table presents the steps we take to approximate the causal effect on lifetime earnings on 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. (2022) to estimate the effect on individual earnings. Row (1) and (2) take the average upward mobility in a household's previous tract from Appendix Table D.15 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 from Append Table D.15. 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).

use data from the 2013 and 2015 waves. While usually the AHS is a stable sample units, the panel was re-sampled 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 C.2. 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.

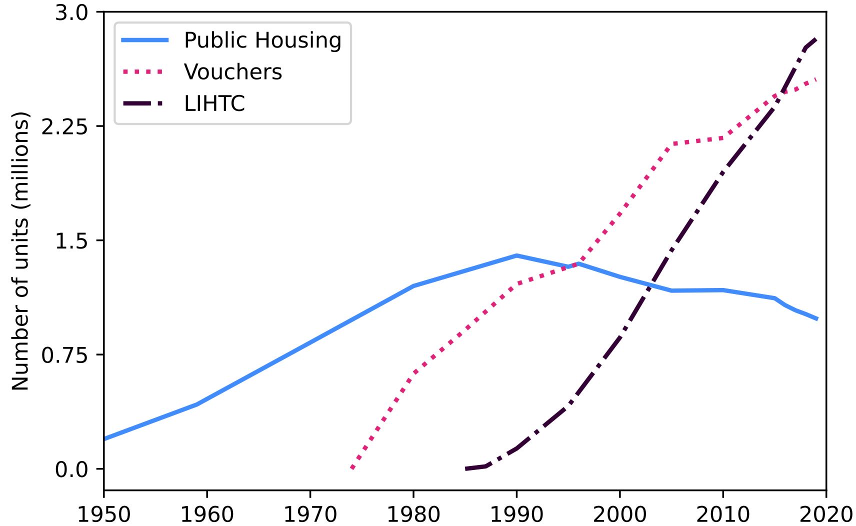
Table C.2: Housing quality: market-rate, LIHTC, and public housing

	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.

D Supplemental tables and figures

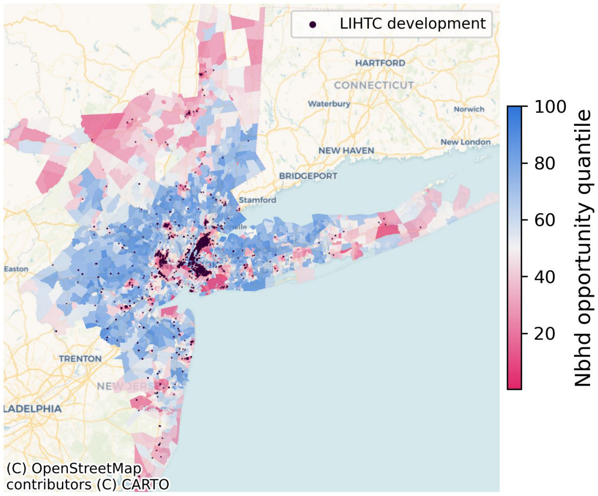
Figure D.1: Subsidized housing stock by year



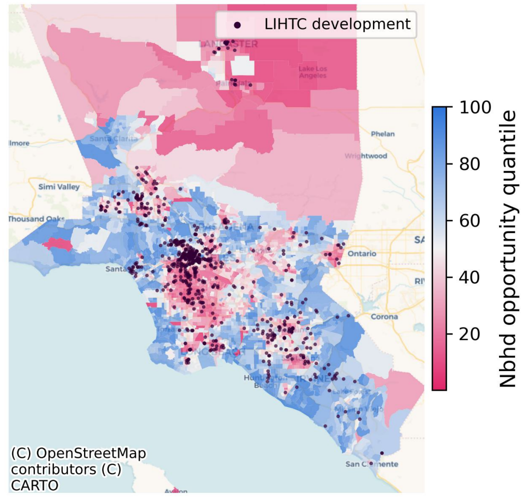
Notes: This figure documents the stock of public housing units, Section 8 housing vouchers, and LIHTC units by year. The underlying data are sourced from Schwartz (2021), HUD PICTRACs, and HUD's LIHTC database. LIHTC units include those funded by both 4% and 9% tax credits. The sample covers the full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

Figure D.2: Neighborhood opportunity maps

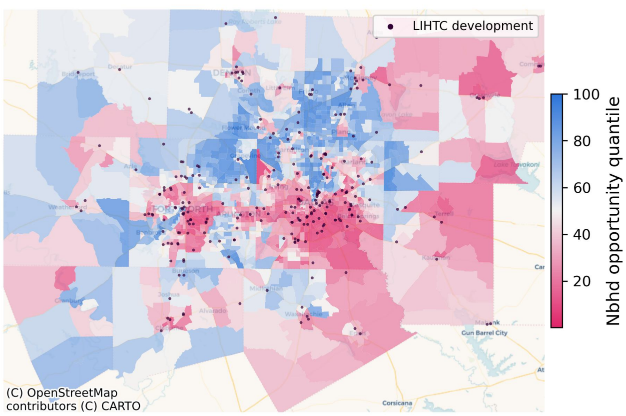
(a) New York City MSA



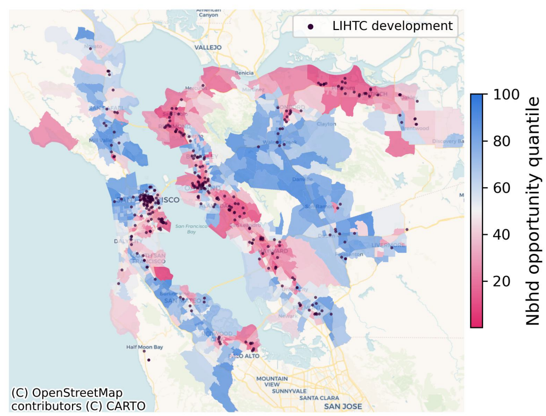
(b) Los Angeles MSA



(c) Dallas MSA

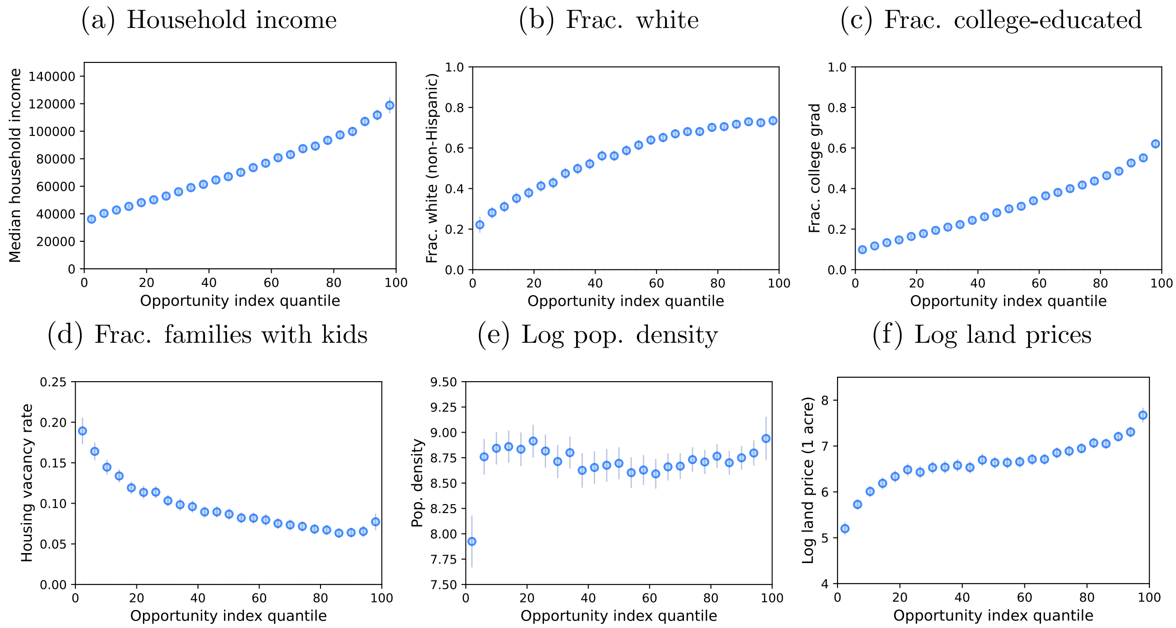


(d) San Francisco-Oakland MSA



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.

Table D.1: Share of households with other government assistance

	Market-rate		LIHTC
Program	All	LIHTC-eligible	At move-in
HUD housing voucher	0.056	0.109	0.252
Food stamps (SNAP)	0.190	0.332	0.516
Supplementary Security income	0.065	0.113	0.195
Social Security income	0.171	0.257	0.345
Cash public assistance	0.038	0.063	0.095

Notes: This table documents the fraction of households who take up various other forms of government assistance. Housing vouchers and social security are available for all households, while the other programs are only available for households sampled by the ACS. To account for differences in the size of each sample in each MSA, each statistic is computed within-MSA first, then across-MSA weighting by the population.

Table D.2: Eligible population: market-rate v. LIHTC characteristics

	Avg. for LIHTC-eligible households in market-rate	Coefficient on is LIHTC (1)	Coefficient on is LIHTC (2)
Financials and education			
Current Adjusted Gross Income (AGI)	15610.0	-1185	308.6
		(30.04)	(77.5)
Avg. AGI in years [-3, 0)	18880.0	-4633	-3617
		(40.27)	(114.9)
Avg. AGI in years (0, 3]	22320.0	-3553	-2984
		(47.67)	(135.1)
Predicted future income rank	0.323	-0.0848	-0.0765
		(0.0005)	(0.0013)
Below federal poverty line	0.5626	0.1219	0.0901
		(0.001)	(0.0026)
Filed taxes this year	0.6693	0.0496	0.0781
		(0.0009)	(0.0025)
Surveyed income (ACS)	34290.0	-10580	-7672
		(344.7)	(426.4)
Childhood family income rank (household head)	0.4312	-0.1075	-0.1036
		(0.001)	(0.0025)
Graduated college (household head)	0.1801	-0.068	-0.0911
		(0.0023)	(0.0035)
Graduated high school (household head)	0.7992	-0.0133	-0.0243
		(0.0031)	(0.0043)
Household structure			
Household has joint filers	0.1408	-0.0513	-0.0274
		(0.0007)	(0.0017)
Household has children (<18yo)	0.4022	0.0113	0.0611
		(0.001)	(0.0023)
Household has seniors (>64yo)	0.2114	-0.0362	-0.1197
		(0.0007)	(0.002)
Race/ethnicity (household head)			
White (non-Hispanic)	0.4404	-0.1431	-0.1012
		(0.001)	(0.0022)
Black (non-Hispanic)	0.2722	0.189	0.1172
		(0.001)	(0.002)
Hispanic	0.2285	-0.007	0.0188
		(0.0008)	(0.002)
Previous tract chars. (household head)			
Miles from prev. tract	5.797	1.109	0.7312
		(0.0205)	(0.0514)
Prev. tract opportunity percentile	0.4093	-0.08	-0.0494
		(0.0006)	(0.0014)
Prev. tract median household income	53150.0	-5918	-3555
		(52.7)	(129.2)
Prev. tract frac. white	0.586	-0.0713	-0.0339
		(0.0006)	(0.0012)

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, while the subsequent two columns document the coefficient on whether a household is in LIHTC from a regression. Column (1) includes fixed effects for MSA interacted with year, and column (2) includes fixed effects for tract interacted with year and controls for unit characteristics, including number of bedrooms, decade of construction, and type of building (e.g., single-family home, small apartment building, and large apartment building). The sample includes market-rate households in the ACS and LIHTC households constructed using the Census-IRS panel (2010-2018, 50 sample MSAs). 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)	0.8694	0.5756
Avg. AGI in years (0, 3]	0.8840	0.6385
Predicted future income rank	0.6760	0.3391
Childhood family income rank (household head)	0.2709	0.03903
Average current AGI by char.		
Black (non-Hispanic)	\$36,560	\$15,420
White (non-Hispanic)	\$63,290	\$14,640
Hispanic	\$44,680	\$18,070
Graduated college (household head)	\$89,660	\$18,120
No college degree (household head)	\$37,780	\$15,050
Graduated high school (household head)	\$58,970	\$16,850
No high school degree (household head)	\$22,810	\$11,180
Household has children (<18yo)	\$56,360	\$21,330
Household does not have children	\$51,750	\$11,420
Household has seniors (>64yo)	\$33,000	\$8,434
Household does not have seniors	\$57,620	\$17,600
Household has joint filers	\$92,180	\$28,680
Household has no joint filers	\$41,910	\$13,520

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)	15040	207.9	460.9	386.9
		(243.6)	(296)	(437.6)
Avg. AGI in years [-3, 0)	14070	864.2	2041	1969
		(208.3)	(259.3)	(349.7)
Avg. AGI in years (0, 3]	19140	853.1	1626	1330
		(354.7)	(444.2)	(655.9)
Predicted future income rank	0.2185	0.0367	0.0579	0.0894
		(0.0034)	(0.0039)	(0.0057)
Below federal poverty line	0.7087	-0.0344	-0.0608	-0.0662
		(0.0056)	(0.0065)	(0.0091)
Surveyed income (ACS)	21890	1868	5695	3662
		(767.3)	(1072)	(1403)
Childhood family income percentile (household head)	0.2868	0.06	0.1005	0.1279
		(0.0051)	(0.0066)	(0.0075)
Graduated college (household head)	0.0857	0.0252	0.0508	0.0853
		(0.006)	(0.0079)	(0.012)
Graduated high school (household head)	0.7444	0.0395	0.0727	0.0918
		(0.0085)	(0.0097)	(0.0112)
Household structure				
Household has joint filers	0.0747	0.0283	0.0449	0.0569
		(0.0037)	(0.0045)	(0.0055)
Household has children (<18yo)	0.4672	-0.043	-0.0489	-0.0876
		(0.0074)	(0.0089)	(0.0116)
Household has seniors (>64yo)	0.1199	0.0353	0.0678	0.1277
		(0.0088)	(0.0116)	(0.0173)
Race/ethnicity of household head				
White (non-Hispanic)	0.1792	0.1711	0.2492	0.3346
		(0.0126)	(0.0161)	(0.0198)
Black (non-Hispanic)	0.5452	-0.1832	-0.225	-0.3207
		(0.0154)	(0.0169)	(0.0182)
Hispanic	0.2227	-0.0083	-0.0488	-0.0496
		(0.0111)	(0.0117)	(0.0138)
Previous tract chars. (household head)				
Miles from prev. tract	6.348	0.6439	1.664	1.933
		(0.1271)	(0.1604)	(0.1798)
Prev. tract opportunity percentile	0.248	0.1127	0.2032	0.2882
		(0.0045)	(0.0055)	(0.0071)
Prev. tract median household income	42200	6140	11390	18410
		(458.2)	(557.1)	(821.3)

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)	14070	725.4	1739	1698
		(103.6)	(137.2)	(189.7)
Avg. AGI in years (0, 3]	19140	660.6	1222	1030
		(132.4)	(173.1)	(243)
Predicted future income rank	0.2185	0.0342	0.0541	0.0861
		(0.0031)	(0.0037)	(0.0057)
Below federal poverty line	0.7087	-0.0302	-0.0521	-0.0596
		(0.0036)	(0.0039)	(0.0051)
Childhood family income percentile (household head)	0.2868	0.0588	0.0982	0.125
		(0.005)	(0.0064)	(0.0074)
Graduated college (household head)	0.0857	0.0249	0.0488	0.0849
		(0.0059)	(0.0078)	(0.0118)
Graduated high school (household head)	0.7444	0.0385	0.0691	0.0909
		(0.0083)	(0.0095)	(0.0109)
Household structure				
Household has joint filers	0.0747	0.0274	0.043	0.0552
		(0.0035)	(0.0042)	(0.005)
Household has children (<18yo)	0.4672	-0.0448	-0.0523	-0.0852
		(0.0058)	(0.0068)	(0.0092)
Household has seniors (>64yo)	0.1199	0.0366	0.0683	0.1229
		(0.0073)	(0.0097)	(0.0147)
Race/ethnicity of household head				
White (non-Hispanic)	0.1792	0.1711	0.2492	0.3333
		(0.0125)	(0.016)	(0.0194)
Black (non-Hispanic)	0.5452	-0.1829	-0.2242	-0.3184
		(0.0154)	(0.0168)	(0.018)
Hispanic	0.2227	-0.0087	-0.0497	-0.0501
		(0.011)	(0.0116)	(0.0138)
Previous tract chars. (household head)				
Miles from prev. tract	6.348	0.651	1.68	1.952
		(0.1272)	(0.1607)	(0.1797)
Prev. tract opportunity percentile	0.248	0.1125	0.203	0.2879
		(0.0045)	(0.0055)	(0.0071)
Prev. tract median household income	42200	6115	11340	18330
		(449.2)	(547.5)	(809.3)

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)	14070	503.8	1527	1394
		(230.1)	(293.1)	(380.1)
Childhood family income percentile (household head)	0.2868	0.0338	0.0591	0.0807
		(0.005)	(0.0077)	(0.0086)
Graduated college (household head)	0.0857	0.0265	0.0563	0.0924
		(0.0068)	(0.009)	(0.0135)
Prev. tract opportunity percentile	0.248	0.082	0.1588	0.2369
		(0.0047)	(0.0059)	(0.0077)
White (non-Hispanic)	0.1792	0.0622	0.0776	0.1238
		(0.0116)	(0.0169)	(0.0215)
Black (non-Hispanic)	0.5452	-0.047	-0.0291	-0.0929
		(0.0144)	(0.0176)	(0.0211)
Hispanic	0.2227	-0.0426	-0.0862	-0.0838
		(0.0119)	(0.0133)	(0.0173)
Controls: nbhd median income decile				
Avg. AGI in years [-3, 0)	14070	264.1	809.5	190.1
		(219.2)	(294.8)	(425)
Childhood family income percentile (household head)	0.2868	0.0508	0.0824	0.1027
		(0.0059)	(0.0084)	(0.0101)
Graduated college (household head)	0.0857	0.0254	0.0518	0.0835
		(0.0064)	(0.0093)	(0.0139)
Prev. tract opportunity percentile	0.248	0.0978	0.1757	0.2477
		(0.0048)	(0.0064)	(0.0087)
White (non-Hispanic)	0.1792	0.1374	0.185	0.2438
		(0.0134)	(0.0186)	(0.0258)
Black (non-Hispanic)	0.5452	-0.1597	-0.1814	-0.258
		(0.0169)	(0.0204)	(0.0242)
Hispanic	0.2227	-0.0013	-0.0346	-0.0285
		(0.0117)	(0.0135)	(0.0175)

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)	32850	12800	23950	39040
		(156.5)	(185)	(229.6)
Childhood family income percentile (household head)	0.4204	0.1042	0.1654	0.216
		(0.0016)	(0.0016)	(0.0016)
Graduated college (household head)	0.2034	0.1197	0.2269	0.3524
		(0.0016)	(0.0017)	(0.0017)
Household has children (<18yo)	0.4944	-0.0729	-0.1184	-0.143
		(0.0017)	(0.0017)	(0.0017)
Black (non-Hispanic)	0.3597	-0.1762	-0.2371	-0.2758
		(0.0017)	(0.0016)	(0.0015)
White (non-Hispanic)	0.3152	0.1939	0.2885	0.3419
		(0.0018)	(0.0018)	(0.0018)
Hispanic	0.2481	-0.0358	-0.0836	-0.1202
		(0.0015)	(0.0015)	(0.0014)
Miles from prev. tract	5.849	0.9771	1.462	1.433
		(0.0371)	(0.0394)	(0.0395)
Prev. tract opportunity percentile	0.3003	0.154	0.2676	0.3639
		(0.001)	(0.0011)	(0.0011)

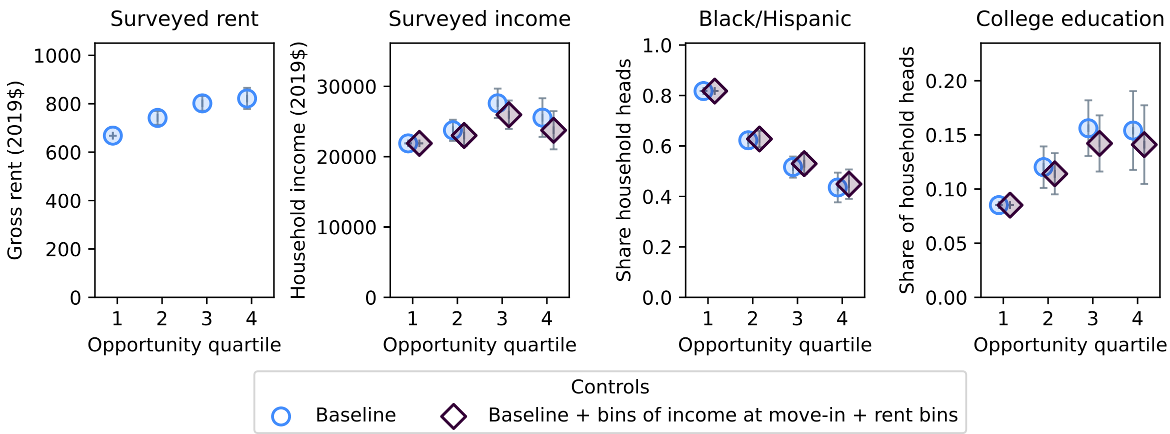
Notes: This table documents how market-rate household characteristics vary by the neighborhood opportunity of the development by regressing each characteristic on indicators for quartiles of within-MSA neighborhood opportunity. The specification includes controls for MSA interacted with year, the income 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 (2010-2018). 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
Childhood family income percentile (household head)	0.4204	0.0848	0.1326	0.1699
		(0.0015)	(0.0016)	(0.0016)
Graduated college (household head)	0.2034	0.0685	0.1341	0.2159
		(0.0015)	(0.0016)	(0.0017)
Household has children (<18yo)	0.4944	-0.0688	-0.1091	-0.1269
		(0.0017)	(0.0018)	(0.0018)
Black (non-Hispanic)	0.3597	-0.1649	-0.2161	-0.2441
		(0.0017)	(0.0016)	(0.0016)
White (non-Hispanic)	0.3152	0.1792	0.2625	0.3045
		(0.0018)	(0.0019)	(0.0019)
Hispanic	0.2481	-0.0304	-0.0726	-0.1022
		(0.0015)	(0.0015)	(0.0015)
Miles from prev. tract	5.849	0.9072	1.35	1.296
		(0.0375)	(0.0406)	(0.0413)
Prev. tract opportunity percentile	0.3003	0.1423	0.2465	0.333
		(0.001)	(0.0011)	(0.0011)

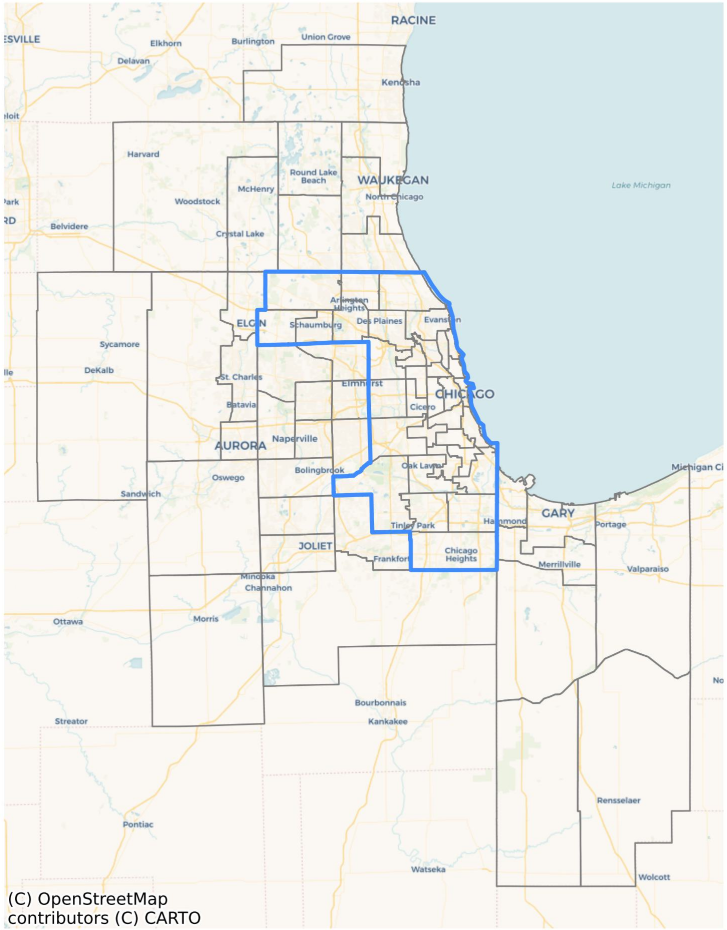
Notes: This table replicates Table D.8, but adds controls for bins of household income. The income bins are constructed using a household's current adjusted gross income. Standard errors are reported in parentheses.

Figure D.4: Household characteristics by neighborhood opportunity with rent controls



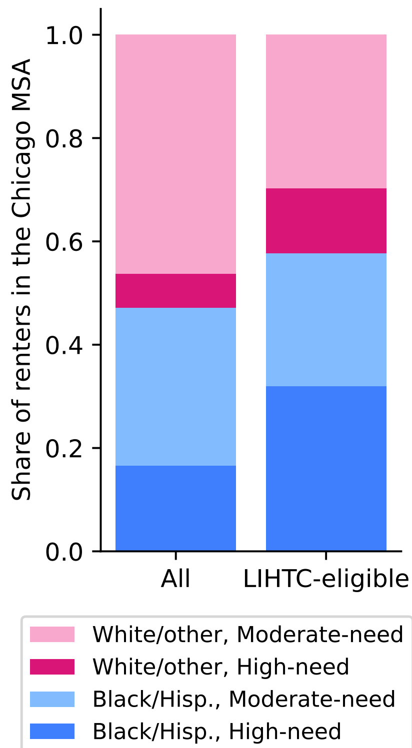
Notes: This figure documents how characteristics of LIHTC households vary by the neighborhood opportunity of the development using the subset of LIHTC households that the ACS surveyed within a year of move-in (2010-2018, 50 sample MSAs). Each point is a coefficient from a regression of a characteristic on indicators for each quartile, shifted up by the average value in the first quartile. 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 surveyed income. Rent is the gross rent reported to the ACS. Each specification also includes controls for the number of bedrooms and the income limit of the unit. 95% confidence intervals are represented by gray bars.

Figure D.5: 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.

Figure D.6: Distribution of household types, Chicago



Notes: This figure documents the distribution of household types in the Chicago MSA during our sample period, 2010-2018. A household is defined as 'high-need' if it is in the bottom quartile of predicted future income among renters, adjusted for age and household size.

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)	0.1293	-0.0264	0.0679	-0.0008
	(0.0247)	(0.0230)	(0.003)	(0.0027)
Share Hispanic (2010)	-0.0602	0.0116	0.0102	0.0125
	(0.0135)	(0.0125)	(0.0023)	(0.0022)
Share non-Hispanic white (2010)	-0.0570	0.0138	-0.0702	-0.0120
	(0.0206)	(0.0197)	(0.0032)	(0.0029)
Share w/ college (2010)	-0.0348	-0.0130	-0.0470	-0.0183
	(0.0136)	(0.0138)	(0.0024)	(0.0024)
Overall opportunity index (percentile)	-0.0746	-0.0142	-0.0724	-0.0199
	(0.0159)	(0.0141)	(0.0033)	(0.0031)
HUD jobs index	-1.241	0.1862	-0.7886	0.6096
	(1.255)	(1.227)	(0.2683)	(0.2653)
Upward mobility index	-10.00	-0.9749	-6.681	-1.420
	(2.032)	(2.026)	(0.3161)	(0.3017)
HUD school index	-5.330	-0.4356	-6.088	-1.487
	(1.844)	(1.743)	(0.3231)	(0.3037)
HUD transit index	-0.2387	-0.8101	1.436	0.4674
	(0.8817)	(0.9476)	(0.1590)	(0.1555)
Log med. hh income (2010)	-0.1010	0.0015	-0.1090	-0.0407
	(0.0304)	(0.0291)	(0.0052)	(0.0050)
Log pop. density (2010)	-0.0780	-0.1168	0.1115	0.0268
	(0.0746)	(0.0777)	(0.0132)	(0.0128)
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. (2022) 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 per sq. mi.	13.29	0.2974
		(0.1341)
Grocery stores per sq. mi.	2.82	-0.0299
		(0.012)
Department stores and supercenters per sq. mi.	0.66	-0.012
		(0.0061)
Civil, social, and religious places per sq. mi.	2.139	-0.0076
		(0.0045)
Entertainment places per sq. mi.	0.5593	0.0014
		(0.0031)
Frac. white (non-Hispanic)	0.5672	0.0005
		(0.0005)
Frac. Hispanic	0.1946	-0.0007
		(0.0004)
Frac Black (non-Hispanic)	0.1643	-0.0003
		(0.0003)
Frac with college degree	0.4168	0.003
		(0.0014)
Frac housing vacant	0.089	-0.0005
		(0.0003)
Median household income	74190	371.9
		(150.2)
Median year structure built	1960	-4.05
		(2.053)
Population density	7868	39.48
		(26.4)

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); department stores and supercenters (4522, 4528, 4523); civil, social, religious places (8131, 8135); 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. The data are at the neighborhood-period level and the sample size is 1800. Standard errors are presented in parentheses.

Table D.11: Instrument first-stage

Covariate	Coefficient
Instrument (z-score)	0.3033
	(0.0750)
2 bedrooms	2.83
	(0.1184)
3+ bedrooms	5.22
	(0.159)
Small apartment building	-1.399
	(0.0956)
Big apartment building	0.1875
	(0.1706)
PUMA fixed effects	✓
N	1800

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	Is prev. option	Gross rent (00s)	Is AH	2 bedrooms	3+ bedrooms	Small apt. building	Big apt. building
Avg. household	-	7.637	-0.2577	0.383	1.254	1.181	0.1029	-0.4348
		(0.0097)	(0.1173)	(0.0497)	(0.3371)	(0.6009)	(0.1718)	(0.0778)
White (non-Hispanic)	0.4496	-0.1116	0.0243	0.5352	-0.1483	-0.2721	-0.0578	-0.3274
		(0.0371)	(0.0122)	(0.106)	(0.066)	(0.0963)	(0.0586)	(0.0696)
Black (non-Hispanic)	0.2913	-0.2121	-0.0086	0.9821	-0.1046	-0.0726	0.0783	0.0416
		(0.0406)	(0.0142)	(0.1006)	(0.0731)	(0.1058)	(0.0639)	(0.0775)
Hispanic	0.1631	0.0728	-0.0286	0.3969	-0.119	-0.1472	-0.0958	-0.4423
		(0.0424)	(0.015)	(0.1125)	(0.0772)	(0.1113)	(0.066)	(0.0842)
Any children	0.3858	0.3405	-0.002	0.3921	0.3109	0.2633	-0.0249	-0.0618
		(0.0276)	(0.0099)	(0.0613)	(0.0511)	(0.0729)	(0.0424)	(0.0565)
Joint filers	0.2002	0.3146	-0.0094	-0.4589	-0.1157	-0.1068	-0.0343	0.1704
		(0.026)	(0.0089)	(0.1026)	(0.0488)	(0.0693)	(0.0406)	(0.0521)
Any seniors	0.154	1.243	0.0239	0.4663	0.0695	0.1649	0.0378	1.206
		(0.0345)	(0.0105)	(0.0498)	(0.0563)	(0.0822)	(0.0518)	(0.0591)
Has voucher	0.0625	-0.1486	0.0065	0.1547	0.1939	0.4027	-0.1909	-0.3216
		(0.0445)	(0.0192)	(0.2758)	(0.0901)	(0.1256)	(0.0698)	(0.099)
Linear proj. on bins								
Income years [-3,0)	45150	-0.0271	0.0092	-0.0802	0.0273	0.009	-0.0177	-0.0042
# of persons	2.352	-0.092	0.011	0.1729	0.3711	0.6856	-0.0752	-0.2397

Notes: This table documents the estimated preference parameters for neighborhood characteristics. Because we recenter **w** to be mean-zero for estimation, each coefficient in the table corresponds to the change in value relative to the average household. As such, computing the equivalent value as if we instead included each characteristic as a binary indicator requires using the difference between the indicator and the average value in the population reported in the first column (i.e., a white (non-Hispanic) household would be 'above average' in that characteristic, but below average in the Black (non-Hispanic) and Hispanic characteristics; computing the total effect requires summing across the three values). Finally, while we estimate the model using nine income bins and four bins of household size, for exposition, we project the estimated coefficients for each bin on the midpoints of each bin (after adjusting to be as if they were estimated as indicators) and report the linear coefficient. Standard errors are reported in parentheses.

Table D.13: Preference heterogeneity: neighborhood characteristics

Household char.	Avg. of char. in population	Frac. white (2010)	Frac. Black (2010)	Frac. Hispanic (2010)	Frac. w/ college (2010)	Log pop. density (2010)	Log med. income (2010)	HUD school index	HUD jobs index	HUD transit index	HUD poverty index	Log # parks nearby
Avg. household					——— Absorbed by neighborhood fixed effects ———							
White (non-Hispanic)	0.4496	1.04	0.5049	0.262	-0.1499	0.2854	0.0159	-0.1413	0.0058	-0.5086	-0.0984	0.0886
		(0.1411)	(0.12)	(0.1016)	(0.065)	(0.0881)	(0.0567)	(0.073)	(0.0302)	(0.0941)	(0.0904)	(0.0482)
Black (non-Hispanic)	0.2913	0.749	1.123	0.216	-0.3445	0.1578	-0.0441	-0.2289	0.0593	-0.2752	0.2292	0.1109
		(0.1634)	(0.1391)	(0.1168)	(0.0754)	(0.0962)	(0.0657)	(0.0804)	(0.0342)	(0.1063)	(0.0999)	(0.0546)
Hispanic	0.1631	0.6545	0.6253	0.491	-0.0523	0.1404	-0.0052	-0.057	0.0212	-0.1827	0.0194	-0.0647
		(0.1658)	(0.1399)	(0.1175)	(0.0784)	(0.1023)	(0.0669)	(0.0835)	(0.0361)	(0.1118)	(0.1054)	(0.0561)
Any children	0.3858	-0.5163	-0.2325	-0.2735	-0.4141	-0.2019	0.183	0.1473	-0.0319	0.055	0.1484	0.0643
		(0.1134)	(0.0975)	(0.0813)	(0.0522)	(0.0619)	(0.0456)	(0.0536)	(0.0236)	(0.0641)	(0.0682)	(0.0383)
Joint filers	0.2002	-0.491	-0.4005	-0.287	-0.1498	-0.0927	0.0823	0.1537	0.0122	0.1163	-0.0429	-0.0475
		(0.1031)	(0.0888)	(0.0743)	(0.0474)	(0.0593)	(0.0414)	(0.0512)	(0.0217)	(0.06)	(0.0643)	(0.036)
Any seniors	0.154	-0.4545	-0.2227	-0.2774	-0.4437	-0.0516	0.2126	0.1031	-0.082	-0.0256	0.1359	-0.0589
		(0.1395)	(0.1204)	(0.1003)	(0.0612)	(0.0735)	(0.0554)	(0.0646)	(0.0287)	(0.0744)	(0.0802)	(0.0458)
Has voucher	0.0625	-0.2629	-0.0616	-0.1328	-0.0703	-0.0772	0.153	-0.1277	-0.0549	-0.0432	0.1352	0.1907
		(0.2136)	(0.1837)	(0.1521)	(0.099)	(0.1037)	(0.0869)	(0.0892)	(0.0408)	(0.1173)	(0.1202)	(0.0668)
Linear proj. on bins												
Income years [-3,0)	45150	-0.0821	-0.0568	-0.0338	0.0046	0.0087	-0.0006	0.0022	0.0063	0.0026	0.0257	-0.0145
# of persons	2.352	0.1531	0.0455	0.0563	0.0529	-0.0113	-0.0576	-0.0343	-0.0061	0.0119	-0.0522	0.0125

Notes: This table documents the estimated preference parameters for neighborhood characteristics. Because we recenter **w** to be mean-zero for estimation, each coefficient in the table corresponds to the change in value relative to the average household. As such, computing the equivalent value as if we instead included each characteristic as a binary indicator requires using the difference between the indicator and the average value in the population reported in the first column (i.e., a white (non-Hispanic) household would be 'above average' in that characteristic, but below average in the Black (non-Hispanic) and Hispanic characteristics; computing the total effect requires summing across the three values). Finally, while we estimate the model using nine income bins and four bins of household size, for exposition, we project the estimated coefficients for each bin on the midpoints of each bin (after adjusting to be as if they were estimated as indicators) and report the linear coefficient. Standard errors are reported in parentheses.

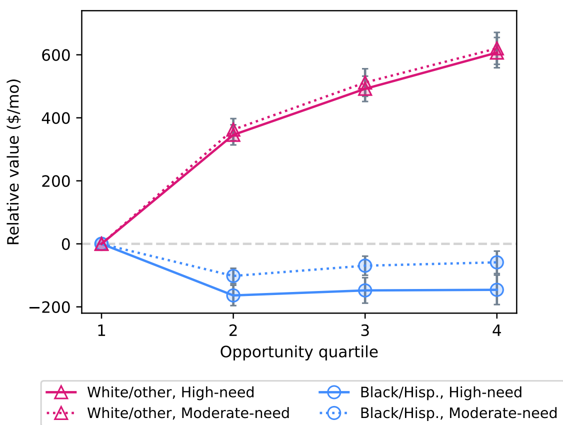
Table D.14: Tenant characteristics: for-profit and non-profit developments

	Chicago MSA		50 Sample MSAs	
	For-profit	Non-profit	For-profit	Non-profit
Adjusted Gross Income (AGI)	12320	13810	14960	14310
	(130.2)	(400.2)	(28.28)	(103)
Avg. AGI in years [-3, 0)	12890	14500	14580	13880
	(156.1)	(480.2)	(33.43)	(122.4)
Predicted future income rank	0.2519	0.2406	0.2419	0.2332
	(0.002)	(0.0055)	(0.0004)	(0.0012)
Graduated college*	-	-	0.1017	0.1153
			(0.0029)	(0.012)
Childhood family income rank*	0.3063	0.2509	0.3241	0.3105
	(0.0041)	(0.0105)	(0.0008)	(0.0029)
Black (non-Hispanic)*	0.5695	0.5936	0.4394	0.4178
	(0.0052)	(0.0158)	(0.0011)	(0.004)
Hispanic*	0.0926	0.1055	0.2026	0.2291
	(0.003)	(0.0099)	(0.0009)	(0.0034)
White (non-Hispanic)*	0.3002	0.2813	0.2984	0.2919
	(0.0048)	(0.0145)	(0.001)	(0.0037)
Household has children	0.3421	0.3514	0.4247	0.4131
	(0.0047)	(0.0144)	(0.001)	(0.0036)

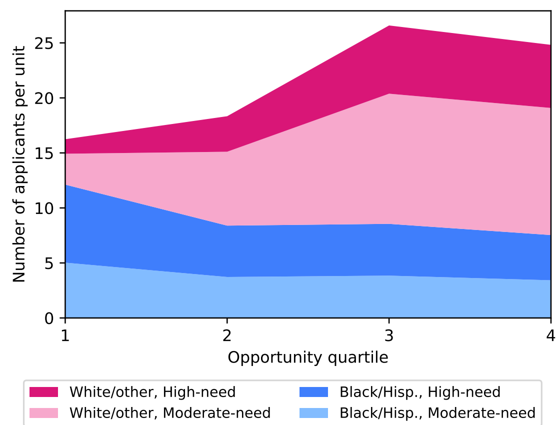
Notes: This table presents average household characteristics for tenants of for-profit and non-profit developments at the time of move-in for the full sample of LIHTC households in the Census-IRS panel. Characteristics with an asterisk (*) are defined for the household head. To account for differences in the relative sample sizes in each MSA, each statistic is computed within-MSA first, then across MSAs weighted by population. The statistics for college education are suppressed for Chicago as the "with college" sample size is below the minimum required for disclosure from the Census. Standard errors of the means are presented in parentheses.

Figure D.7: Applications and ex-post value

(a) Ex-post value for recipients ($/month)



(b) Simulated number of applications



Notes: This figure documents the simulated number of applications and the ex-post value of receiving a unit. Each point is the average for a simulated development built in each PUMA in the corresponding quartile. The values are plotted relative to the average value for each group of the average development built in the lowest quartile. Gray bars represent 95% confidence intervals from bootstrapped standard errors.

Table D.15: Household characteristics by opportunity (model-predicted)

	Quartile of neighborhood opportunity			
	Q1	Q2	Q3	Q4
Avg. AGI in years [-3, 0)	11410	11830	11970	11930
	(2538)	(2503)	(2488)	(2484)
Household has children (<18yo)	0.319	0.2596	0.2483	0.2498
	(0.0117)	(0.0121)	(0.0124)	(0.0127)
Household head graduated college	0.1455	0.1959	0.2097	0.2197
	(0.0159)	(0.0124)	(0.0116)	(0.0111)

Notes: This table documents the characteristics of households in a simulated new affordable housing development, split by the quartile of neighborhood opportunity in which the development is sited. Bootstrapped standard errors are reported in parentheses.

Table D.16: Comparison of counterfactuals: additional household characteristics

	Income at move-in		Frac. w/ children		Frac. high-need	
	Q1	Q1→Q4	Q1	Q1→Q4	Q1	Q1→Q4
Baseline						
60% AMI	\$11,410	+\$521.6	0.319	-0.0692	0.4968	-0.114
	(2538)	(170.8)	(0.0117)	(0.008)	(0.0204)	(0.0104)
HHs and developers						
No $\boldsymbol{\alpha}$ heterog. ($\boldsymbol{\alpha} = \mathbf{0}$)	\$12,990	+\$550.1	0.2681	-0.063	0.4418	-0.0934
	(2461)	(195.7)	(0.0082)	(0.0074)	(0.0197)	(0.0096)
Fair lottery ($\boldsymbol{\phi} = \mathbf{0}$)	\$10,990	+\$550.2	0.3017	-0.0631	0.4962	-0.1109
	(2612)	(193.3)	(0.0124)	(0.0077)	(0.0242)	(0.0116)
Alternative policies						
30% AMI	\$6,634	+\$527.1	0.2582	-0.047	0.6321	-0.1185
	(2677)	(134.5)	(0.0124)	(0.0074)	(0.0283)	(0.0122)
Income-based rents	\$10,700	+\$548.8	0.3047	-0.0611	0.5082	-0.1134
	(2582)	(166.7)	(0.0116)	(0.0076)	(0.021)	(0.0102)
Local preferences	\$10,760	+\$511.6	0.3088	-0.0643	0.5374	-0.1837
	(2638)	(278.8)	(0.0116)	(0.01)	(0.0228)	(0.0167)

Notes: This table extends Table 3 to additional household characteristics. 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 require that at least 50% of new tenants come from the surrounding neighborhood. 'High-need' is defined as having predicted future income in the bottom quartile of renters, adjusted for age and household size. Bootstrapped standard errors are reported in parentheses.