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

Cody Cook†
Job Market Paper

Pearl Z. Li‡

Ariel J. Binder§

January 1, 2024

(Click here for latest version)

Abstract

How does the location of affordable housing affect tenant welfare, the distribution of assistance, and broader social objectives such as racial and economic integration? Using administrative data on households living in units funded by the Low-Income Housing Tax Credit (LIHTC), we first show that tenant characteristics such as income, race, and education vary widely across neighborhoods, despite common eligibility thresholds. To quantify the welfare implications, we develop and estimate a residential choice model in which households choose from both market-rate and affordable housing options, where the latter must be rationed. Using the estimated model, we show that moving a new development to a more opportunity-rich neighborhood increases aggregate tenant welfare and reduces both racial and economic segregation, but is also more costly and disproportionately benefits more moderate-need, non-Black/Hispanic households. This change in the distribution of assistance arises in part because of the rationing: households that only apply for assistance in opportunity-rich neighborhoods crowd out other households willing to apply anywhere. Relative to the initial choice of location, other policy levers—such as lowering the eligibility thresholds—have limited effects.

*We are grateful to our advisors Lanier Benkard, Rebecca Diamond, Liran Einav, Matthew Gentzkow, Paul Oyer, and Paulo Somaini for their guidance and support throughout the project. We are also thankful for feedback from Claudia Allende, Nick Bloom, Bharat Chandar, Ignacio Cuesta, Denise DiPasquale, Ingrid Gould Ellen, Ed Glaeser, Zane Kashner, John List, Neale Mahoney, Kate Pennington, Peter Reiss, Winnie van Dijk, Shosh Vasserman, John Voorheis, Ali Yurukoglu, and many seminar participants. Any opinions and conclusions expressed herein are those of the authors and do not reflect the views of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance of the confidential source data (Project #7529092, CBDRB-FY2023-CES010-017, CBDRB-FY2023-CES023-006, and CBDRB-FY24-CES014-012). This research was supported by the George P. Shultz Dissertation Support Fund at the Stanford Institute for Economic Policy Research.

†Stanford GSB. Corresponding author. Contact: codycook@stanford.edu

‡Stanford University. Contact: pearlzli@stanford.edu

§US Census Bureau. Contact: ariel.j.binder@census.gov

1 Introduction

Central to many programs that provide affordable housing to low-income households is a choice of where to build. While early programs such as public housing often built developments in historically 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, affordable housing policy has prioritized providing housing in areas with lower poverty rates, greater economic opportunity, and less racial segregation. Initiatives in this vein include local 'inclusionary zoning' laws requiring that new market-rate developments set aside units for low-income households, state policies requiring that each municipality builds its '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 of the development 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 is less likely to have positive spillovers on the surrounding neighborhood (Diamond and McQuade, 2019). One tradeoff that has received less attention is that *where* affordable housing is built can affect *who* receives 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 residential choice 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 and city-wide integration. Finally, we compare the effects of changing the location of affordable housing

[1] See Turner, Popkin and Rawlings (2009) for a history of early programs. 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.2.

[2] This quote is taken from the Department of Housing and Urban Development (HUD) page on Affirmatively Furthering Fair Housing (source). The secretary of HUD, Marcia Fudge, recently 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" (source). New York City, San Francisco, and other major cities have announced affordable housing plans that "ensure diverse and inclusive neighborhoods."

to other policy levers, such as lowering the income limits used for means-testing.

We build a panel of households living in LIHTC and market-rate rental units by combining data on individual tax records, residential addresses, and Census survey responses for the universe of US residents. For each household, we observe their annual income, race, ethnicity, household structure, and childhood family income (i.e., how well-off each individual's parents were when they were growing up). To proxy for underlying need, we estimate each household's future income based on characteristics observed prior to moving into affordable housing. For housing units, we observe the rent, characteristics of the unit and neighborhood, and, for LIHTC units, the income limit. While we do not observe applications for LIHTC units, we can identify the population of eligible households and observe which households receive a unit. Our primary sample covers households in the 50 most populous metro areas between 2010 and 2018.

We begin by documenting that the characteristics of affordable housing tenants vary widely across neighborhoods, even though the rent and income limits are constant within a city. While the *average* household living in a LIHTC unit exhibits greater need and is more likely Black than other eligible households, the differences are attenuated—and sometimes reversed—for developments built in opportunity-rich neighborhoods. To classify neighborhoods, we define an index of neighborhood opportunity that combines measures of school quality, jobs access, transit access, poverty, and upward mobility. 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 within households with similar incomes at move-in—the characteristic used for means-testing—in part because current income is far less correlated with race, education, and even future income 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 decisions, 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 household 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 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. The key intuition is that household 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, 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 in which neighborhood they are placed. We find that tenant welfare is increasing in the level of neighborhood opportunity. However, the increase in the cost of providing affordable housing in more opportunity-rich neighborhoods exceeds the increase in tenant welfare. To measure costs, we estimate the opportunity cost of setting aside a housing unit for the LIHTC program rather than renting it out as a market-rate unit. We use a hedonic regression to predict the market value of each unit, then define the 'implicit subsidy' as the gap between the LIHTC rent and the estimated market value. The estimated implicit subsidy increases from \$213 per month (18% discount off of market-rate) in the bottom quartile of neighborhood opportunity to \$671 per month (41% discount) in the top quartile. Tenant welfare, meanwhile, increases by a more modest \$151 per month for a new unit built in the top instead of bottom quartile.

However, the benefits 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. The total household surplus for Black and Hispanic households \$273 per month *less* for a unit built in the top instead of bottom quartile of neighborhood opportunity, primarily due to lower odds of being allocated a unit rather than lower ex-post value of receiving a unit. Many moderate-need and White (non-Hispanic) households *only* apply to affordable housing built in high-opportunity neighborhoods, which—because units are rationed—crowds out other 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 in opportunity-rich neighborhoods (DeLuca, Wood and Rosenblatt, 2019; Bergman et al., 2023).

Turning to other considerations that may enter the social planner's objective, we evaluate the effects of location on segregation, lifetime earnings of children, and spillovers on neighbors. First, we show that affordable housing in high-opportunity neighborhoods reduces racial/ethnic and economic residential segregation, although changes in the composition of tenants across neighborhoods dampen the magnitude. 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 about half and the effects on economic integration by about a quarter. This creates a nuanced tradeoff for policymakers: while providing affordable housing in higher-opportunity neighborhoods reduces city-wide racial/ethnic segregation, it also leads to fewer minority households in affordable housing.[3] Second, we use estimates from the Opportunity Atlas (Chetty et al., 2022) to assess the impact on lifetime earnings for children living in the development, which may not be fully internalized in our measure of household surplus. On net, we estimate that the average new LIHTC unit in the top quartile of neighborhood opportunity would increase the discounted lifetime earnings of children living within by +\$266 per month more than a unit in the bottom quartile (or +\$132,000 per child). Finally, we use estimates from Diamond and McQuade (2019) on the heterogeneous effects of a new LIHTC development on neighbors 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 of neighborhood opportunity, or −\$203 per unit-month if amortized over 15 years at a 3% discount rate.

Relative to the initial choice of location, many policy levers available post-construction have only modest effects on racial/economic integration and the distribution of assistance. We simulate four potential policy changes: lower income limits, income-based rents, fair lotteries, and priority for local residents. 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. Using a fair lottery to ration units (i.e., removing any influence of developers) lowers the average income of residents by only 4%, with similarly small effects on other margins. Finally, giving priority for half of the units 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 in a development, which further reduces the potential to promote integration.

Our results contribute to several literatures in public and urban economics. A large body of work has studied the tradeoffs associated with place-based affordable housing programs, including the potential effects on the surrounding neighborhood (Baum-Snow, 2007; Diamond and McQuade, 2019), crowding out of market-rate construction (Sinai and Waldfogel, 2005; Eriksen and Rosenthal, 2010; Soltas, 2023), and the potential for affordable housing to perpetuate segregation (McClure, 2006; Ellen, O'Regan and Voicu, 2009; Freedman and McGavock, 2015; Ellen, Horn and O'Regan, 2016; Ellen, Horn and Kuai, 2018; Davis, Gregory and Hartley, 2023). We build on this work by showing that the choice of location is also implicitly a choice of tenants, which in turn affects

[3] While outside the scope of this paper, general equilibrium re-sorting after a new development enters may amplify the partial equilibrium effects estimated here (Davis, Gregory and Hartley, 2023; Almagro, Chyn and Stuart, 2023).

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

Other work has quantified the benefits for households of 'moving to opportunity,' 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).[4] The evidence on neighborhood effects has led to interest among policymakers in programs that encourage voluntary moves to opportunity by low-income households. However, providing low-income households with rental vouchers rarely leads to such moves without additional interventions (Lens, Ellen and O'Regan, 2011; Collinson and Ganong, 2018; Bergman et al., 2023). Similarly, we find that changing the location of affordable housing alone is unlikely to 'pull' households to higher-opportunity neighborhoods, partly because of crowding out in the rationing process.

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 (Nichols and Zeckhauser, 1982; Currie and Gahvari, 2008).[5] Our setting introduces two wrinkles to this literature. First, whether an eligible household receives affordable housing depends not only on their own take-up decision, but also on the decisions of other households and the mechanism used to ration units. Second, while the government sets income limits, the residual rights of control when allocating 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 intermediaries with misaligned incentives may lead to 'slippage' of resources (Olken, 2006, 2007; Basurto, Dupas and Robinson, 2020). In our case, we find that developers favor higher-income applicants when allocating units.

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; Fu and Gregory, 2019; Couture et al., 2023). 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. While the mechanisms used to ration affordable housing have often been studied in theory, few empirical applications exist.[6] One notable exception is Waldinger (2021), which uses applications for public housing in Cambridge to quantify the tradeoff between providing better matches and targeting applicants with the greatest need. To separate household preferences from the mechanism for rationing units *without* seeing applications, we combine information on how similar households make decisions in the market-rate sector with data on moves in and out of affordable housing developments.

[4] See, also, Wilson (1987); Jencks and Mayer (1989); Brooks-Gunn et al. (1993); Rosenbaum (1995); Currie and Yelowitz (2000); Katz, Kling and Liebman (2001); Oreopoulos (2003); Sharkey and Faber (2014); Chetty and Hendren (2018); van Dijk (2019); Chyn (2018); Derby (2019).

[5] In-kind transfers can improve targeting if demand is positively correlated with unobserved need (Nichols and Zeckhauser, 1982; Blackorby and Donaldson, 1988; Besley and Coate, 1991; Kleven and Kopczuk, 2011), but may *worsen* targeting if the ordeals disproportionately deter those with the greatest need (Bertrand, Mullainathan and Shafir, 2004; Mullainathan and Shafir, 2013). Empirical applications have found that which effect dominates varies across settings (Alatas et al., 2019; Finkelstein and Notowidigdo, 2019; Deshpande and Li, 2019).

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

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), which is both the largest and fastest-growing source of affordable housing in the US, exceeding both public housing at its peak and tenant-based housing voucher programs (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 (~7% of the rental housing stock), 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. Tax credits are awarded through a competitive application process. Each state is allocated a per-capita budget, then reviews applications from developers and scores them according to a Qualified Allocation Plan (QAP). States have significant latitude in determining the scoring criteria for their QAP. Common criteria include points for onsite amenities, cost-effectiveness, and features of the neighborhood. Unlike programs such as inclusionary zoning, the vast majority of LIHTC developments include only affordable units. While we will abstract away from many of the supply-side details in this paper, we describe them in greater detail in Appendix Section A.1.

There is some tension between the neighborhoods targeted by the federal legislation and how states choose to implement the legislation. At the federal level, the LIHTC program requires that states award an additional 30% of tax credits to developments built in areas with high poverty rates or a high percentage of low-income households ('Qualified Census Tracts'). At the state level, however, as of 2018 there are 29 states that award points for building in explicitly defined 'opportunity' areas, and 20 other states that use 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 changed where developers build new LIHTC developments (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).

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. To measure household income, developers collect recent pay stubs, bank statements, and reported earnings from assets or other sources and then extrapolate to infer anticipated annual income. Often, developers rely on third-party verification services to validate employment earnings. Developments are periodically audited for compliance; any violation can result in lost tax credits.

Rent and income limits are set 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.[7] 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; for example, a 2-bedroom unit is rented at 30% of the income limit for a 3-person household (even if rented to a 2-person household). In 2019, the 60% AMI income limits for a 3-person household in a 2-bedroom unit in the 50 Metropolitan Statistical Areas (MSAs) in our sample ranged from $26,760 in parts of the Memphis MSA (monthly rent of $669) to $87,060 in the San Francisco-Oakland-Berkeley MSA (monthly rent of $2176). Households can remain in their unit even if their income grows to exceed the limit.

Demand for units generally far exceeds supply, so units must be rationed. The processes used to ration vacant units vary both across cities and developers. For instance, New York City and San Francisco use online platforms to run lotteries for new units, often receiving many thousand applications per unit (Haag, 2020). Other cities leave it up to developers to allocate open 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. In informal interviews with developers, the most commonly cited concern is an applicant's ability to pay rent.

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 dataset covering renter households in both market-rate and LIHTC units. This section describes our primary data sources,

[7] 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 Clarke (2009) and Stagg (2018). The most commonly applied exceptions are HUD's Hold Harmless rule, which allows properties to hold rents constant even if AMI declines year-to-year, and a provision of the Housing and Economic Recovery Act (HERA) of 2008 that allowed properties to start increasing rents as AMIs increased, without waiting for them to reach their pre-Recession levels.

the samples used for analyses, and definitions and summary statistics for the main variables used throughout. Appendix Section B contains additional details.

3.1 Data sources

Tax and migration records. We combine administrative data on individual tax records, decennial Census responses, and migration histories 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; the full process for identifying individuals is described in Wagner and Lane (2014). The tax records cover income tax returns (e.g., 1040 forms) and third-party information returns (e.g., W-2 forms). The tax returns data are available for 1994-1995 and 1998-2019, and information returns are available starting in 2005.

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 be used to link records across different data sources.

American Community Survey. We supplement the baseline panel of individuals 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 each individual's educational attainment, which we use to augment our baseline panel.

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.[8] 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.[9]

[8] 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.

[9] While the earliest LIHTC properties date back to 1987, many of these properties were no longer in service as an affordable development by 2018. LIHTC is a decentralized program and data collection relies on property managers reporting accurate data. Some properties reported addresses that were either poorly formatted or lacking

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.[10] 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 unique address identifiers. We then assemble individuals living in a development into households using a combination of spousal, claimer-dependent, and shared address relationships; we describe this process in Appendix Section B.2. Most analyses 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 renter household as living in a market-rate unit if it is not in a LIHTC unit or any HUD-assisted housing unit (e.g., public housing or project-based Section 8). The sample includes households that use a housing voucher to pay for rent, which we can observe using a register of voucher recipients from HUD. 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 main samples.

3.3 Variable definitions and summary statistics

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

Household income and LIHTC eligibility. We define household income as the sum of Adjusted Gross Income (AGI) for all household members.[11] 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.

unit numbers such that they could not be linked by Census staff to MAFIDs; in Table B1, we provide a balance table of development and neighborhood characteristics for properties in-sample and out-of-sample.

[10] A handful of MSAs have insufficient coverage of the 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.

[11] Income for joint filers is divided equally between the two individuals so that their income is not double-counted.

[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. Bee et al. (2023) discuss some issues with measuring income for low-income households in more depth.

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 the claimer or claimers ('parents') when an individual was under 18 years old. We follow Chetty et al. (2022) and identify parents based on the first tax return for which someone is claimed as a dependent. Household income is coded as zero in years where the parents do not file a tax return.[13] We then measure an individual's rank in their birth cohort's nationwide parental income distribution. 1994 is the first year we can observe claimer-dependent relationships, so the earliest birth cohort for which we can measure CFI is 1978. Using ranks rather than levels helps account for mechanical changes in CFI across cohorts; for example, in earlier cohorts we observe parents' household income only when the child is nearly 18 years old, while for later cohorts we observe household income across a longer period.

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 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 in the household 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 for each household. We proxy for marital status using whether the head of household files jointly with a spouse in a given year. We define a household as containing children if the household head has any dependents under 18 or, in the case of non-filers, if we observe an individual living at the address under 18 years old. We define a household as containing seniors if we observe an individual over 64 years old in the household.

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. For LIHTC households, we use characteristics *prior* to move in. We then construct future income ranks by adjusting predicted future income by household size using an equivalence scale and ranking each household within the distribution of renter households in our sample MSAs. We

[13] W-2 forms are not available before 2005, so we cannot use information returns as an alternative measure of income for non-filers.

rank each household within 5-year age bins (based on the head of household's age) to account for life-cycle differences in earnings. Appendix Section B.5 provides additional details.

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.

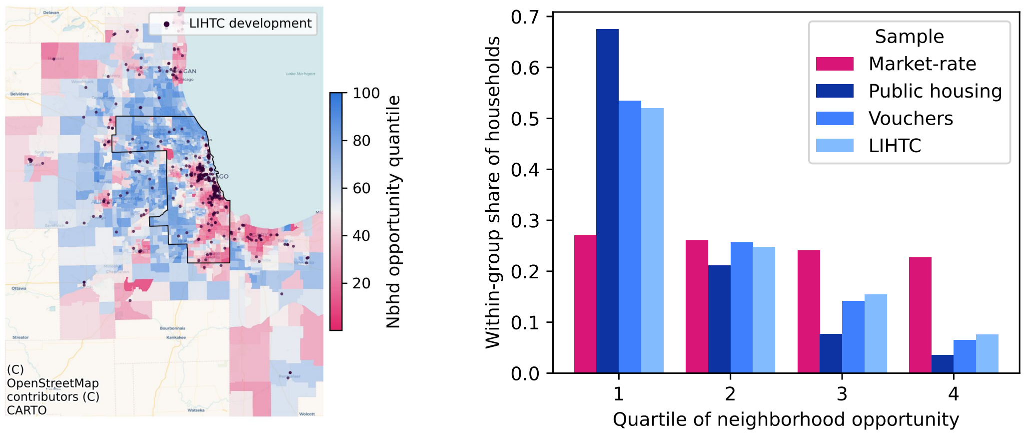
Rent. For each LIHTC unit, we compute the rent based on the unit's income limit and number of bedrooms. The regulated rent ceiling for LIHTC units includes the cost of utilities such as electricity, gas, water, and sewage; in cases where the tenant pays for utilities, the developer must compute a 'utility allowance' that is deducted from the monthly rent they collect. In rare cases, developers may price a vacant unit below the rent ceiling if they are otherwise unable to fill the unit. For market-rate units, we use the gross rent reported to the ACS, which 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." To create the index, we combine five neighborhood characteristics commonly used by policymakers. The first four statistics are indices of job access, school proficiency, transit access, and poverty from the Affirmatively Furthering Fair Housing Tool (AFFH-T) published by HUD. These data are intended to help local jurisdictions assess the state of fair housing in their communities. The final statistic is a measure of 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 of each of the five inputs and then computing where each neighborhood falls in the within-MSA 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, land prices, and housing occupancy rates (Figure 1).

Figure 1 Panel (a) plots a map of neighborhood opportunity in Chicago, overlaid with the location 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 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

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. We identify whether a household lives in public housing or has a voucher in the year surveyed by linking the ACS to HUD PICTRACS.

households with vouchers. A similar pattern exists if we instead divide neighborhoods by their median household income or the share of residents who are White (Figure B.2).

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 living 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. In terms of family structure, LIHTC households are more likely to have children and less likely to have a married couple. LIHTC households also move further from their past neighborhood and come from areas with lower opportunity, lower income, and fewer White (non-Hispanic) residents.[14] The gaps are magnified if we compare LIHTC households to other households that also recently moved.

4 Who lives in affordable housing?

In this section, we describe the characteristics of affordable housing along two dimensions: average differences between LIHTC households and eligible households living in market-rate units and differences in LIHTC household characteristics across levels of neighborhood opportunity. On average, households living in LIHTC developments are less likely to have a White (non-Hispanic) household

[14]Households living in LIHTC are disproportionately likely to receive assistance from housing vouchers, food stamps, Supplemental Security Income, and other government assistance programs (Table D1).

Table 1: Market-rate and LIHTC household characteristics

	Market-rate			LIHTC
	All	LIHTC-eligible	LIHTC-eligible movers	At move-in
Financials and education				
Current 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 (within-MSA moves)*	6.234	5.797	6.290	6.955
Prev. tract opportunity percentile*	0.473	0.409	0.425	0.329
Prev. tract median household income*	$58,160	$53,150	$54,310	$46,990
Prev. tract frac. white (non-Hispanic)*	0.628	0.586	0.601	0.512
N	2495000	1014000	357000	512000

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. Childhood family income is only available if the household head was claimed as a dependent in 1994-1995 or 1998-2005. To account for differences in the relative sample sizes in each MSA, each statistic is computed within-MSA first, then across MSAs, weighting by the total population.

head and exhibit greater levels of need. However, compared to other LIHTC developments, those in high-opportunity neighborhoods house tenants who exhibit lower levels of need and who are more likely to have a White (non-Hispanic) household head, despite having the same rent and income limits as developments in other parts of the city.

4.1 Average differences in who receives LIHTC

We investigate who receives a LIHTC unit by comparing the characteristics of LIHTC recipients to income-eligible households who do not live in LIHTC in each of 50 most populous MSAs.[15] We

[15]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

focus on a subset of household characteristics from Table 1 that relate to potential goals such as racial/ethnic integration and targeting assistance based on need.

To compare LIHTC households to other eligible households, 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 living in a market-rate unit observed in the ACS. The results are documented in Figures 2 and the raw coefficients are reported in Table D2. Table D2 documents differences by additional characteristics, including family structure and the characteristics of a household's previous neighborhoods.

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). The difference between LIHTC households and other eligible households in income at the time of move-in is only 8%. However, larger differences arise in characteristics that are 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, and has a household head that grew up in a family that was 11 percentiles (26%) lower in the parental income distribution for their birth cohort. To form a single proxy for need, we combine many characteristics observed before move-in to estimate predicted future income rank. The average LIHTC household is 8 percentiles (26%) lower in the distribution of predicted future income than the average eligible household living in a market-rate unit. Similar gaps arise in other characteristics; for example, LIHTC households are 3% more likely to have a child, 36% less likely to include a married couple, and moved from a tract that was 8 percentiles (20%) lower in the distribution of neighborhood opportunity (Table D2).

There are also large differences in the racial/ethnic composition of LIHTC households compared to that of other eligible households. The average LIHTC household is 69% more likely to be Black (non-Hispanic) than LIHTC-eligible household heads in market-rate units. This stark difference comes with a commensurate reduction in the share of households with a White (non-Hispanic) household head. In contrast, the share of Hispanic household heads is similar in the two populations. These significant gaps by race echo the disproportionate representation of Black households in public housing in earlier decades (Massey and Denton, 1998).

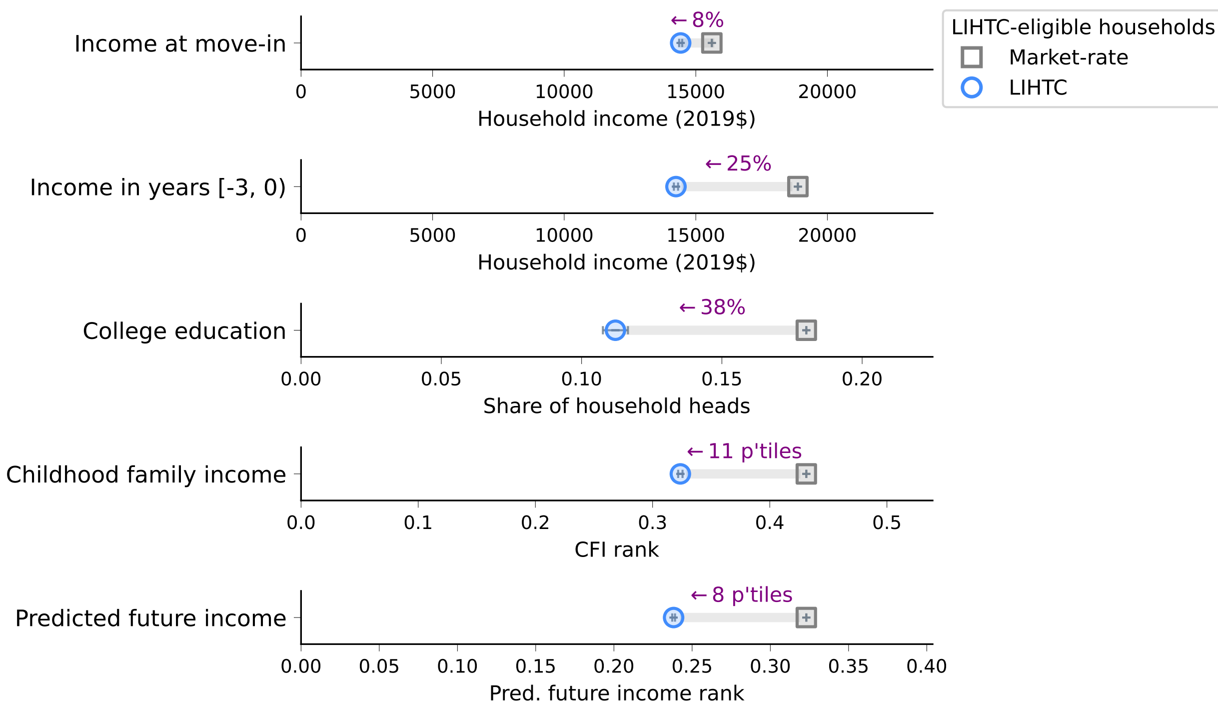
4.2 Differences in LIHTC household characteristics across neighborhoods

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

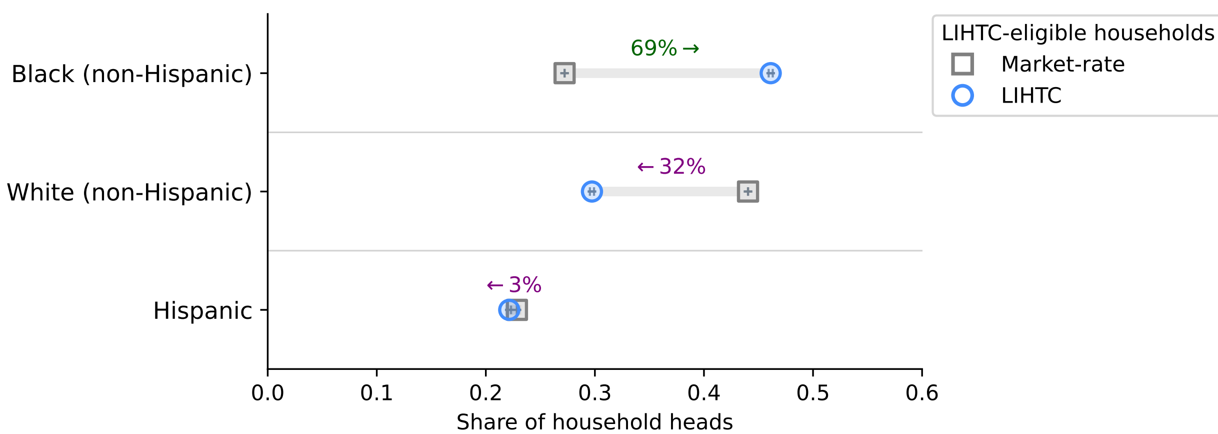
use lower income limits (e.g., 50% AMI), the results are similar if we restrict the sample to just 60% AMI units.

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 based on 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 constructed using the Census-IRS panel (2010-2018, 50 sample MSAs). 95% confidence intervals are represented by gray bars.

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 D4, D5, D7, and D8.

Proxies for a household's level of need—especially those not used for means-testing—are decreasing in neighborhood opportunity. These differences arise despite fixed rent and income limits across different neighborhoods within a city.[16] Relative to LIHTC developments in the bottom quartile of neighborhood 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. In contrast, average income at the time of move-in is relatively flat across neighborhoods, increasing by only 3% from the bottom to top quartile of neighborhood opportunity. In Table D4, we show that LIHTC households in higher-opportunity neighborhoods are also less likely to have children, more likely to include a married couple, move from further away, and come from tracts that are higher opportunity.[17]

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 have a Black or Hispanic head of household, compared to just 39% in the top quartile. White (non-Hispanic) households, in contrast, 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; 61% of market-rate households in the bottom quartile of opportunity have a Black or Hispanic head of household compared to just 21% in the top quartile (Table D7). The magnitude of these differences in LIHTC household characteristics across levels of neighborhood opportunity is large enough to reverse the direction of the differences between the average LIHTC household and the average eligible household – while LIHTC households are more likely to be Black or Hispanic than the average eligible household, households living in developments in the top quartile are *less* likely to be Black or Hispanic.

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

[16] LIHTC rent regulations set a maximum rent, but developers may price below the maximum if there is insufficient demand. Figure D.4 documents that the gross rent reported to the ACS by LIHTC households is slightly increasing in neighborhood opportunity, although this could be due to misreporting. In the sample of LIHTC households surveyed by the ACS, adding controls for reported gross rent has little effect on the patterns documented in this section (see Figure D.4).

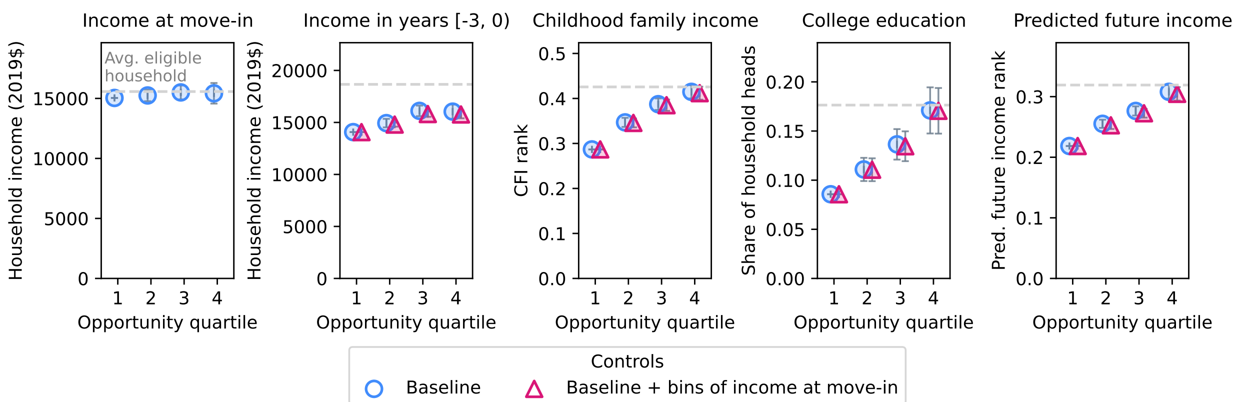
[17] In Table D6, we explore whether these patterns across levels of neighborhood opportunity can be explained by specific characteristics of the neighborhood, such as the median household income or the race/ethnicity of other residents. Adding controls for bins of the share of neighborhood residents who are 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.

are much weaker once we condition on being eligible for LIHTC, which restricts attention to the left-tail of the income distribution (Table D3). For example, the correlation between current income and childhood family income drops from 0.27 in the overall population to 0.04 in the LIHTC-eligible population. Similarly, while White (non-Hispanic) households earn nearly 75% more than Black (non-Hispanic) households in the general population, the racial income gap completely disappears within the LIHTC-eligible population. Even the correlation between current income and income in the three preceding years drops from 0.87 for all renters to 0.58 for LIHTC-eligible renters.

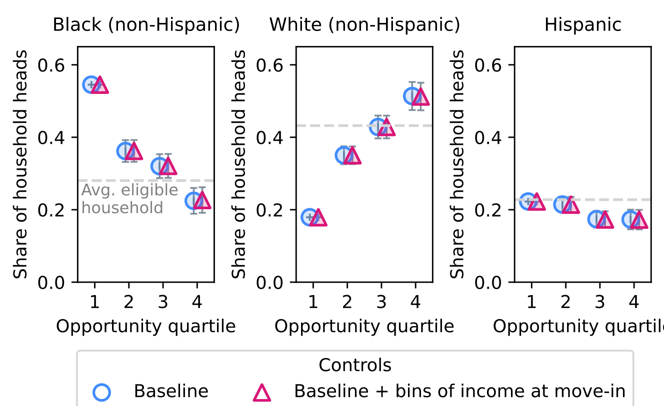
Differences in the LIHTC population across neighborhoods can stem from both household preferences (i.e., who applies for assistance) as well as the process used to ration units among applicants. To help disentangle the role of these two forces, we next build a structural residential choice model with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

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 residential choice 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 developers.

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 $\mathcal{J}^{\text{AH}}$ and market-rate options $\mathcal{J}^{\text{MR}}$. Each housing option $j \in \mathcal{J}$ is a tuple of neighborhood, number of bedrooms, building type (single-family, small apartment building, and large apartment building), and an income limit, where the income limit for market-rate units is infinite. The supply of units of each option is denoted s_j and is taken as exogenous. Options outside the metropolitan area are included as a single outside option in $\mathcal{J}^{\text{MR}}$ 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. In the data, we observe each household's choice in a given year and where they lived the year prior (j_i^0). We include as household characteristics bins of average income in the three years prior, indicators for household size, race/ethnicity, presence of children, presence of seniors, presence of a married couple, and whether the household has a housing voucher. Based on their current income and household size, a household may be eligible to apply for a subset of affordable housing options, $\mathcal{J}_i^{\text{AH}} \subseteq \mathcal{J}^{\text{AH}}$.

Household i receives the following indirect utility from option j:

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

where $\mathbf{x}_j$ is a vector of housing and neighborhood characteristics, 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. The housing and neighborhood characteristics 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 parks nearby from OpenStreetMaps.[18]

[18] We treat neighborhood characteristics as exogenous throughout the paper. In the case of racial/ethnic shares, this assumption implies that preferences for living in neighborhoods with large same-race/ethnicity shares are driven by correlated preferences for neighborhood characteristics that are proxied for by the racial/ethnic shares rather than for the identity of one's neighbors directly ('homophily'). Recent empirical evidence on the underlying cause of same-race/ethnicity preferences is mixed, with some papers finding that these preferences primarily reflect sorting on unobserved neighborhood amenities (Caetano and Maheshri, 2021) and others contending that they are primarily due to homophily (Bayer et al., 2022; Davis, Gregory and Hartley, 2023).

This formulation deviates from the canonical residential choice model presented in Bayer, Ferreira and McMillan (2007) in two ways. First, we incorporate adjustment costs (κ_i) incurred for households selecting any option other than their endowed choice. This allows the model to generate realistic move-out rates, which will be an important empirical moment for estimating preferences specific to affordable housing. Second, we add a single parameter that captures the difference in utility associated with affordable housing, conditional on other characteristics (α_i). The difference could stem, for example, from unobserved differences in the average quality of market-rate and affordable housing options or any hassle or stigma associated with affordable housing.

Heterogeneity in α_i is a key determinant of the targeting properties of affordable housing. If the value of affordable housing is positively correlated with household need, then those with greater need will be more likely to apply for assistance (Nichols and Zeckhauser, 1982; Alatas et al., 2016). In contrast, if the utility is negatively correlated with need, then affordable housing will disproportionately attract tenants with lower levels of need. For example, this could be the case if those with the greatest need have limited bandwidth for overcoming the barriers associated with taking up assistance (Mullainathan and Shafir, 2013). Moreover, the relative scale of α_i and its correlation with preferences for housing and neighborhood characteristics $\boldsymbol{\gamma}_i$ will affect how much demand for affordable housing varies based on location. At one extreme, if heterogeneity in the utility of affordable housing far exceeds heterogeneity in preferences for neighborhood characteristics, then changes to the location of an affordable development will have little impact on who takes up assistance.

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 of i choosing $j \in \mathcal{J}^{MR}$ is given by the usual logit formulation from 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 whether to apply to each affordable housing option, 2) developers make offers to applicants, and 3) households accept a single offer. In our model, the only situation in which a household would apply for a development but not accept an offer is if they receive multiple offers. Without a price mechanism to equilibrate supply and demand, the offer probabilities must adjust in equilibrium to clear the market.

Households decide whether to apply for each affordable housing option based on their preferences for the housing and neighborhood characteristics of their affordable housing option compared to their preferences for other options in the city. We assume households can apply for affordable housing developments without cost—beyond those captured by α_i—such that household i will apply to an affordable option $j \in \mathcal{J}^{\mathrm{AH}}$ if they prefer it to their current housing and best market-rate option. Households can apply to multiple affordable housing options, and each application decision is made independently. The probability household i applies to option j is given by

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

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

We can compute the expected number of applications for development j that would come from a subset of households (e.g., households in a particular income bin) by summing over the corresponding application probabilities for each household. Affordable housing options with characteristics more desired by certain types of households will receive more applications from those households.

Estimating the utility specific to affordable housing (α_i) requires taking a stance on the mechanism used to ration units among interested households. In practice, LIHTC developers can legally screen applicants based on their credit score, eviction history, and some minimum income, but not their race/ethnicity, age, family structure, or other characteristics protected by the Fair Housing Act. We approximate the allocation mechanism as a weighted lottery, with weights that are common across developers but 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 $\pi_{ij} = \max\left\{\pi_j\phi_i, 1\right\}$, where weights $\phi_i = \phi_0 + \sum_k \phi_k \widetilde{w}_{ik}$ are common across options 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 example, this mechanism nests a waitlist in which households are randomly ordered and, upon reaching the top of the queue, are offered a unit with some probability that varies only by their observables $\widetilde{\mathbf{w}}$.

In the absence of a price mechanism, supply and demand are equalized through the baseline offer probabilities at each development (π_j), which must adjust to satisfy the market-clearing condition:

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

Households may apply but ultimately reject an offer for a unit if they receive multiple offers. In practice, LIHTC developers make offers sporadically as vacancies arise. Households that would receive multiple offers in a year 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 in the model may choose to apply to only their favorite developments—rather than all options that are better than their market-rate options—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 household outcomes in the model.

6 Estimation

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

We estimate the model using data on repeated cross-sections of household decisions for the Chicago-Naperville-Elgin MSA (henceforth 'Chicago MSA'), the third-largest metro area.[19] We aggregate observations into 3-year periods between 2010 and 2018, denoted by t. To consistently measure move-out rates even when aggregated to 3-year periods, we define each market-rate household's housing choice as where they were living when surveyed by the ACS and their past housing location (j_i^0) based on where they lived one year prior. While we suppressed time subscripts for ease of exposition above, we now rewrite utility as $u_{ijt} = \delta_{jt} + \lambda_{ijt} + \varepsilon_{ijt}$ and add time subscripts to the supply of units (s_{jt}), offer probabilities (π_{jkt}), 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 and discretize bedrooms as 0-1, 2, and 3+. Note that this definition of a neighborhood is geographically larger than the Census tracts used in prior sections (see Figure D.5 for a map).[20]

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

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

[19] Chicago is also a convenient setting as its housing market is mostly made up of market-rate units and LIHTC units, having demolished most of their public housing stock. New York City, in contrast, includes many rent-controlled/stabilized units, public housing units, and other affordable housing developments funded by the city and not by the LIHTC program.

[20] The ACS data used for estimation is only a 1% annual sample, so defining housing options using the smaller Census tracts leads to many options with zero observed shares. Moreover, comparing how a household that moved trades off their chosen location with their previous location requires observing the rent for their previous location. Since the ACS is a cross-section, we can only observe the rent if some other household is sampled in that option in the current period. Aggregating to PUMAs, each containing approximately 100,000 individuals, solves many of these issues. For neighborhood characteristics—including our measure of neighborhood opportunity—we take the population-weighted average across Census tracts within each PUMA.

where we normalize elements in $\mathbf{w}_i$ to be mean zero across households such that each common component corresponds to the population average.

The non-idiosyncratic components of utility u_{ijt} can then be rewritten as

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

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

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. It 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.

6.1 Estimation of preferences for housing and 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 preferences for rent and housing/neighborhood characteristics ($\boldsymbol{\gamma}_\ell$ and β_ℓ), and adjustment costs ($\boldsymbol{\kappa}$) using Maximum Likelihood Estimation. For a candidate vector of parameters $\widetilde{\boldsymbol{\theta}}^{\mathrm{MR}} = \left\{\widetilde{\boldsymbol{\delta}}, \widetilde{\boldsymbol{\gamma}}_\ell, \widetilde{\beta}_\ell, \widetilde{\boldsymbol{\kappa}}\right\}$, the pseudo log-likelihood of the observed choices is given by

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

where $\mathbb{1}_{j_i=j}$ is an indicator for household i choosing option j. Conditional on selecting a market-rate option, preferences for affordable housing ($\boldsymbol{\alpha}$) have no impact on choices and so do not affect the likelihood function.

To ease computation, we use a contraction mapping to recover the mean utilities ($\widetilde{\boldsymbol{\delta}}$), which leverages the equilibrium condition that supply and demand must be equal:

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

When predicted demand exceeds supply for a given option, the mean utilities will be nudged down by the contraction mapping to reduce demand.

Given the estimated mean utilities $\widehat{\boldsymbol{\delta}}$, we can estimate the baseline preference parameters γ_0 and β_0 by regressing the mean utilities on housing/neighborhood characteristics and rent. However, we first need an instrument to address the endogeneity of rents with the unobserved amenities ξ_{jt}; options with higher unobserved amenities will have higher equilibrium rents.

Instrumenting for rent. We develop a new instrument for rents that isolates shifts in the residual supply for housing options stemming from broad trends in cities' demographic and industry composition. 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, we rely on a combination of population changes over time and a relatively inelastic housing supply (Saiz, 2010; Baum-Snow and Han, 2022), which can lead to changes in the pressure on rents for different housing options over time.[21] The key intuition is that housing options that are popular among shrinking demographic groups (e.g., families with kids) will face less rent pressure in later periods than housing options that are popular among growing demographic groups (e.g., unmarried 20-30 year-olds).

We construct the instrument in a similar manner to shift-share instruments (Bartik, 1991; Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2022). The 'shifts' are nationwide trends in the population and the 'shares' are based on pre-period estimates of the share of individuals of different types who would choose each housing option. To construct the shares, we use an auxiliary model to estimate individual preferences for housing options using data on the housing choices of both renters and homeowners between 2005 and 2009, before our main study period. We classify each individual over the age of 21 using four characteristics: the industry of their primary employer, ten-year age bins (e.g., 21-29, 30-39, ...), whether they are married, and whether they have children.[22] We then estimate how preferences for the components of each housing option—neighborhood, number of bedrooms, and size of building—vary by these individual characteristics. We describe this procedure in detail in Appendix Section C.1.

Next, we compute the expected change in the number of individuals who would choose option j each period due solely to nationwide trends in the empirical distribution of individual types. 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). Indexing unique combinations of the (discrete) individual characteristics with b, we denote the number of such individuals in the pre-period as N_b and the growth rate between the pre-period and period t as g_{bt}, which is computed based on the change in the number of individuals with characteristics b in all *other* cities in our sample. For each housing option, we construct our instrument as

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

[21] Even in markets where supply is more elastic, developers may be inattentive to how predictable changes in demographics (e.g., aging) will affect demand, similar to the finding in DellaVigna and Pollet (2007) that stock market investors are inattentive to the effects of demographic shifts on the profits of companies in age-sensitive sectors such as toys, beer, and nursing homes.

[22] 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. NAICS codes are assigned at the establishment level while EINS are at the firm level; for EINs with multiple NAICS codes, we use the code with the highest total establishment-level employment. We define an individual as 'married' if they file taxes with a spouse and as having children if they claim a dependent.

where $\widehat{P}_{jb}$ is the probability an individual with characteristics b selects option j, estimated using individual residential choices from 2005 to 2009.

The instrument captures the exposure of a housing option to population changes over time. For a given individual in the market, options where $z_{jt} > 1$ will likely have less residual supply after other renters and homeowners have made their decisions, which—given inelastic supply—will push up the rent for that option. For example, a value of 1.1 would indicate that, all else equal, 10% more individuals would be interested in choosing that option in the given period relative to the pre-period. To isolate just within-neighborhood variation in z_{jt}, we add neighborhood fixed effects to Equation 5, which will absorb any neighborhood-level unobserved amenities that are time-invariant.[23] With neighborhood fixed effects $\psi_{g(j)}$, the estimating equation becomes

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

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.

Satisfying the exclusion restriction requires that within-neighborhood variation in the unobserved demand shocks across time and across different housing types (e.g., bedroom sizes) is orthogonal to the within-neighborhood variation in our instrument. There are two main threats to exogeneity. First, unobserved characteristics of a housing option may respond endogenously to changes in demand. In Table D9, we show that our instrument is associated with small and often insignificant changes in the counts of various types of establishments (e.g., restaurants and grocery stores) and other neighborhood characteristics. Second, 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, as in the current specification, demand shocks ξ_{jt} are common across all households, then changes to who is in the market will have no effect on the estimated demand shocks. If, instead, the true demand shocks systematically vary across households, then an increase in households of a given type will skew the estimated demand shocks towards the underlying demand shocks for this type. This assumption could be weakened by incorporating additional observables into the model (such that less preference heterogeneity loads onto the unobservables) or by allowing the demand shocks ξ_{jt} to vary by household characteristics.

Comparison to alternative instruments. A common approach to identify the disutility of rent in this literature is to instrument using characteristics of other neighborhoods. This approach is inspired by the differentiated products literature: characteristics of other products in the market affect equilibrium prices, but are—arguably—uncorrelated with unobserved quality (Berry, Levinsohn and Pakes, 1995). These instruments were first used in the context of residential choice in

[23] Including neighborhood fixed effects will also absorb average preferences for characteristics in $\mathbf{x}_{jt}$ that do not vary over time. However, we still estimate how preferences for these characteristics vary by household observables.

Bayer, Ferreira and McMillan (2007) (BFM) and remain popular today.[24] In general, papers tend to restrict to characteristics of neighborhoods at least three miles away, use 'immutable' characteristics of the physical housing supply, and exclude characteristics such as neighborhood demographics.

There are two potential concerns with BFM instruments. First, 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.[25] Second, BFM instruments are transformations of variables that are included in the demand specification (i.e. the $\mathbf{x}$), which can make the estimates especially sensitive to any potential model misspecification (Andrews et al., 2023). In contrast, our instrument uses *external* variation from broader population trends to isolate exogenous variation in *within-neighborhood* rents over time. The final column of Table 2 presents estimates using BFM-style instruments. The results are broadly similar, although—consistent with a positive correlation between BFM instruments and unobserved amenities—the coefficient on rent is attenuated towards zero.

Heterogeneity in household preferences. We present the full set of estimated preference parameters in Tables D11 and D12. 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, which could reflect either homophily or correlated preferences for unobservables. Higher-income households tend to be less sensitive to higher rents and put more weight on amenities like school quality and job access. Larger households naturally prefer larger units. All households face substantial adjustment costs for leaving their endowed housing option.

6.2 Estimation of lottery weights and preferences for affordable housing

To estimate preferences for affordable housing ($\boldsymbol{\alpha}$) and the lottery weights developers use for households of different income bins ($\boldsymbol{\phi}$), 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 households move out of affordable housing, and the covariance between moving out and household characteristics. The intuition for separating heterogeneity in developer lottery weights from heterogeneity in household preferences is that developer preferences only affect who moves in, while household preferences affect both move-in and move-out decisions.

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

[24] Recent examples include Anagol, Ferreira and Rexer (2021); Barwick et al. (2021) and Calder-Wang (2021). Variants of the instrument include using changes in plausibly exogenous characteristics over time (e.g., Almagro and Domınguez-Iino, 2023), 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). To improve first-stage relevance, researchers often concentrate many instruments into a single one by solving for the market-clearing rents if demand depended only on the exogenous characteristics, in the spirit of the optimal instruments literature (Chamberlain, 1987; Reynaert and Verboven, 2014).

[25] In Appendix Section C.2, we document that many commonly used characteristics exhibit strong spatial correlation and illustrate via simulation how this can lead to biased estimates of the disutility of rent.

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	0.1029	0.5061	0.1906
	(0.1718)	(0.0529)	(0.1569)
Big apartment building	-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.

candidate vector of parameters. The moment conditions take the form of

$$\mathbb{E}\left[m_t^{(q)} - \widehat{m}_t^{(q)} \mid \boldsymbol{\theta}\right] = 0 \tag{11}$$

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

$$\widehat{m}_t^{(q)} = \frac{\sum_{i \in \mathcal{I}_t}\left(w_i \times \sum_{j \in \mathcal{J}_t^{\mathrm{AH}}} P_{ijt}^{\mathrm{alloc}}\right)}{\sum_{i \in \mathcal{I}_t}\sum_{j \in \mathcal{J}_t^{\mathrm{AH}}} P_{ijt}^{\mathrm{alloc}}} \tag{12}$$

where w_i is an element of either $\mathbf{w}_i$ or $\widetilde{\mathbf{w}}_i$ and $P_{ijt}^{\mathrm{alloc}} = P_{ijt}^{\mathrm{apply}} \times \pi_{jk(i)t} \times P_{ijt}^{\mathrm{accept}}$ is the equilibrium probability that household i is allocated to affordable housing option j in period t.

By Assumption 2, the probability of accepting an offer is $\frac{1}{N}$ for a household receiving N offers. This probability is challenging to compute directly as the space of potential sets of offers grows exponentially in the number of affordable housing options. However, because offer probabilities are small and the number of affordable housing options is large, we can approximate the distribution of the number of other offers a household receives conditional on receiving an offer at j as a Poisson distribution with arrival rate $\rho_{ijt} = \sum_{j' \in \mathcal{J}_t^{\mathrm{AH}}; j' \neq j}(P_{ij't}^{\mathrm{apply}} \times \pi_{j'k(i)t})$ (Le Cam, 1960). The probability of accepting an offer is then approximated as:

$$P_{ijt}^{\text{accept}} \approx \sum_{n=0}^{\left|\mathcal{J}_t^{\text{AH}}\right|-1} \underbrace{\left(\frac{e^{-\rho_{ijt}}\rho_{ijt}^{n}}{n!}\right)}_{\substack{\text{Prob of n} \\ \text{other offers}}} \underbrace{\left(\frac{1}{1+n}\right)}_{\substack{\text{Prob accept if} \\ \text{n other offers}}} \tag{13}$$

The sample analogues $(m_t^{(q)})$ are computed as the average of each characteristic in $\mathbf{w}_i$ and $\widetilde{\mathbf{w}}_i$ among households who move into a LIHTC unit in a given period.

Move-out moments. For households endowed with an affordable housing unit $j_i^0 \in \mathcal{J}^{\text{AH}}$, we estimate the rate at which they choose to move out.[26] In practice, moves to other affordable housing options are rare, so for simplicity we model it as a decision to move to a market-rate option.[27] With logit errors, the probability each household moves out is

$$P_{it}^{\text{moveout}} = \frac{\sum_{j\in\mathcal{J}_t^{\text{MR}}} \exp\left(\delta_{jt} + \lambda_{ijt}\right)}{\exp(\delta_{j_i^0 t} + \lambda_{ij_i^0 t}) + \sum_{j\in\mathcal{J}_t^{\text{MR}}} \exp\left(\delta_{jt} + \lambda_{ijt}\right)} \tag{14}$$

We then compute the mean probability of moving out, as well as the covariance with household characteristics:

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

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

For both the sample analogues and the model-predicted moments, we use annual move-out rates rather than period-to-period move-outs to match the construction of move-outs in the ACS, where a household's endowed option j_i^0 is their housing choice in 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 $\mathbf{w}_i$. We use bins of average income in the three years prior in $\mathbf{w}$ and bins of current income in $\widetilde{\mathbf{w}}$ to reflect that developers only observe current income; both sets of income bins are included in the moment conditions. While for market-rate estimation we use eight bins of household income with the highest being for households earning over \$100,000, for affordable housing estimation we combine the top four bins into a single bin of >\$40,000 as there are few eligible households in the higher-income bins. We compute standard errors using 250 bootstrap samples of households.

Estimated parameters. Figure 4 Panel (a) plots the distribution of the value of affordable housing across LIHTC-eligible households. We estimate that the average household values an

[26] Figure B.3 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.3.

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

affordable housing unit at \$218/mo more than an observably similar market-rate unit. The positive value suggests that any stigma or hassle costs are likely smaller than other unobserved quality differences. We investigate potential differences in unobserved quality in Table D13 by comparing LIHTC units sampled by the American Housing Survey (AHS) to nearby public housing and market-rate units. While the AHS sample is small (only 1400 LIHTC units), it includes a richer set of housing characteristics than our estimation data. Unlike public housing units, LIHTC units in the AHS are much newer, have fewer maintenance issues, and are less likely to have roaches or barred windows than market-rate units in the same neighborhood.[28] The perhaps surprising result that households place *positive* value on living in LIHTC specifically is echoed in ethnographic 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, less overcrowding in units, a greater sense of community, and feeling like the development was a 'safe-haven' in their neighborhood.

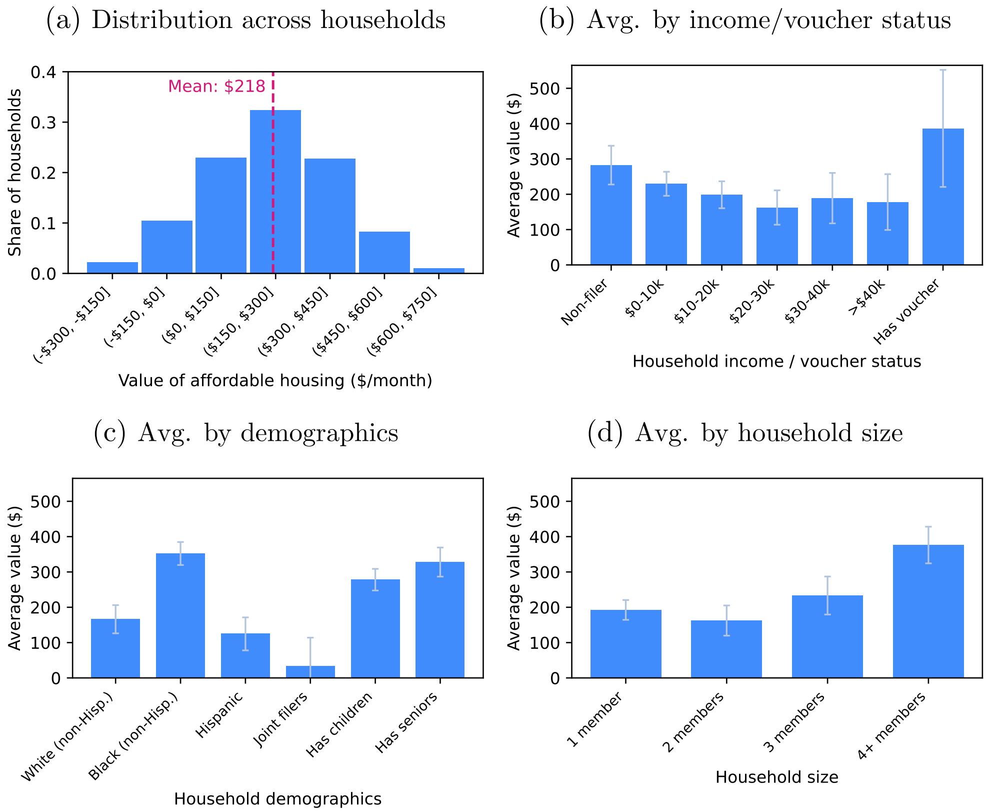
Figure 4 Panels (b)-(d) document heterogeneity in the value of affordable housing, computed as the average of α_i/β_i across all eligible households with a given characteristic. The average Black-led household valuing affordable housing at \$352 per month compared to just \$166 for the average White (non-Hispanic) household. The value of affordable housing is especially high for families with children (\$278) or seniors (\$328) and especially low for households with a married couple (\$33). These estimates imply that households that are smaller, do not have children, include a married couple, or have a White (non-Hispanic) household head are all less likely to apply for a unit, regardless of the development's location.

While lower-income households prefer affordable housing more than higher-income households, developers prefer to select higher-income households when rationing units. The value of affordable housing decreases from \$282 for households that did not file taxes in the prior three years to \$178 for households whose average household income exceeded \$40,000 a year. Developers, in contrast, put the lowest weight on households that did not file taxes the year that they apply and the highest weight on households whose annual income exceeded \$40,000 a year. Table 3 reports the relative lottery weights on different household characteristics. Households in the highest income bin are weighted 1.6 times more than households in the lowest income bin, although the estimates are noisy and non-monotonic in income. 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.[29]

[28]LIHTC units have also experienced less rent growth historically than market-rate units (Figure D.6). 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.

[29]Market-rate landlords in Chicago were allowed to discriminate based on source of income (i.e. whether a household had a voucher) until 2023, while LIHTC developers were already barred from discriminating on source of income nationwide. 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: Value of affordable housing to households (α_i/β_i)



Notes: This figure 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. Gray bars represent 95% confidence intervals from bootstrapped standard errors.

6.3 Discussion

Estimating demand under rationing is challenging as observed quantities do not correspond to demand at the observed price. We rely on two ingredients: a parallel market in which we can estimate demand for characteristics of the rationed good and assumptions about the mechanism used for rationing. Together, these allow us to identify preferences for living in affordable housing ($\boldsymbol{\alpha}$) separately from developers' influence on allocations ($\boldsymbol{\phi}$).

However, our approach comes with important caveats. First, while we treat observed 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, experimental studies continue to find evidence of discrimination against Black and Hispanic households searching for housing (Ahmed and Hammarstedt, 2008; Ewens, Tomlin and Wang, 2014). By one estimate, Black and Hispanic households need to expend 10-30% more effort when searching for housing to achieve the same level of utility as their White counterparts (Christensen and Timmins, 2021). Similarly, although we assume that households have full information about their choice set, they may be disproportionately likely to know about options closer to their existing home. To the extent that some households

Table 3: Developer lottery weights ($\boldsymbol{\phi}$)

Household characteristic ($\widetilde{\mathbf{w}}$)	Relative weight ($\boldsymbol{\phi}$)
Baseline (ϕ_0): non-filers	1
Current income: (\$0, \$10k]	+0.3016
	(0.1119)
Current income: (\$10k, \$20k]	+0.2636
	(0.1157)
Current income: (\$20k, \$30k]	+0.1672
	(0.1332)
Current income: (\$30k, \$40k]	+0.1724
	(0.1414)
Current income: >\$40k	+0.6415
	(0.24)
Has voucher	+0.4692
	(0.2901)

Notes: This table 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. Bootstrapped standard errors are reported in parentheses.

are disproportionately discriminated against in high-opportunity neighborhoods or are less likely to know about options in such neighborhoods, our estimates would understate the value these households place on the characteristics of high-opportunity 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 $\widetilde{\mathbf{w}}_i$, in practice developers may screen on characteristics beyond what we include in $\widetilde{\mathbf{w}}_i$ 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 disproportionately prefer to house. For example, if developers prefer households with children, our estimate of the value of affordable housing for such households will be biased upwards. While discrimination based on the presence of children, age, disability, gender, and race/ethnicity is illegal under the Fair Housing Act, developers may influence which households live in their development through subtle methods, such as how they advertise vacancies and whether they rely on referrals from current tenants.

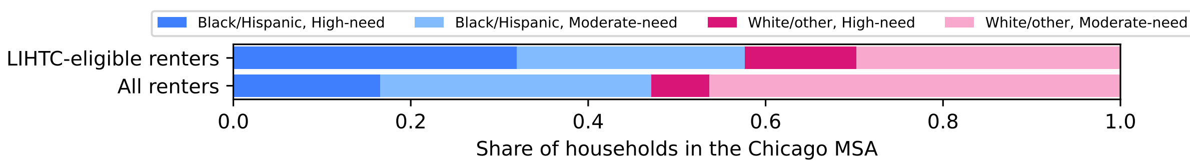
7 Results

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.[30] We then simulate which households receive affordable housing and how much they value it, holding fixed market-rate supply and neighborhood characteristics, which, in reality, may respond endogenously to the location of a new affordable housing development. 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 (Figure 5).

Figure 5: Renter types for counterfactuals (Chicago MSA)



Notes: This figure documents the share of each of our four renter types in the Chicago MSA. '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. LIHTC eligibility is determined using the 60% AMI income limits.

Composition of LIHTC developments. Consistent with the descriptive evidence, which households receive a unit depends on the location. Panel (a) of Figure 6 documents how the distribution of household types in the simulated development varies by the quartile of neighborhood opportunity. For developments in the top quartile of neighborhood opportunity, 29% of households are Black-/Hispanic households and 38% are considered high-need based on their predicted future income. In contrast, for developments in the bottom quartile, 72% of households are Black/Hispanic and 50% are considered 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 D14).

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,

[30] 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 for each unit at 60% of AMI. In practice, the government does not directly select where to locate a new LIHTC development. In Appendix Section A.3 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.

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 because of the lower share of same-race/ethnicity residents in these neighborhoods, which outweighs the improvements in school quality, transit access, and other amenities. However, this decrease for Black/Hispanic households is small relative to the increase for White/other households, who are about 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.[31] 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; 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 living in the unit.

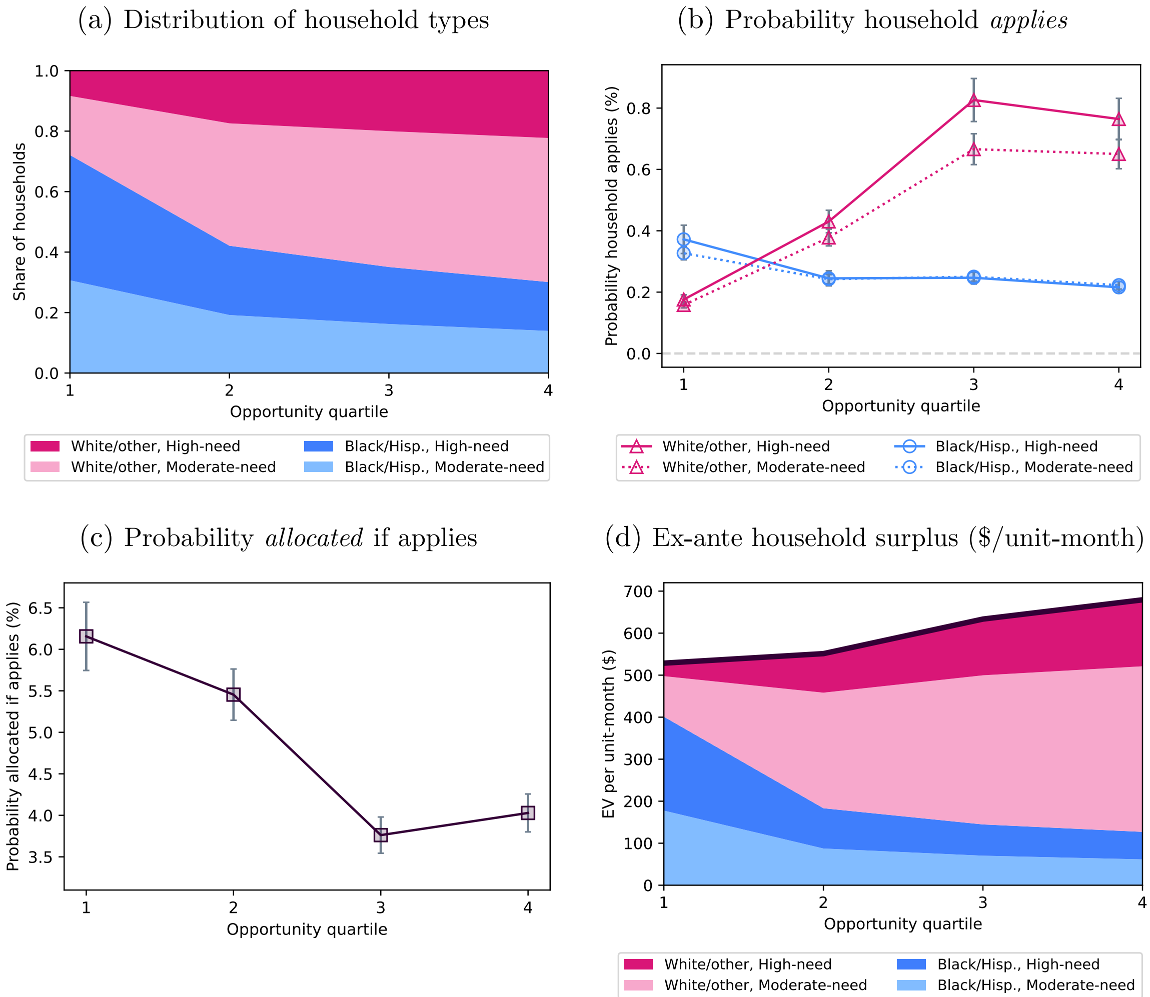
Household surplus. To quantify the effects of location on household surplus, we compute the willingness-to-pay (WTP) of each household for the construction of the new development as the equivalent variation (EV) in units of monthly rent.[32] A household's WTP depends on its probability of being allocated 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.

Total household surplus increases by \$151 per unit-month (from \$529 to \$680) for a development built in the top quartile of neighborhood opportunity instead of the bottom quartile (Figure 6). However, the gains do not accrue evenly across households. Instead, building in high-opportunity neighborhoods is a transfer across both racial/ethnic and economic lines. 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).

[31] 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 D4).

[32] 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 (Figure B.3), so their number of lifetime moves may decrease.

Figure 6: Composition and value of a new LIHTC development

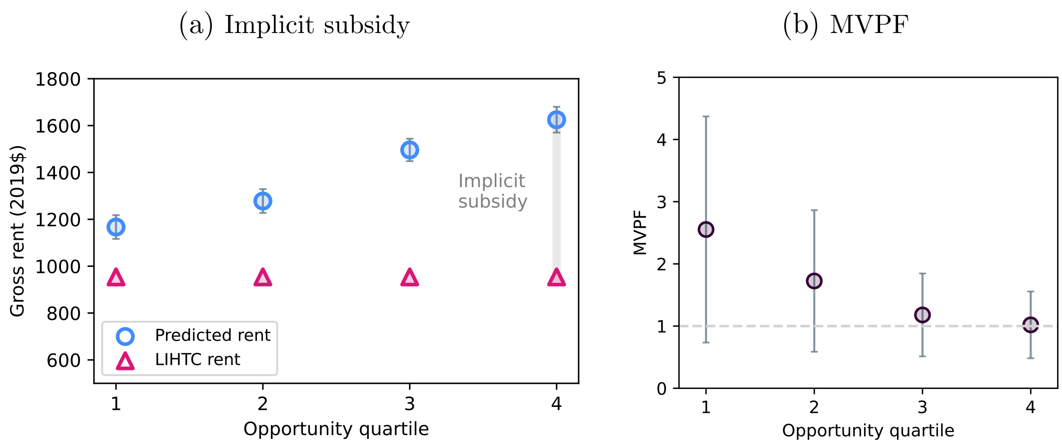


Notes: This figure documents how the composition of tenants and the value derived from a new development varies based on location. Each point is the average for a simulated development built in each PUMA in the corresponding quartile. Application (allocation) probabilities are for applying (being allocated) to any unit in the simulated development. Household surplus is computed as the equivalent variation in monthly rent based on differences in expected utilities pre/post-new development. '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. Gray bars represent 95% confidence intervals from bootstrapped standard errors.

Costs. For each LIHTC unit, we measure costs as the 'implicit subsidy,' i.e. the difference between its regulated LIHTC rent and an estimate of how much the same unit would rent as a market-rate unit. Conceptually, the implicit subsidy captures the opportunity cost of setting aside a market-rate unit to be instead rented out as a LIHTC unit. To estimate the market value of a LIHTC unit, we use a hedonic regression estimated on the sample of market-rate units observed in the ACS (see Appendix Section B.4 for details).[33] Panel (a) of Figure 7 plots the LIHTC-regulated rent and

[33]One concern with this hedonic approach is that we may overstate the increase in the market-value of LIHTC units in high-opportunity if the unobserved quality of market-rate units is increasing in neighborhood opportunity in ways that the unobserved quality of LIHTC units is not. In future versions, we plan to adopt the approach from Oster (2019) to help quantify the role of unobserved quality differences.

Figure 7: Implicit subsidies and the Marginal Value of Public Funds (MVPF)



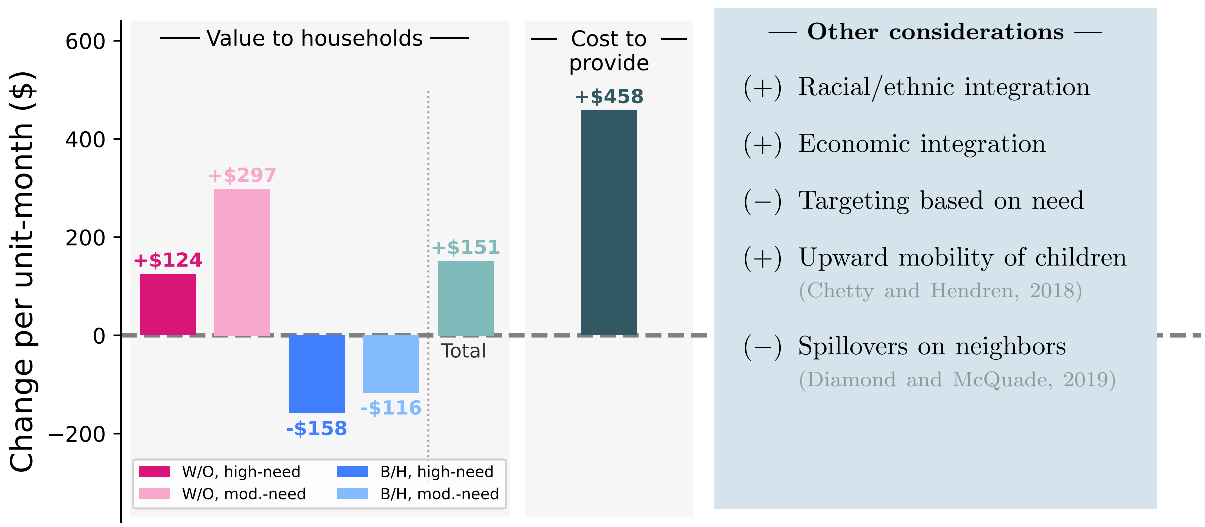
Notes: This first panel documents the 'implicit subsidy,' or the difference between the regulated rent for a LIHTC unit and an estimate of the rent if the same unit were a market-rate unit. The second panel plots the Marginal Value of Public Funds (MVPF), computed as the total household surplus divided by the implicit subsidy. Grey bars represent bootstrapped 95% confidence intervals. The data cover the Chicago MSA (2016-2018) to match the sample used for counterfactuals. Note that the large standard errors for the MVPF stem primarily from uncertainty in the overall level of household surplus; standard errors for the differences between quartiles are far smaller.

estimated market-rate rent for LIHTC units in different quartiles of neighborhood opportunity. The implicit subsidy for a typical LIHTC unit increases from \$213 per month (18% discount off of market-rate) in the bottom quartile to \$671 per month (41% discount) in the top quartile.

A related question is how large the fiscal costs of procuring a new LIHTC unit are to the government. In Appendix Section B.4, we show that the number of per-unit tax credits awarded to developments is almost flat across levels of neighborhood opportunity in the city. The number of tax credits awarded is 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; Schwartz, 2021). We do not observe these additional subsidies, but anecdotal evidence suggests they are more common for developments built in expensive neighborhoods.

To weigh the value to households against the costs to provide, we compute the Marginal Value of Public Funds (MVPF) Hendren and Sprung-Keyser (2020). The MVPF of a public program is the ratio of marginal benefits to the marginal cost, including any fiscal externalities (e.g., if a program generates additional tax revenue, its MVPF should be commensurately lower). An MVPF greater than 1 implies that each dollar spent generates more than a dollar of value. In our case, we compute the MVPF as the ratio of household surplus to the implicit subsidy, setting aside effects on other margins. The average MVPF falls from 2.5 in the bottom quartile of neighborhood opportunity to 1.01 in the top quartile (Figure 7). However, the standard errors are large and allow for a wide range of MVPFs at each quartile – an MVPF of less than one is within the 95% confidence interval for all quartiles. This stems largely from uncertainty in the overall level of household surplus; standard errors for the *differences* between quartiles are much smaller.

Figure 8: 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.

Net effects of location. Figure 8 summarizes some of 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, but 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, 2023) 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 LIHTC contributed to cementing racial segregation in Texas.[34] The initial complaint was filed by the Inclusive Communities Project (ICP) in 2008 against the Texas Department of Housing and Community Affairs (DHCA), alleging that the LIHTC program in Texas "perpetuates racial segregation" because its "failure to correct the disproportionate allocation of housing tax credits to low-income minority areas" (ICP v. DHCA, 2008). On appeals, the case eventually 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 policies for awarding LIHTC funding and, in some cases, shift funding priorities towards high-opportunity neighborhoods, which rarely have large minority shares (Owens and Smith, 2023).

Using our estimated model, we evaluate the effect of where LIHTC is built on residential segregation, which depends on the composition of the development compared to that of the surrounding neighborhood and where tenants would otherwise live. We use the following index of residential isolation[35] between groups A and B (in our case, Black/Hispanic and White/other or high-need and moderate-need):

$$\text{Isolation} = \overbrace{\frac{1}{|\text{A}|}\sum_{i\in\text{A}} \underbrace{\text{fracA}_{g(i)}}_{\substack{\text{Home nbhd}\\ \text{frac. A}}}}^{\text{Avg. exposure to A by A}} - \overbrace{\frac{1}{|\text{B}|}\sum_{i\in\text{B}} \text{fracA}_{g(i)}}^{\text{Avg exposure to A by B}} \tag{15}$$

where $g(i)$ indexes the neighborhood of resident i and $\text{frac}A_{g(i)}$ is the residential exposure to residents of group A, measured as the fraction of neighborhood g's population that belong to group A. This measure captures the difference in residential exposure to residents of group A by individuals who are themselves of group A versus those of group B. 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)

The marginal impact on city-wide isolation of any single development will be small and depend on the size of the simulated development. To provide a baseline for comparison, we first simulate a version where we move both the development *and* current 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. As shown in Figure 9, developments built in the bottom quartile of opportunity increase both economic and racial/ethnic isolation on the margin, while moving these developments and their tenants to higher opportunity neighborhoods would

[34] 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.2.

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

steadily decrease both isolation measures.

We then allow the tenants of the development to change as we move the development to different neighborhoods ('with sorting,' in Figure 9). In this case, the development composition becomes closer to that of the neighborhood, dampening effects on integration. 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 used for means-testing restrict the extent of tenant sorting by income; allowing tenants to re-sort dampens the effect on economic integration by just 29%.

The effects on integration are driven by who moves into the development and where they move from. We decompose these effects by again simulating who sorts into the development but holding fixed where they come from. To do so, we sample previous neighborhoods from the distribution of previous neighborhoods of households who move into the simulated developments built in the bottom quartile. The change in where households move from can explain about a fourth of the gap between the 'sorting' and 'no sorting' versions for racial/ethnic isolation in the top quartile and about half of the gap for economic isolation.

7.3 Effects on children & neighbors

Other considerations may enter into the social planner's decision of where to build affordable housing beyond those we evaluate here, including spillovers on the surrounding neighborhood, long-run effects on children, and any general equilibrium responses. To contextualize our results alongside other tradeoffs, 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.

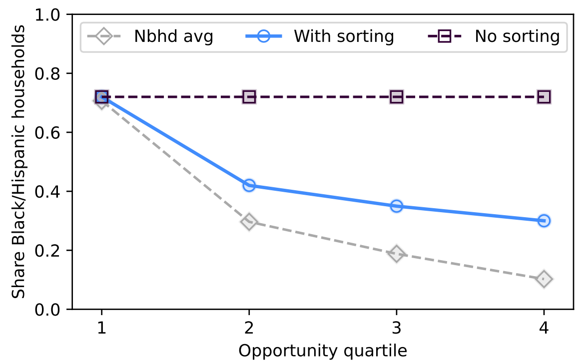
Upward mobility of children. We estimate the effects of location on the future earnings of children living in the development using data from the Opportunity Atlas (Chetty et al., 2022), which is based on the upward mobility of the 1978-1983 birth cohorts.[36] While our estimates of household surplus will capture some of the effects on children, the household may not fully internalize the long-run benefits for children when choosing where to live.

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;

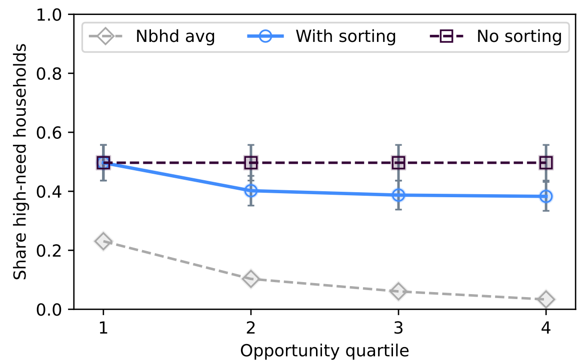
[36] While Chetty et al. (2022) provide evidence that the upward mobility measures for neighborhoods are generally stable over time, large changes to neighborhoods that affect the local schools or other local policies may affect the upward mobility of residents (Derenoncourt, 2022). In addition, sampling error in the Opportunity Atlas can lead to an upward bias in the difference in ranks between two neighborhoods (Andrews, Kitagawa and McCloskey, 2023; Mogstad et al., 2023).

Figure 9: Effect of location on residential isolation

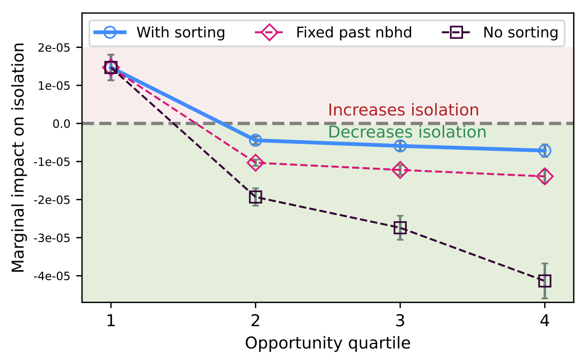
(a) Development v. nbhd: race/ethnicity



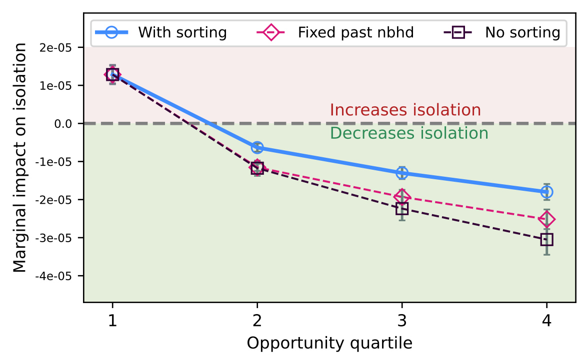
(b) Development v. nbhd: need



(c) Impact on racial/ethnic isolation



(d) Impact on economic 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. 'Fixed past neighborhood' allows for new tenants to sort into the development, but samples them from the distribution of home locations for tenants moving into developments built in the bottom quartile. Bootstrapped 95% confidence intervals are represented with gray bars.

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). Table D15 details the complete set of steps.

We find 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). Among the assumptions used to reach these 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) estimate the effect of a new LIHTC development on neighboring renters, homeowners, and landlords. They provide estimates for eight classifications of Census block groups based on whether the block group is over 50% Black/Hispanic ('high-minority) and quartiles of median household income across the distribution of block groups with a LIHTC development, each defined using the 1990 Census. Their estimates of the total welfare effect of a new LIHTC development range from +\$211 million for developments in high-minority block groups in the lowest income quartile to −\$12 million for developments in low-minority block groups in the highest income quartile.

We match each block group to our measure of neighborhood opportunity in Chicago, then use their per-household estimates to compute the aggregate effect of a new development built in the block group based on the number of renters, homeowners, and landlords within 1.5 miles.[37] Assuming constant effects within each of their eight block group categories, we estimate that a development built in the top quartile of neighborhood 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 value of this welfare difference is −\$203 per unit-month if we amortize the effects over the first 15 years of the development with 3% discount rate.

7.4 Counterfactual rationing processes & parameters

We now evaluate other changes to the LIHTC program that, depending on the social planner's objective, may be complementary to the choice of location. We look at four changes to the processes for screening tenants, rationing units, and collecting rents, as well as one change in household preferences.

1. **Lower income limit (30% AMI).** Lower income limits from 60% of the Area Median Income (AMI) to 30% AMI, which also reduces the rents charged to households

[37] 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. To be consistent with their block group definitions, we use the 1990 Census to categorize block groups, then match each block group to the corresponding PUMA used to define neighborhoods in our counterfactuals.

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 or with a housing voucher
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
4. **Fair lottery.** Equalize the lottery weights so that developers have no influence on the allocation of units to applicants
5. **No $\boldsymbol{\alpha}$ heterogeneity.** Remove any heterogeneity in preferences specific to affordable housing

We measure the effects of each counterfactual on household surplus, the distribution of assistance, and residential segregation. Table 4 presents the results for simulated developments in the bottom quartile of neighborhood opportunity (Q1), as well as the change from the bottom to top quartile of neighborhood opportunity (Q1→Q4). Figure 10 illustrates the effect on racial/ethnic and economic segregation.

Table 4: Comparison of counterfactuals

	WTP ($/unit-mo.)		Frac. Black/Hisp.		Future income rank		Frac. w/ college	
	Q1	Q1→Q4	Q1	Q1→Q4	Q1	Q1→Q4	Q1	Q1→Q4
60% AMI	$528.6	+$150.7	0.7201	-0.4201	0.2857	+0.0508	0.1455	+0.0742
	(185.6)	(17.73)	(0.0202)	(0.0279)	(0.0166)	(0.0045)	(0.0159)	(0.0078)
30% AMI	$865.0	+$160.1	0.7326	-0.4137	0.2390	+0.048	0.1286	+0.067
	(188.1)	(20.7)	(0.0206)	(0.0275)	(0.0193)	(0.0049)	(0.0172)	(0.0081)
Local preferences	$776.2	+$258.3	0.7714	-0.4926	0.2682	+0.0864	0.1290	+0.1055
	(187.8)	(22.71)	(0.0228)	(0.033)	(0.0177)	(0.0075)	(0.017)	(0.013)
Income-based rents	$789.0	+$160.5	0.7363	-0.4092	0.2813	+0.0507	0.1437	+0.0728
	(187.0)	(18.93)	(0.0211)	(0.0273)	(0.0168)	(0.0045)	(0.0161)	(0.0077)
Fair lottery	$540.5	+$149.2	0.7099	-0.4183	0.2863	+0.0502	0.1478	+0.0739
	(186.1)	(21.89)	(0.0206)	(0.0276)	(0.0172)	(0.0049)	(0.0159)	(0.0078)
No $\boldsymbol{\alpha}$ heterog.	$402.7	+$262.1	0.6423	-0.3965	0.3072	+0.0414	0.1746	+0.0748
	(183.3)	(13.14)	(0.0158)	(0.0265)	(0.0156)	(0.0041)	(0.0145)	(0.0078)

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.

The first policy lowers the income limits to 30% of AMI. This creates more value for households, largely due to the reduced rents, which are set as a function of the income limit. The lower limits naturally disqualify many higher-income households, leading to more economic integration and housing tenants with lower predicted future income. The effects of lowering the income limits on average household income at the time of move-in—shown in Table D16—are much larger than the effects on other characteristics. As the descriptive evidence suggested, lowering the income limits alone has only small effects on the distribution of assistance by race/ethnicity or other proxies for need such as the fraction of households with a college-educated household head. Using income-based rents also generates more surplus by charging lower rents, but has little effect on other household characteristics (even predicted future income).

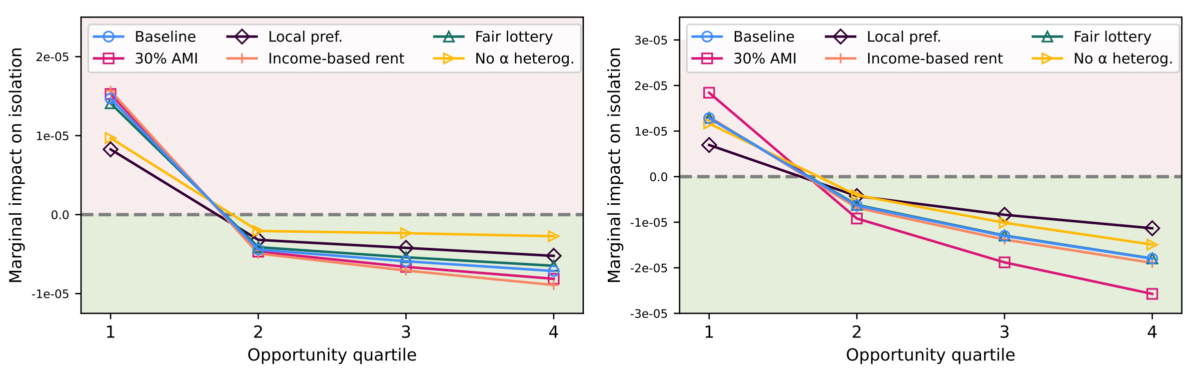
Prioritizing households who live in the same neighborhood as the development generates greater household surplus by selecting households who value the characteristics of the neighborhood more. New York City is currently being sued over whether its policy of giving priority to local residents perpetuates racial segregation in the city (Winfield v. City of New York, 2015). We find that local preferences keep the distribution of race/ethnicity and income across the city closer to the status quo, which further dampens any effects (either positive or negative) on integration. However, prioritizing local residents may accomplish other policy goals not captured by our framework, such as reducing the displacement of long-time neighborhood residents following new construction (Pennington, 2021).

The final two rows shut down heterogeneity in either developer weights on households ($\boldsymbol{\phi}$), i.e. allocate units with a fair lottery, or heterogeneity in preferences for affordable housing ($\boldsymbol{\alpha}$). Heterogeneity in developer 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, any effects on the composition are second order to the changes across neighborhoods in which households apply. In contrast, heterogeneity in household preferences for affordable housing ($\boldsymbol{\alpha}$)—documented in Figure 4—leads to more Black/Hispanic households (+22%) and high-need households (+4%) in the top quartile of neighborhood opportunity than if all households valued affordable housing equally. This preference heterogeneity also increases the positive effects on integration of building in high-opportunity neighborhoods.

Figure 10: 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.

8 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 heterogeneity in household demand for neighborhoods. 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 that have 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 with pathways to higher-opportunity neighborhoods that they may not be able to afford otherwise. However, some of the potential effects are offset by how changes to household demand interact with the process used to ration units. 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, 2023) and ongoing 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. Once subset to the left tail of the income distribution, the remaining differences in current income are a poor predictor of other proxies for persistent need such as education, longer-run income, and childhood family income. 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, too.

References

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

Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A Olken, and Julia Tobias. 2012. "Targeting the Poor: Evidence from a Field Experiment in Indonesia." *American Economic Review*, 102(4): 1206–1240.

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

Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A. Olken, Ririn Purnamasari, and Matthew Wai-Poi. 2019. "Does Elite Capture Matter? Local Elites and Targeted Welfare Programs in Indonesia." *AEA Papers and Proceedings*, 109: 334–339.

Alderman, Harold. 2002. "Do local officials know something we don't? Decentralization of targeted transfers in Albania." *Journal of Public Economics*, 83(3): 375–404.

Almagro, Milena, and Tomas Domınguez-Iino. 2023. "Location Sorting and Endogenous Amenities: Evidence from Amsterdam." *Working paper*, 81.

Almagro, Milena, Eric Chyn, and Bryan A. Stuart. 2023. "Urban Renewal and Inequality: Evidence from Chicago's Public Housing Demolitions." https://www.nber.org/papers/w30838.

Anagol, Santosh, Fernando V. Ferreira, and Jonah M. Rexer. 2021. "Estimating the Economic Value of Zoning Reform." https://www.nber.org/papers/w29440.

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

Andrews, Isaiah, Nano Barahona, Matthew Gentzkow, Ashesh Rambachan, and Jesse M Shapiro. 2023. "Causal Interpretation of Structural IV Estimands."

Andrews, Isaiah, Toru Kitagawa, and Adam McCloskey. 2023. "Inference on Winners." *The Quarterly Journal of Economics*.

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

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

Barwick, Panle Jia, Shanjun Li, Andrew R. Waxman, Jing Wu, and Tianli Xia. 2021. "Efficiency and Equity Impacts of Urban Transportation Policies with Equilibrium Sorting." https://www.nber.org/papers/w29012.

Basurto, Maria Pia, Pascaline Dupas, and Jonathan Robinson. 2020. "Decentralization and efficiency of subsidy targeting: Evidence from chiefs in rural Malawi." *Journal of Public Economics*, 185(C). Publisher: Elsevier.

Baum-Snow, N. 2007. "Did Highways Cause Suburbanization?" *The Quarterly Journal of Economics*, 122(2): 775–805.

Baum-Snow, Nathaniel, and Lu Han. 2022. "The microgeography of housing supply." *Work in progress.*

Bayer, Patrick, Fernando Ferreira, and Robert McMillan. 2007. "A Unified Framework for Measuring Preferences for Schools and Neighborhoods." *Journal of Political Economy*, 115(4): 588–638. Publisher: The University of Chicago Press.

Bayer, Patrick, Marcus D. Casey, W. Ben McCartney, John Orellana-Li, and Calvin S. Zhang. 2022. "Distinguishing Causes of Neighborhood Racial Change: A Nearest Neighbor Design." https://www.nber.org/papers/w30487.

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

Bee, Adam, Joshua Mitchell, Nikolas Mittag, Jonathan Rothbaum, Carl Sanders, Lawrence Schmidt, and Matthew Unrath. 2023. "National Experimental Wellbeing Statistics." *CES Working Paper.*

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

Berry, Steven, and Philip Haile. 2016. "Identification in Differentiated Products Markets." *Annual Review of Economics*, 8(1): 27–52. _eprint: https://doi.org/10.1146/annurev-economics-080315-015050.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile prices in market equilibrium." *Econometrica: Journal of the Econometric Society*, 841–890.

Bertrand, Marianne, Sendhil Mullainathan, and Eldar Shafir. 2004. "A Behavioral-Economics View of Poverty." *The American Economic Review*, 94(2): 419–423. Publisher: American Economic Association.

Besley, Timothy, and Stephen Coate. 1991. "Public Provision of Private Goods and the Redistribution of Income." *The American Economic Review*, 7.

Blackorby, Charles, and David Donaldson. 1988. "Cash versus Kind, Self-Selection, and Efficient Transfers." *The American Economic Review*, 78(4): 691–700. Publisher: American Economic Association.

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

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-Experimental Shift-Share Research Designs." *The Review of Economic Studies*, 89(1): 181–213.

Brooks-Gunn, Jeanne, Greg J. Duncan, Pamela Kato Klebanov, and Naomi Sealand. 1993. "Do Neighborhoods Influence Child and Adolescent Development?" *American Journal of Sociology*, 99(2): 353–395. Publisher: University of Chicago Press.

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

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

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

Chamberlain, Gary. 1987. "Asymptotic efficiency in estimation with conditional moment restrictions." *Journal of Econometrics*, 34(3): 305–334.

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

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

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter. 2022. "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility." https://www.nber.org/papers/w25147.

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

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

Christensen, Peter, and Christopher Timmins. 2021. "The Damages and Distortions from Discrimination in the Rental Housing Market." https://www.nber.org/papers/w29049.

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

Chyn, Eric, Robert Collinson, and Danielle Sandler. 2023. "The Long-Run Effects of Residential Racial Desegregation Programs: Evidence from Gautreaux." *Working paper*.

Clarke, Bud. 2009. "Housing and Economic Recovery Act: Median Incomes and Rent Growth at LIHTC Properties." https://www.housingfinance.com/management-operations/housing-and-economic-recovery-act-median-incomes-and-rent-growth-at-lihtc-properties_o. Section: Management & Operations.

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

Collinson, Robert, and Peter Ganong. 2018. "How Do Changes in Housing Voucher Design Affect Rent and Neighborhood Quality?" *American Economic Journal: Economic Policy*, 10(2): 62–89.

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

Couture, Victor, Cecile Gaubert, Jessie Handbury, and Erik Hurst. 2023. "Income Growth and the Distributional Effects of Urban Spatial Sorting." *The Review of Economic Studies*, rdad048.

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

Cummings, Jean L., and Denise DiPasquale. 1999. "The Low-Income Housing Tax Credit An Analysis of the First Ten Years." *Housing Policy Debate*, 10(2): 251–307. Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.1999.9521332.

Currie, Janet, and Aaron Yelowitz. 2000. "Are public housing projects good for kids?" *Journal of Public Economics*, 75(1): 99–124.

Currie, Janet, and Firouz Gahvari. 2008. "Transfers in Cash and In-Kind: Theory Meets the Data." *Journal of Economic Literature*, 46(2): 333–383.

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

Davis, Morris A, Jesse Gregory, and Daniel A Hartley. 2023. "Preferences over the Racial Composition of Neighborhoods: Estimates and Implications." *Working paper*.

DellaVigna, Stefano, and Joshua M. Pollet. 2007. "Demographics and Industry Returns." *American Economic Review*, 97(5): 1667–1702.

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

Derby, Elena. 2019. "Does Growing Up in Tax-subsidized Housing Lead to Higher Earnings and Educational Attainment?" *SSRN Electronic Journal*.

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

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

Diamond, Rebecca. 2016. "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980–2000." *American Economic Review*, 106(3): 479–524.

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

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

Ellen, Ingrid Gould, and Keren Mertens Horn. 2018. "Points for Place: Can State Governments Shape Siting Patterns of Low-Income Housing Tax Credit Developments?" *Housing Policy Debate*, 28(5): 727–745. Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.2018.1443487.

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

Ellen, Ingrid, Katherine O'Regan, and Ioan Voicu. 2009. "Siting, Spillovers, and Segregation: A Re-examination of the Low Income Housing Tax Credit Program." In *Housing Markets and the Economy: Risk, Regulation, Policy; Essays in Honor of Karl Case.* , ed. Edward Glaeser and John Quigley, 233–267. Cambridge, Mass:Lincoln Institute for Land Policy.

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

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

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

Freddie Mac. 2018. "Opportunity Incentives in LIHTC Qualified Allocation Plans." https://mf.freddiemac.com/docs/Opportunity_Incentives_in_LIHTC_Qualified_Allocation_Plans.pdf.

Freedman, Matthew, and Tamara McGavock. 2015. "Low-Income Housing Development, Poverty Concentration, and Neighborhood Inequality." *Journal of Policy Analysis and Management*, 34(4): 805–834. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/pam.21856.

Fu, Chao, and Jesse Gregory. 2019. "Estimation of an Equilibrium Model With Externalities: Post-Disaster Neighborhood Rebuilding." *Econometrica*, 87(2): 387–421.

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

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

Geyer, Judy, and Holger Sieg. 2013. "Estimating a model of excess demand for public housing: A model of excess demand." *Quantitative Economics*, 4(3): 483–513.

Goetz, Edward G. 2018. *The one-way street of integration: Fair housing and the pursuit of racial justice in American cities.* Cornell University Press.

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

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

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

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

Hartman, Chester, and Gregory Squires. 2009. *The Integration Debate: Competing Futures For American Cities.* Routledge. Google-Books-ID: EaORAgAAQBAJ.

Hart, Oliver, Andrei Shleifer, and Robert W. Vishny. 1997. "The Proper Scope of Government: Theory and an Application to Prisons*." *The Quarterly Journal of Economics*, 112(4): 1127–1161.

Hendren, Nathaniel, and Ben Sprung-Keyser. 2020. "A Unified Welfare Analysis of Government Policies*." *The Quarterly Journal of Economics*, 135(3): 1209–1318.

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

ICP v. DHCA. 2012. https://clearinghouse.net/doc/77143/. *U.S. District Court for the Northern District of Texas, 3:08-CV-0546-D.*

ICP v. DHCA. 2015. *U.S. Supreme Court, 13-1371.*

Jencks, Christopher, and Susan E. Mayer. 1989. *The Social Consequences of Growing Up in a Poor Neighborhood: A Review.* Center for Urban Affairs and Policy Research, Northwestern University. Google-Books-ID: TnjGOgAACAAJ.

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

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

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

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

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

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

Ludwig, Jens, Greg J. Duncan, Lisa A. Gennetian, Lawrence F. Katz, Ronald C. Kessler, Jeffrey R. Kling, and Lisa Sanbonmatsu. 2013. "Long-Term Neighborhood Effects on Low-Income Families: Evidence from Moving to Opportunity." *American Economic Review*, 103(3): 226–231.

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

McClure, Kirk. 2006. "The low-income housing tax credit program goes mainstream and moves to the suburbs." *Housing Policy Debate*, 17(3): 419–446.

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

Meck, S, R Retzalff, and J Schwab. 2003. "Regional approaches to affordable housing. Report for the American Planning Association–Planning Advisory Service." Report.

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

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

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

Novogradac. 2022. "LIHTC Equity Pricing Trends." https://www.novoco.com/resource-centers/affordable-housing-tax-credits/lihtc-equity-pricing-trends.

Oates, Wallace E. 1972. *Fiscal Federalism.* Harcourt Brace Jovanovich. Google-Books-ID: nh6zAAAAIAAJ.

Olken, Benjamin A. 2006. "Corruption and the costs of redistribution: Micro evidence from Indonesia." *Journal of Public Economics*, 90(4-5): 853–870.

Olken, Benjamin A. 2007. "Monitoring Corruption: Evidence from a Field Experiment in Indonesia." *Journal of Political Economy*, 50.

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

Oster, Emily. 2019. "Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics*, 37(2): 187–204. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/07350015.2016.1227711.

Otero v. NYCHA. 1973. *United States Court of Appeals, Second Circuit, 484 F.2d 1122.*

Owens, Ann, and Rebecca Brooks Smith. 2023. "Producing affordable housing in higher-opportunity neighborhoods: Incentives in California's LIHTC program." *Journal of Urban Affairs*, 0(0): 1–29. Publisher: Routledge _eprint: https://doi.org/10.1080/07352166.2023.2288582.

Pennington, Kate. 2021. "Does Building New Housing Cause Displacement?: The Supply and Demand Effects of Construction in San Francisco." https://papers.ssrn.com/abstract=3867764.

Phillips, David C. 2017. "Landlords avoid tenants who pay with vouchers." *Economics Letters*, 151: 48–52.

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

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

Reynaert, Mathias, and Frank Verboven. 2014. "Improving the performance of random coefficients demand models: The role of optimal instruments." *Journal of Econometrics*, 179(1): 83–98.

Rosenbaum, James E. 1995. "Changing the geography of opportunity by expanding residential choice: Lessons from the Gautreaux program." *Housing Policy Debate*, 6(1): 231–269. Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.1995.9521186.

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

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

Sharkey, Patrick, and Jacob W. Faber. 2014. "Where, When, Why, and For Whom Do Residential Contexts Matter? Moving Away from the Dichotomous Understanding of Neighborhood Effects." *Annual Review of Sociology*, 40(1): 559–579. _eprint: https://doi.org/10.1146/annurev-soc-071913-043350.

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

Soltas, Evan. 2023. "Tax Incentives and the Supply of Low-Income Housing."

Stagg, Thomas. 2018. "What you Need to Know About Income Limits." https://www.novoco.com/notes-from-novogradac/what-you-need-know-about-income-limits.

Thakral, Neil. 2016. "The Public-Housing Allocation Problem: Theory and Evidence from Pittsburgh." *Working paper.*

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

van Dijk, Winnie. 2019. "The socio-economic consequences of housing assistance." *Working paper*, 58.

Wagner, Deborah, and Mary Lane. 2014. "The Person Identification Validation System (PVS): Applying the Center for Administrative Records Research and Applications' (CARRA) Record Linkage Software." *CARRA Working Papers.* Number: 2014-01 Publisher: Center for Economic Studies, U.S. Census Bureau.

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

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

Wilson, James Q. 1989. *Bureaucracy: What Government Agencies Do and why They Do it.* Basic Books. Google-Books-ID: I7DW2BVUULgC.

Wilson, William Julius. 1987. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy, Second Edition.* Chicago, IL:University of Chicago Press.

Winfield v. City of New York. 2015. *U.S. District Court for the Southern District of New York, 15-cv-05236.*

Wong, Maisy. 2013. "Estimating Ethnic Preferences Using Ethnic Housing Quotas in Singapore." *The Review of Economic Studies*, 80(3): 1178–1214.

Appendices

A Background on US affordable housing policy

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

Construction process. 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 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.[38] 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.[39]

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.[40] 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

[38] 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.

[39] 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).

[40] 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.

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

A.2 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 relevant cases here; the summaries below draw from the text of each case as well as Goetz (2018) and Schwartz (2021), which contain more comprehensive overviews.

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.

Many of the recent studies on neighborhood effects can trace their lineage to the Gautreaux resettlement program. An analysis of the labor market outcomes for adults and youth who were part of the resettlement found positive effects on those households who moved to the suburbs but also recognized the limitations of the resettlement for estimating causal effects (Rosenbaum, 1995). In part motivated by these results, HUD used the program as a model for its larger scale 'Moving to Opportunity' experiment in 1994, which led to hallmark findings on the causal effects of neighborhoods on both adults and children (Katz, Kling and Liebman, 2001; Ludwig et al., 2013; Chetty, Hendren and Katz, 2016).

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. The purpose of racial integration is to benefit the community as a whole, not just certain of its members" (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).

New Jersey's Mount Laurel Doctrine (1983). The Mount Laurel doctrine is an early example of 'fair share housing,' where each local jurisdiction is required to build housing suitable for low-income households. The law stems from two decisions by the New Jersey Supreme Court. The first ruling in 1975 outlawed many exclusionary zoning practices in deciding that municipalities must provide a realistic pathway for the construction of developments for low-income households. This was expanded by a second ruling in 1983, which required each local government to build their 'fair share' of low-income housing and authorized private developers to petition courts for permission to proceed with development in municipalities that have refused to authorize sufficient affordable housing (this latter provision is often referred to as a 'builders remedy'). In 1985, New Jersey established the Council on Affordable Housing (COAH) to determine the level of need in each housing region in the state and allocate unit requirements. Between 1985 and 2000, the Mount Laurel doctrine led to over 60,000 units of affordable housing in New Jersey (Meck, Retzalff and Schwab, 2003).

Fair share housing and the builder's remedy today are seen as tools for overcoming local opposition to new housing construction by moving decision-making to higher tiers of government, whose preferences encompass all residents of a broader jurisdiction rather than only the incumbents of a small municipality (Oates, 1972).

ICP v. Texas DHCA (2015). In Section 7.2, we provided an overview of the case between the Inclusive Communities Project (ICP) and the Texas Department of Housing and Community Affairs (DHCA). We provide a more comprehensive timeline with additional details 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 case was remanded to the district court to apply those standards.
  - 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, maintaining the high barrier of proof required. 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 where there was no disparate treatment or intention.

Winfield v. City of NY (ongoing). 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). As of November 2023, the case is still ongoing.

A.3 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. However, there are additional considerations that can lead to the mislabeling of QCTs both above and below the thresholds. For example, within a metro area, only 20% of the population can live within a QCT. For each year, we rank tracts within a metro area by the criteria used for each 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.[41]

[41] DDAs are assigned at varying levels of geographies including counties, towns, and metro-areas. Mike Hollar at

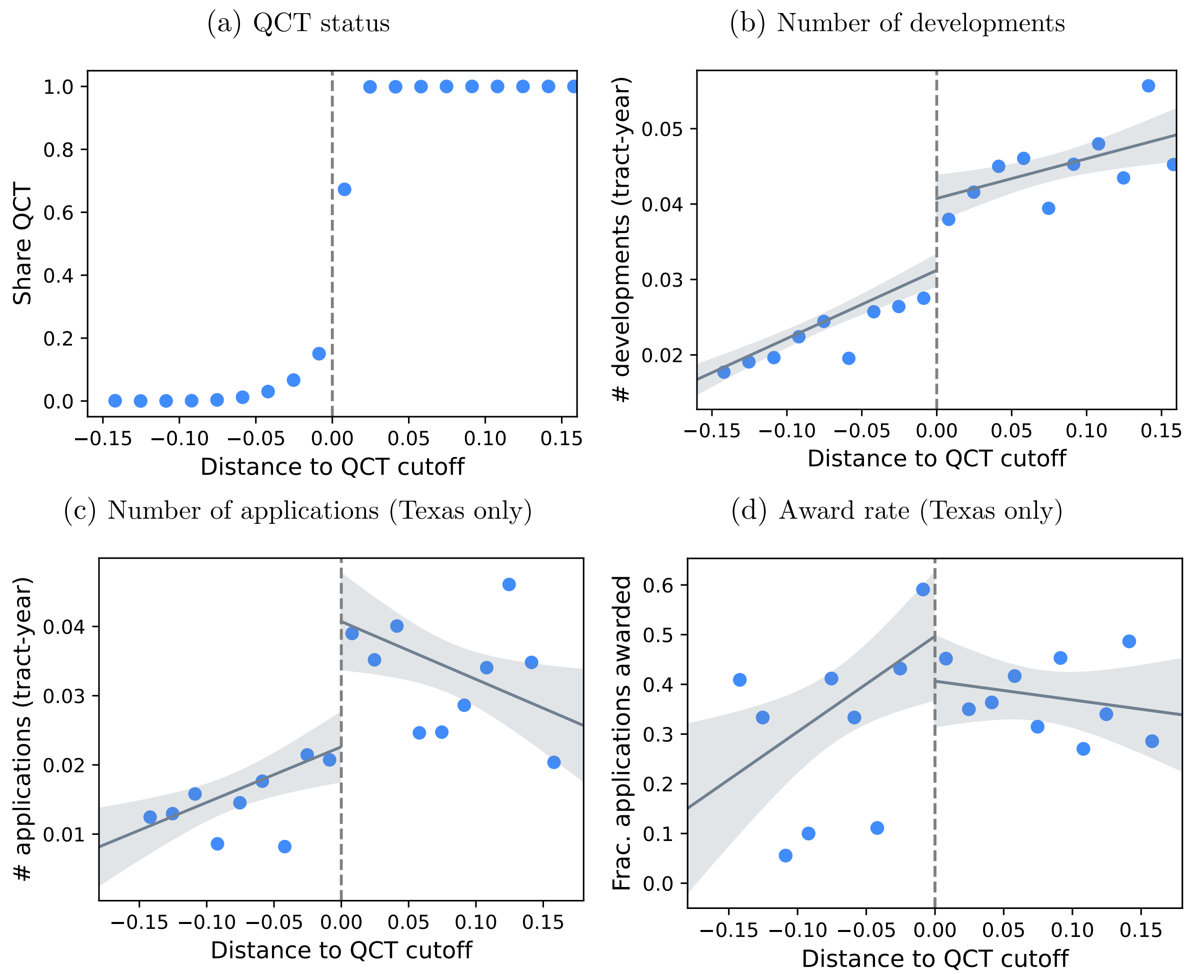
Figure A.1 panel (a) shows the share of tracts that are classified as a QCT around the threshold. The discontinuity is fuzzy, and we both classify QCTs as non-QCTs and vice-versa. One known cause is the exceptions made for small tracts near the 20% population threshold; HUD will try to include any smaller tracts past the threshold that would not push the total QCT population over 20% of the metro area, even if doing so means excluding larger tracts that are otherwise ranked more highly. 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 manually fix addresses that do not match to coordinates or that return implausible results (e.g., an address in a different city than the one listed on the application). 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.

HUD was kind enough to share digitized records of which Census geographies are classified as a DDA each year. To be conservative, I exclude any county that intersects a DDA geography.

Figure A.1: LIHTC development around QCT threshold



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

B Data construction and supplemental analyses

B.1 LIHTC properties and units

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

We link individuals to LIHTC units using the MAFIDs that Census staff assign to each unique address in the country. MAFIDs are persistent over time, so while the data from HUD cover 2018 and 2019, we can identify residents of the units in earlier years. In many developments, this match rate is low, often because the development reported poorly formatted addresses or addresses that lacked unit-level details. Developments with poor MAFID match rates must be excluded from the sample, as the MAFIDs are critical for linking individuals to units to then form into households. Table B1 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 B1: Balance table of properties

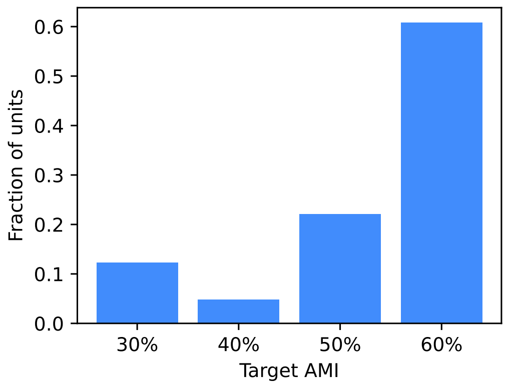
Characteristic	In-sample	Out-of-sample	Normalized diff.	T-statistic
Development characteristics				
MAFID match rate	0.8558	0.07969	3.037	141.4
Year placed in service	2007	2006	0.1971	9.191
# LIHTC units	105.4	94.89	0.1055	4.912
# total units	107.7	96.38	0.1091	5.077
Nonprofit developer	0.1915	0.2143	-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
KFR index	33.48	31.91	0.05704	2.658
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. 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 average of the two within-group variances. All statistics are computed within-MSA first, then across-MSA weighting by the population.

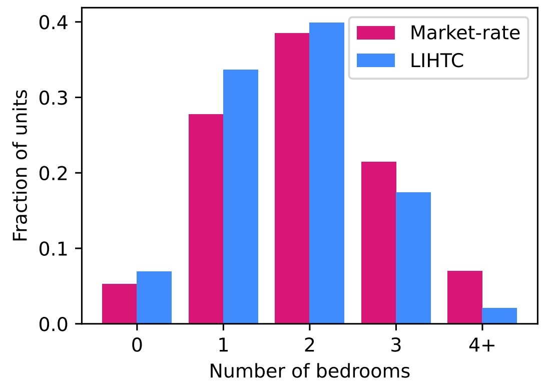
The HUD data includes information on the income limit threshold for each unit as well as the number of bedrooms. Figure B.1 documents the distribution of these two characteristics across sample LIHTC units. Compared to market-rate units, LIHTC units have fewer bedrooms on average.

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.

Figure B.2 compares the distribution of LIHTC units across space to public housing and market-rate units as well as the locations of households with vouchers for use in the private market. LIHTC units are more likely to be located in the top quartile of neighborhood median income or fraction White (non-Hispanic) than other affordable housing programs.

B.2 Forming individuals into households

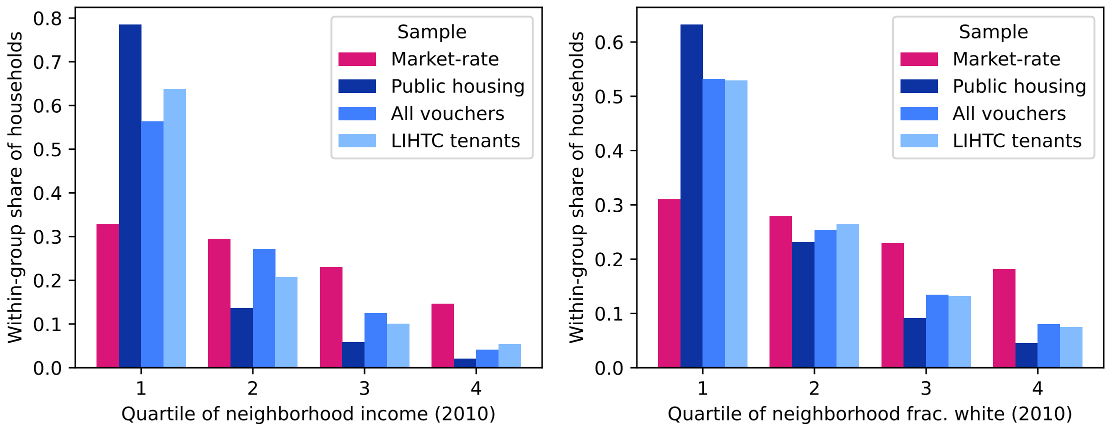
To combine individuals within a property into households, we start with the set of individuals who match based on their address to a given LIHTC development in a given year. While we link individuals to MAFIDs that are, in principle, at the individual unit level, in practice many individuals match to 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[42] 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

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

Figure B.2: Subsidized housing tenants by neighborhood characteristics



(a) Median household income (b) Frac. White (non-Hispanic)

Notes: Each bar is the fraction of households in the ACS in each within-MSA quartile of neighborhood characteristics for the 50 sample CBSAs (2010-2018). Median household income and the fraction of White (non-Hispanic) residents are based on tract-level data from the 2010 Census. We identify whether a household lives in public housing or has a voucher in the year surveyed by linking the ACS to HUD PICTRACS.

co-residence. We exclude cases where there were ten or more individuals observed in the MAFID in the same year

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

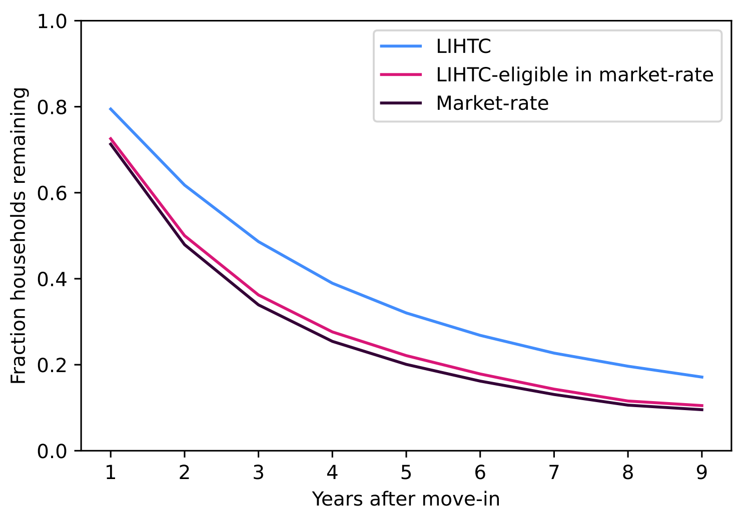
We then define households as the simply connected components of the graph, which allows for two individuals to be in the same household even if they are not directly linked. For example, consider three individuals labeled A, B, and C. If A and B are married, they will be placed in the same household. 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 (usually, there is only a single MAFID).

B.3 Move-out rates

We define move-in/move-out rates by following the head of household in both the market-rate and LIHTC samples. A move-in is defined based on the first year that the head of household is observed in a given building. A move-out is defined based on the last year that the head of household is observed in a given building *or* the first year they are observed filing taxes elsewhere (whichever comes first).[43] 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 often 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).

Figure B.3 plots the share of households remaining in their unit after 1, 2, . . . , nine years. LIHTC residents have substantially lower turnover than market-rate units. However, about 20% of LIHTC households are still only observed in the development for a single year (compared to 71% for market-rate households). Table B2 documents the fraction of households still living in the development after one year and after three years, split by household characteristics. 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.

Figure B.3: Move-outs: fraction remaining by # years after move-in



Notes: This figure documents the fraction of households remaining in a unit each year by the time since move-in, split by whether they are in a LIHTC unit, a market-rate unit, or in a market-rate unit and are LIHTC-eligible. 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.

B.4 Estimating the cost of new LIHTC units

We estimate the potential costs of building a LIHTC development in different neighborhoods using two approaches. First, 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. However, this may underestimate the full cost to the government of a new development, as LIHTC

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

Table B2: 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-Hispanic)	0.7062	0.3145	0.7237	0.3397	0.7961	0.4773
Black (non-Hispanic)	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
Household size: 1	0.7159	0.3484	0.7251	0.3679	0.7672	0.4745
Household size: 2	0.6981	0.3103	0.7035	0.3366	0.7987	0.4790
Household size: 3	0.7153	0.3439	0.7207	0.3597	0.8260	0.5034
Household size: 4 or more	0.7375	0.3702	0.7398	0.3760	0.8358	0.5079
Household income: non-filer	0.6935	0.3991	0.6904	0.4058	0.8056	0.5507
Household income: ($0, $10k]	0.7104	0.3170	0.7159	0.3270	0.7667	0.4384
Household income: ($10k, $20k]	0.7094	0.3132	0.7230	0.3342	0.7907	0.4676
Household income: ($20k, $30k]	0.7215	0.3316	0.7406	0.3643	0.8120	0.4963
Household income: ($30k, $40k]	0.7323	0.3450	0.7553	0.3791	0.8197	0.5092
Household 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.

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).

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

B.4.1 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 $[\$93531, \$210699]$.

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 (2022) 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.[44] 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 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.

Land sales. 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

[44] The raw data are stored as raster files. Nate Baum-Snow kindly shared the tract-level aggregates they constructed for Baum-Snow and Han (2022).

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.

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.

To train our model of land prices, we use the popular machine learning framework XGBoost (eXtreme Gradient Boosting), which uses a tree-based learning algorithm. (Chen and Guestrin, 2016). We tune the hyperparameters controlling the maximum tree depth, number of boosting rounds, and subsample size using a cross-validated grid search. For each state, we train the model on an 80% sample and evaluate the model accuracy on a 20% holdout. Our outcome is the log sale price of the parcel, adjusted for inflation. For features, we use the PUMA, year and month of sale, log acres, and characteristics of the Census tract, including the fraction flat plains, average level of development, WRLURI (with an indicator if missing), housing vacancy rate, log population density, log median household income, fraction White, fraction below poverty, log number of offices within 1 mile, and log number of parks within 1 mile. Averaging across states and weighting by the number of sales, the average R^2 is 0.57 on the holdout sample. The most important features are consistently the level of existing development, the housing vacancy rate, and the median household income. Given the estimated model, we predict the price of 1-acre, 5-acre, and 10-acre parcels of land sold in each tract-year and then take the average per-acre predicted price as our index.[45]

B.4.2 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 B.4 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

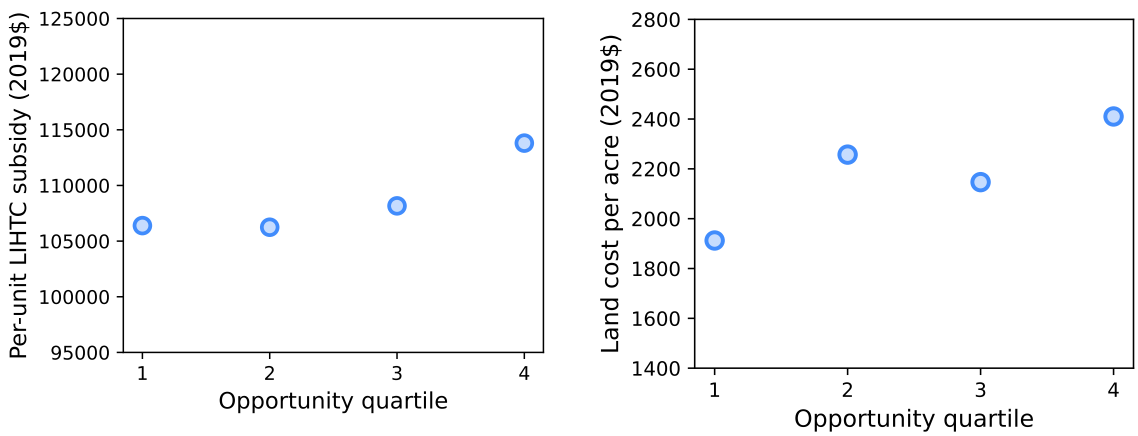
[45] We can observe a small sample of parcels that were sold specifically for purposes of building a LIHTC development using data from Costar, a commercial real estate company. The 25th, 50th, and 75th percentiles of acreage are, respectively, 0.82 acres, 3.49 acres, and 8.56 acres.

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 B.4: LIHTC costs

(a) Tax credit subsidy

(b) Land value



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.

B.4.3 Estimating 'implicit subsidies' for LIHTC

Our second 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. This abstracts from many of the intricacies of the supply side of LIHTC and instead imagines that units were supplied by first renting them from the market-rate sector and offering them at the LIHTC rent level, with the gap being the implicit subsidy.

The average rent ceiling for LIHTC units in Chicago between 2016 and 2018—the period we use for counterfactuals—was \$954. This 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.

We then estimate how much each unit in the simulated development in Section 7.1 would rent for as market-rate units using a hedonic regression. Using the sample of market-rate units, 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.

B.5 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:[46]

- 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.

[46] See here for additional details.

C Technical appendix

C.1 Constructing an instrument for market-rate rents

The 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 the mapping of the population to the number selecting each housing option. 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 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.

We use individuals rather than households so that we can use the full population, rather than the annual 1% samples from the ACS, although we will abuse our notation slightly by indexing both individuals and households by i. 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 filing to identify spouses and dependents (under 18 years old).

Using the data on individual choices of housing options, we use a logit model—similar to a standard discrete choice setup—to estimate the relationship between individual and housing option characteristics. We index each unique combination of the (discrete) individual characteristics with b, then write the utility an individual with characteristics b gets from option j as:

$$\begin{aligned} v_{ij} &= \theta_b^{\text{beds}} * \text{bedrooms}_j + \theta_b^{\text{PUMA}} * \text{PUMA}_j + \theta_b^{\text{building}} * \text{buildingType}_j + \varepsilon_{ij} \\ &= v_{b(i)j} + \varepsilon_{ij} \end{aligned}$$

where bedrooms_j and PUMA_j are vectors of indicators for each unit size or neighborhood and ε_{ij} are type-1 extreme value errors.

We parameterize each θ_b as the sum of the characteristics going into each type b. For example:

$$\theta_b^{\text{beds}} = \theta_{b,industry}^{\text{beds}} + \theta_{b,age}^{\text{beds}} + \theta_{b,married}^{\text{beds}} + \theta_{b,kids}^{\text{beds}}$$

where we again use vectors of indicators for each discrete characteristic (e.g., industry).

The probability an individual with characteristics b selects option j is then given by:

$$P_{jb} = \frac{\exp v_{bj}}{\sum_{j' \in \mathcal{J}} \exp v_{bj'}} \tag{16}$$

We estimate the parameters using Maximum Likelihood. 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. In a simplified case where housing options were just neighborhoods and there was a single individual type, the probability $\widehat{P}_{bj}$ would be the shares of individuals of each type in each neighborhood.

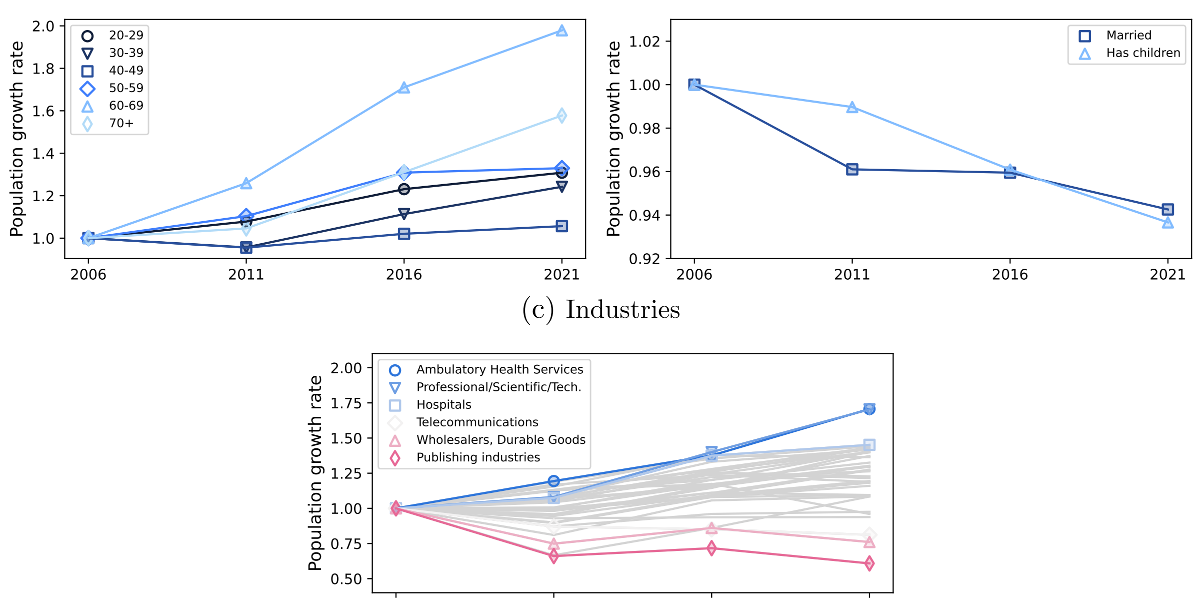
Next, we combine the estimated choice probabilities $\widehat{P}_{bj}$ with changes to the population to identify housing options that we expect are experiencing more or less 'rent pressure' in later periods relative to the pre-period. Figure C.1 plots the growth rates in the household characteristics used to form the instrument.[47]. 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.

Figure C.1: Growth rate in instrument components

(a) Age bins (b) Family structure



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.

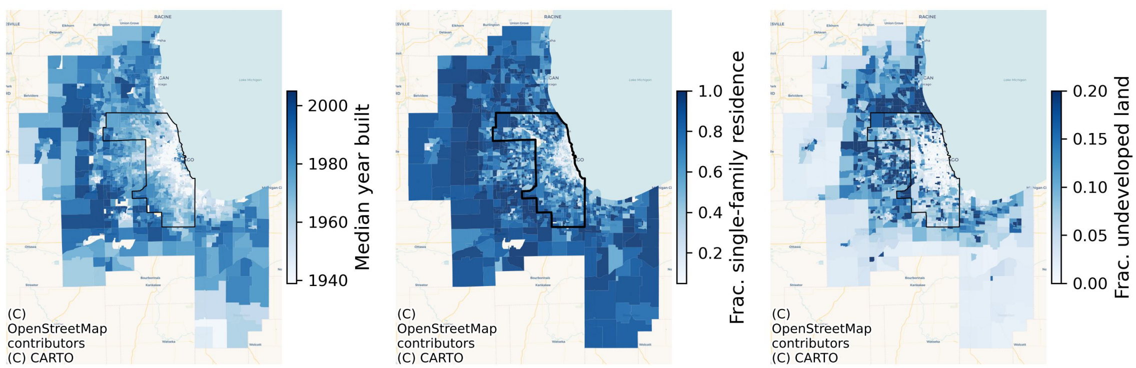
[47]We document these using data available publicly (the 5-year ACS), although results look similar when constructed using the same sources that we use to construct the instrument internally.

C.2 Simulation of BLP-style instruments for rent

We show via simulations that instrumenting for rent using plausibly exogenous housing characteristics can fail to recover the true parameters when there is spatial correlation in both unobserved quality and in the characteristics used as instruments. Many of the characteristics commonly used 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.

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

Simulation set-up. We construct a 25×25 grid of housing options indexed by j and an equivalent number of households indexed by i. Each housing option has two discrete observed characteristics ($x_j^1, x_j^2 \in \{0, 1\}$), some unobserved quality (ξ_j), and rent (r_j), which will be determined in equilibrium to clear the market.

Household i receives utility from option j of

$$\begin{aligned} u_{ij} &= -\beta r_j + \gamma_i^1 x_j^1 + \gamma_i^2 x_j^2 + \xi_j + \varepsilon_{ij} \\ &= \delta_j + \lambda_{ij} + \varepsilon_{ij} \end{aligned}$$

where preferences for housing characteristics vary by random coefficients, each drawn from a standard normal distribution. We treat the random coefficients as known, approximating our full model where preferences vary by observed household characteristics. For simulations, we use the following parameters:

$$
\begin{aligned}
&\beta = 1 \\
&\gamma_i^1 = 1.5 + \nu_i^1 \\
&\gamma_i^2 = 1 + \nu_i^2 \\
&\nu_i^1, \nu_i^2 \sim \mathcal{N}(0,1)
\end{aligned}
$$

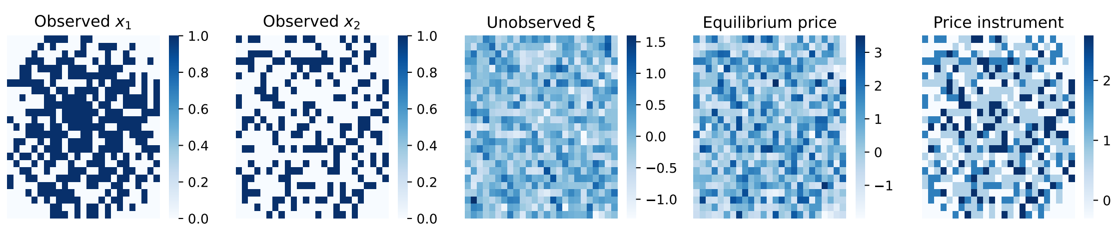
After initializing the set of housing options, households, and preferences, we solve for the equilibrium rents r_j that clear the market – i.e. $D(r_j, \mathbf{x}; \beta, \boldsymbol{\gamma}, \boldsymbol{\nu}) = 1 \; \forall j$, where we compute demand as

$$
D(r_j, \mathbf{x}; \beta, \boldsymbol{\gamma}, \boldsymbol{\nu}) = \sum_i \frac{\exp \delta_j + \lambda_{ij}}{\sum_{j'} \exp \delta_{j'} + \lambda_{ij'}}
$$

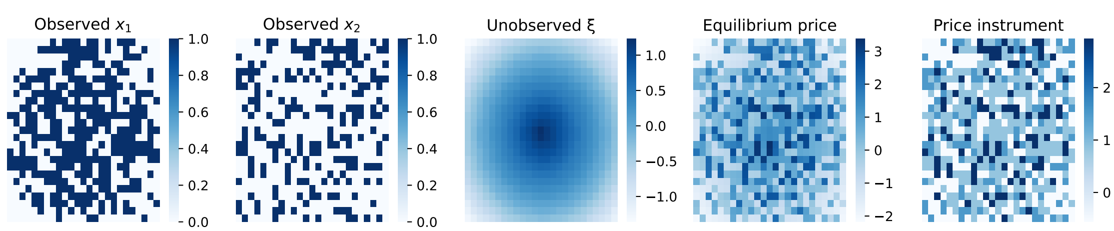
We construct x^1 to be negatively correlated with distance from the center of the grid, while x^2 is randomly drawn. For the base case, we assume $\xi \overset{iid}{\sim} \mathcal{N}(0, 0.5)$, such that there is no spatial correlation in unobserved quality. We then add spatial correlation in unobserved quality by making ξ negatively correlated with distance from the center of the grid. To do so, we hold the distribution of ξ fixed but reorder them in descending order by distance. Figure C.3 plots an example draw of characteristics.

Figure C.3: Simulated city

(a) Base case: uncorrelated ξ



(b) Spatially correlated ξ



Estimation. We recover preferences following the procedure outlined in Bayer, Ferreira and McMillan (2007). We construct an instrument for rents by solving for the market-clearing price of each option if households had preferences for only the exogenous characteristics.

1. Estimate $\widehat{\delta}$ based on observed choices and known heterogeneous parameters ($\boldsymbol{\nu}$)

2. For an initial guess of β (e.g., set $\widetilde{\beta} = -0.5$), estimate $\widehat{\delta}_j + \widetilde{\beta} r_j = \gamma^1 x_j^1 + \gamma^2 x_j^2 + \xi_j$ to recover guesses of preferences for exogenous characteristics ($\widetilde{\gamma}^1$, $\widetilde{\gamma}^2$)
3. Solve for market clearing rents (r_j^{IV}) if household have preferences only over exogenous characteristics and $\xi = 0$
4. Estimate $\widehat{\delta}_j = -\beta r_j + \gamma^1 x_j^1 + \gamma^2 x_j^2 + \xi_j$ via two-stage least squares using r_j^{IV} to instrument for rents
5. To ensure the estimates are not sensitive to the initial guess, repeat steps 2-4 using the estimated $\widehat{\beta}$ until the estimates converge.

Note that this could also be estimated in a single step using GMM with moment conditions of the form $\mathbb{E}[\xi r^{IV}] = 0$, $\mathbb{E}[\xi \mathbf{x}] = 0$, and market clearing conditions (see Appendix B of Calder-Wang, 2021).

Simulation results. The first two columns of Table C1 document the results. As expected, when the instrument is uncorrelated with the unobserved quality, the OLS estimate of the rent coefficient is biased towards zero but we can recover the true preference parameters using the constructed instruments. The second two columns of Table C1 create either positive or negative correlation between x^1 and ξ. This violates the exclusion restriction, as the rent instrument is now positively correlated with the unobserved quality. The estimated coefficients are biased towards zero and the willingness-to-pay for x^1 will be overstated. If instead the correlation is negative, the bias goes in the other direction.

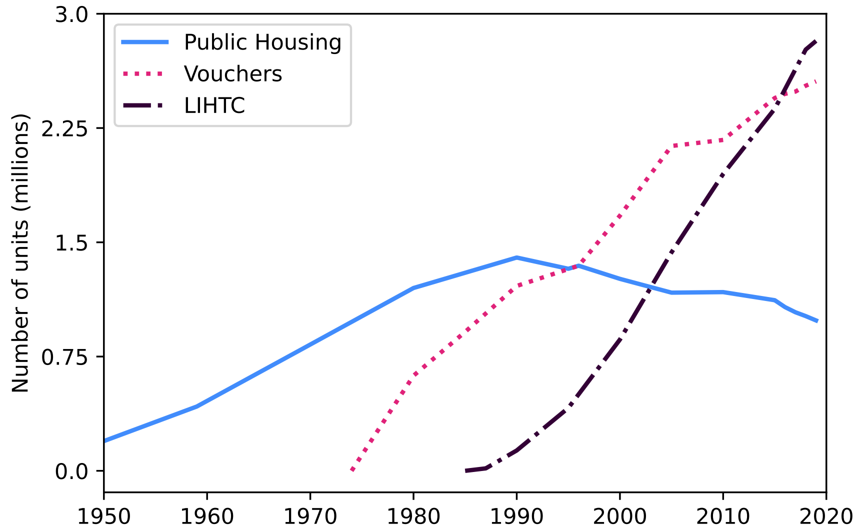
Table C1: Simulation of BLP-style rent instruments

		$Corr(\xi_j, d_j) = 0$, $Corr(\mathbf{x}_j, d_j) < 0$		$Corr(\xi_j, d_j) < 0$, $Corr(\mathbf{x}_j, d_j) < 0$		$Corr(\xi_j^1, d_j) < 0$, $Corr(\mathbf{x}_j^1, d_j) > 0$	
	Actual	OLS	IV	OLS	IV	OLS	IV
β	-1	-0.486	-0.996	-0.53	-0.825	-0.471	-1.143
		[-0.55, -0.423]	[-1.068, -0.934]	[-0.581, -0.469]	[-0.867, -0.77]	[-0.539, -0.389]	[-1.239, -1.05]
γ^1	1	0.824	1.0	0.962	1.109	0.661	0.922
		[0.76, 0.88]	[0.949, 1.055]	[0.896, 1.025]	[1.053, 1.159]	[0.592, 0.725]	[0.851, 0.982]
γ^2	2	1.114	1.996	1.148	1.62	1.13	2.307
		[0.969, 1.261]	[1.862, 2.126]	[1.021, 1.267]	[1.519, 1.713]	[0.952, 1.269]	[2.15, 2.49]
F-stat			541.293		1473.664		172.049

Notes: Each simulation is run 250 times. We report the median estimate as well as the 5th and 95th percentile of estimates in brackets.

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.

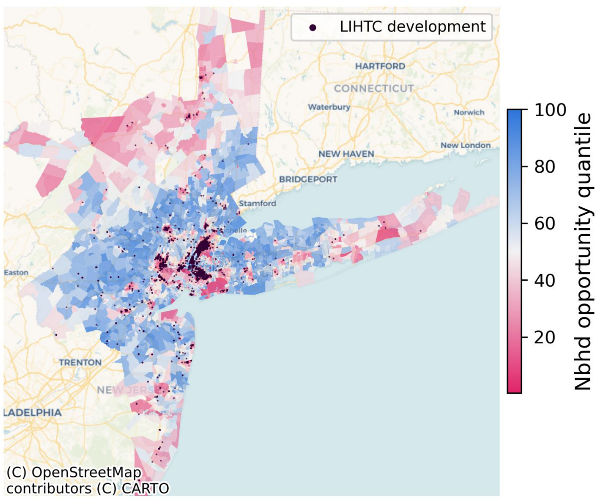
Table D1: Share of households with other government assistance

	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

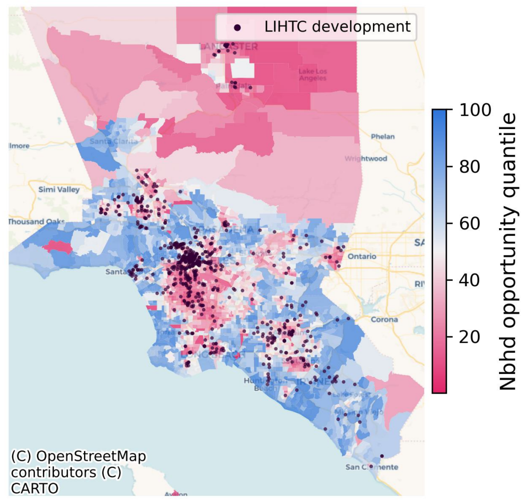
Notes: This table documents the fraction of households who take up various other forms of government assistance. Housing vouchers and social security are available for all households, while the other programs are only available for households sampled by the ACS. To account for differences in the size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

Figure D.2: Neighborhood opportunity maps

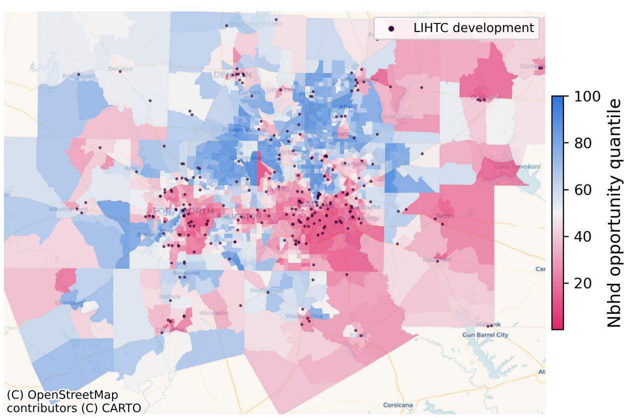
(a) New York City MSA



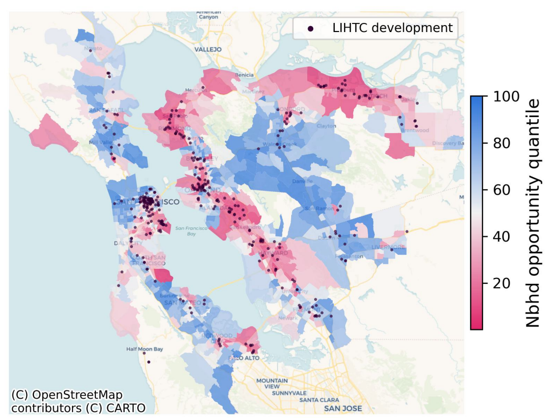
(b) Los Angeles MSA



(c) Dallas MSA

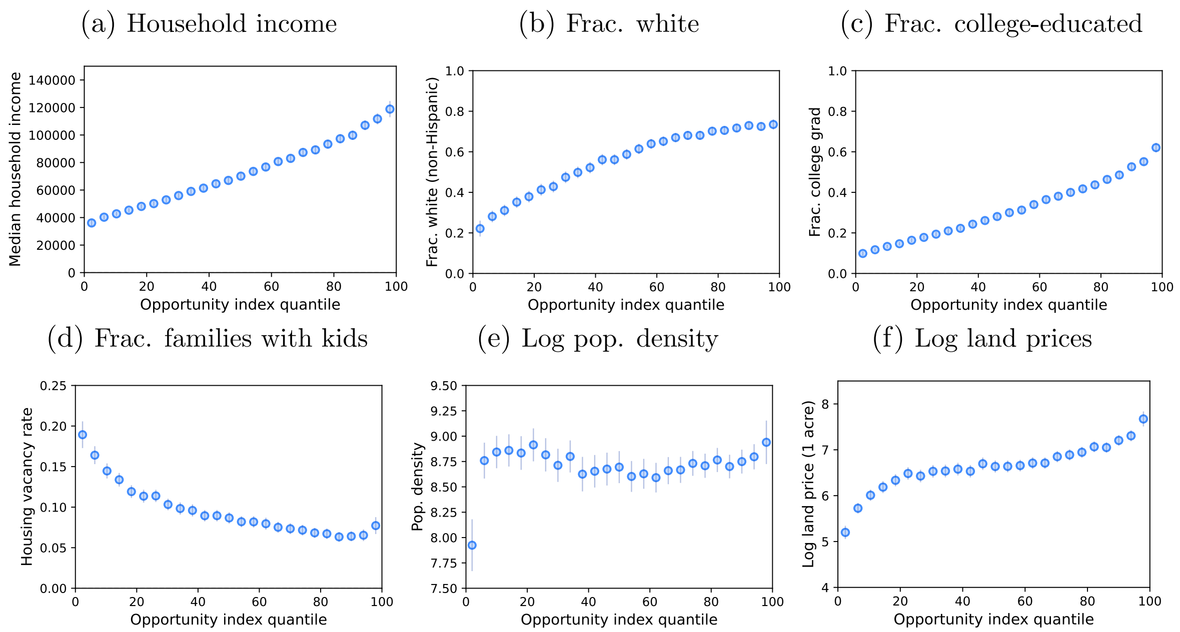


(d) San Francisco-Oakland MSA



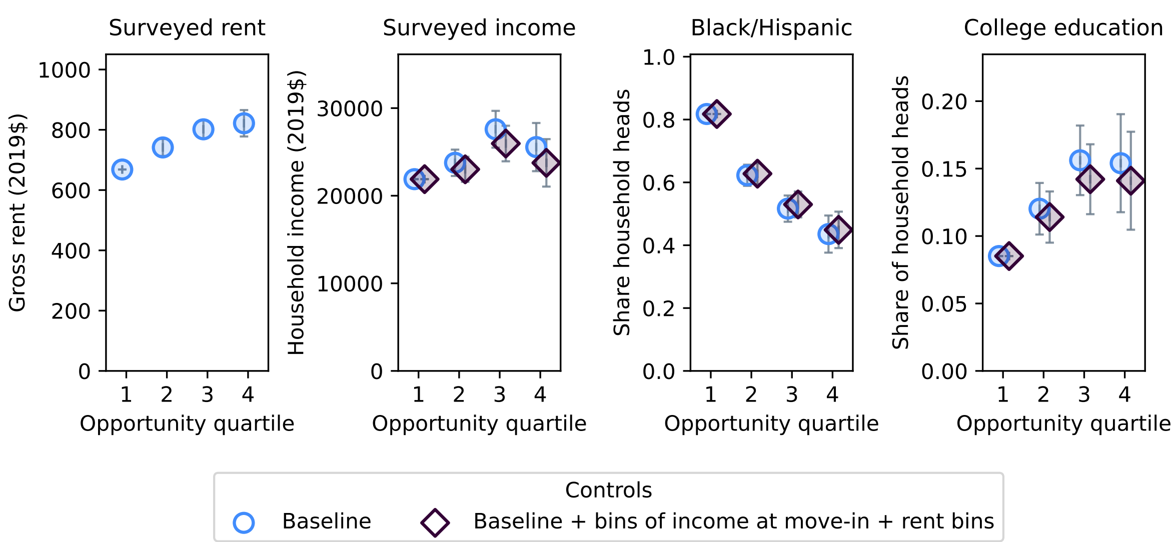
Notes: This figure plots spatial variation in our index of neighborhood opportunity and the location of LIHTC developments across four of the most populous metro areas in the US.

Figure D.3: Neighborhood opportunity measure



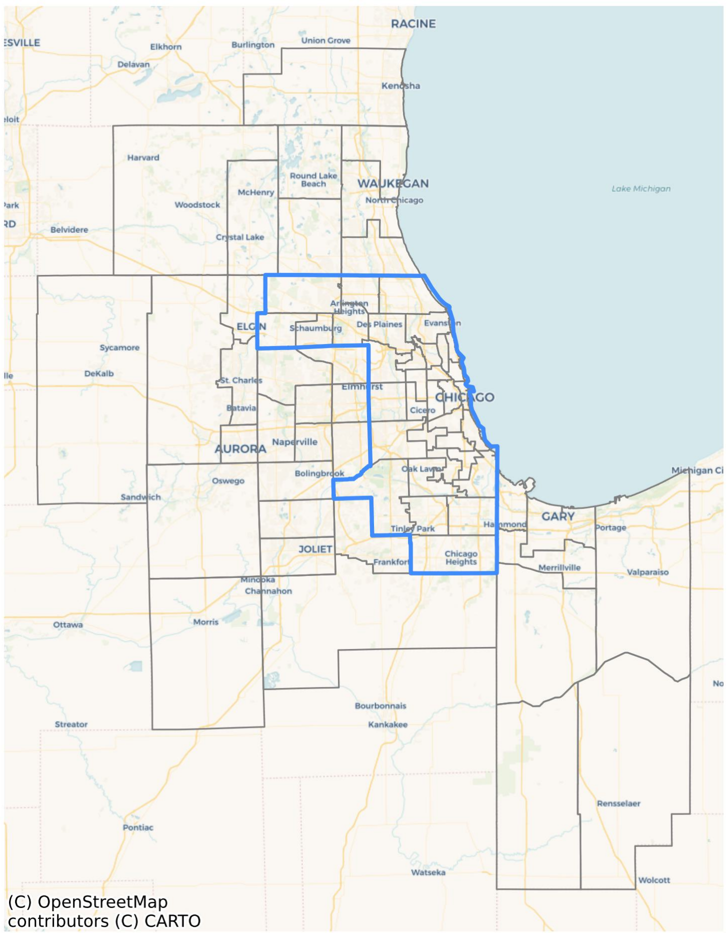
Notes: Each panel plots a binscatter between tract-level correlations between neighborhood opportunity and various neighborhood characteristics. The first five panels use characteristics from the 2015 5-year ACS. Income is inflated to 2019 dollars. The final panel uses an estimated index of land prices.

Figure D.4: 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.

Table D2: 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. Unit characteristics include 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 D3: 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 D4: LIHTC household chars. by neighborhood opportunity

		Quartile coefficients		
	Q1 avg.	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 D5: 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 D4, 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 D6: 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 D4, 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 D7: 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 D8: 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 D8, 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 D9: 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 D10: 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 D11: 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 D12: 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

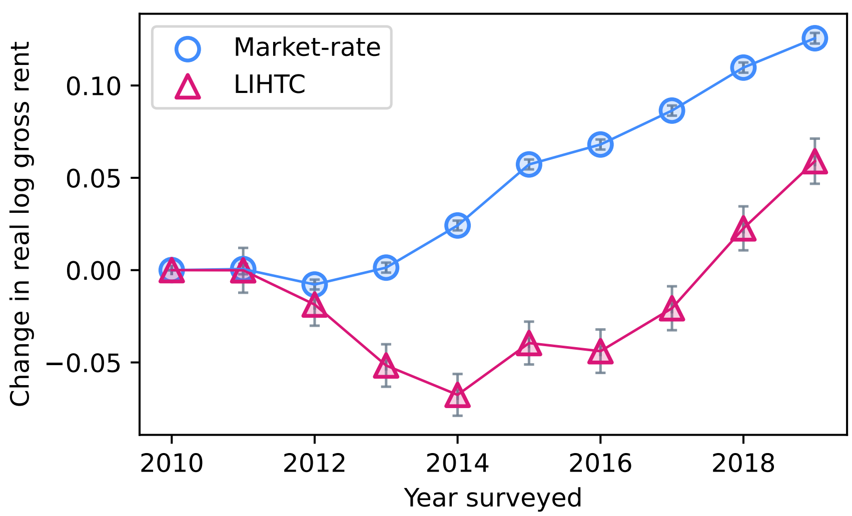
Notes: This table documents the estimated preference parameters for neighborhood characteristics. Because we recenter **w** to be mean-zero for estimation, each coefficient in the table corresponds to the change in value relative to the average household. As such, computing the equivalent value as if 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 D13: Housing quality: market-rate, LIHTC, and public housing

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

Notes: This table documents housing quality differences using the 2013 and 2015 American Housing Survey, subset to units in the 50 sample CBSAs. The coefficients are from a regression of a housing characteristic on indicators for whether the unit is LIHTC or public housing (with market-rate being the holdout group) and fixed effects for neighborhood (PUMA) and year. 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.

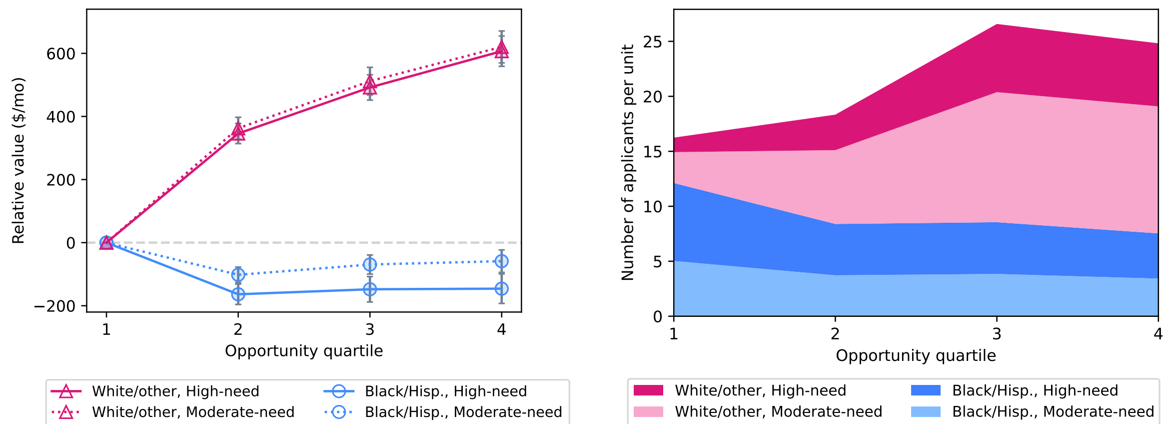
Figure D.6: Rent growth: market-rate vs. LIHTC



Notes: This figure documents the growth in real rents between 2010 and 2019 in the American Community Survey, split by LIHTC and market-rate. Each point is a coefficient from a regression of log gross rent on indicators for the year of the survey. 95% confidence intervals are represented by gray bars.

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 D14: 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)
Prev. tract opportunity percentile	0.3117	0.3305	0.3345	0.3367
	(0.0034)	(0.0029)	(0.003)	(0.0032)

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 D15: 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	Causal effect on undiscounted lifetime income per unit-month (=([13]*[16])/(18*12))	$704.8	$1732.8
18	Causal effect on discounted lifetime income 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 D14 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 D14. 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).

Table D16: Comparison of counterfactuals: additional household characteristics

	Current income		Frac. w/ children		Frac. high-need	
	Q1	Q1→Q4	Q1	Q1→Q4	Q1	Q1→Q4
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)
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)
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)
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)
Fair lottery	\$10,990	+\$550.2	0.3017	-0.0631	0.4962	-0.1109
	(2612)	(193.3)	(0.0124)	(0.0077)	(0.0242)	(0.0116)
No $\boldsymbol{\alpha}$ heterog.	\$12,990	+\$550.1	0.2681	-0.063	0.4418	-0.0934
	(2461)	(195.7)	(0.0082)	(0.0074)	(0.0197)	(0.0096)

Notes: This table extends Table 4 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. Bootstrapped standard errors are reported in parentheses.