Can Moves to Opportunity be Constructed? Evidence from the Low-Income Housing Tax Credit*

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Abstract

Low-income households often cannot afford to live in opportunity-rich neighborhoods. We investigate the mobility impacts of the Low-Income Housing Tax Credit (LIHTC), a large and fast-growing federal housing affordability program which subsidizes the construction of rent-restricted housing for low-income tenants. We estimate causal impacts by linking propietary application and waitlist data from a large LIHTC developer to administrative address history data. Preliminary evidence suggests that successful LIHTC applicants experience mixed mobility outcomes, although we observe substantial heterogeneity based on the quality of neighborhoods that applicants move from.

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1 Introduction

The neighborhood one lives in plays a central role in shaping lifetime economic and social prospects. A growing body of causal evidence establishes that both children and adults benefit from living in high opportunity neighborhoods. However, many low-income families are priced out of living in high-opportunity neighborhoods. The average household in the bottom quintile of the income distribution only retains about $500 per month after paying for housing (Larrimore and Schuetz, 2017). Half of the renter-occupied households in this quintile spend over 60% of their incomes on rent (Mateyka and Yoo, 2023). Given the strong correlation between rental prices and neighborhood quality (Chetty et al., 2018), many low-income families are closed off from accessing the benefits of high opportunity neighborhoods.

Policymakers have primarily attempted to address constraints on upward neighborhood mobility using a variety of demand-side solutions. However, most of these efforts have not had the desired effects in practice, or otherwise introduce new problems to be solved. For example, one potential solution is to place price ceilings on rent in high opportunity areas. But the clear downside of such a policy is that it would tend to reduce the supply of rental housing and thus limit the geographic mobility of households (Diamond et al., 2019). A policy that has been more effective in increasing opportunity has been housing vouchers, as implemented in the famous "Moving to Opportunity" (MTO) experiment. Vouchers were found to increase the future incomes of young children whose families were given them (Chetty et al., 2016). However, the capacity of voucher programs to induce moves to better neighborhoods is ultimately limited by high levels of oversubscription and the opposition of private landlords, and targeted MTO programs are defunct in most areas with high demand for affordable housing today. While some case management programs have met with success, such programs are expensive and difficult to scale.

In this paper, we analyze tenant-level mobility impacts of the Low-Income Housing Tax Credit (LIHTC), the largest and fastest-growing federal housing affordability program. The LIHTC provides tax credits for developers to build housing for low-income individuals, and so acts as a supply-side instrument for the generation of new affordable units. In particular, we ask if individuals who obtain a LIHTC-subsidized unit move to higher opportunity neighborhoods than similar individuals who did not obtain them. We characterize moves to LIHTC using a diverse battery of tract-level measures, reflecting the fact that neighborhood-level "opportunity" is a multi-faceted concept with no single definition. Using proprietary data from a large private developer of LIHTC-funded housing, we identify both the sending and receiving neighborhoods of LIHTC tenants and supply the first evidence on the degree to which moves to LIHTC provide a ladder up to better neighborhoods.

As of this writing, we have completed a descriptive analysis of moves by applicants who are successfully placed in LIHTC-funded units. We report suggestive evidence that, across our various measures, individuals from lower-opportunity neighborhoods tend to do better in terms of tract-level opportunity after moving to a LIHTC unit, while individuals from higher-opportunity neighborhoods tend to do worse. These findings suggest that state policies which influence the location of LIHTC construction play an outsized role in shaping the mobility impacts of the program. In future work, we will analyze the outcomes of unsuccessful applicants, who provide a valid counterfactual at the individual-level. In order to observe post-application migration for non-placed applicants, we plan to link applicant data to address histories for a large sample of US adults, obtained from the marketing firm Infutor.

This paper adds to a large and growing literature on the impacts of neighborhoods on resident outcomes. Neighborhood effects are complex and appear to operate through numerous channels. Neighborhood segregation affects exposure to successful peers and role models, school-quality, safety, and access to nearby jobs (Chetty et al., 2020). Social capital—the interconnectedness of individuals in a community—creates networks and social support which facilitate development and provide informal insurance against harm (Chetty et al., 2022). Communities with stable, intact families tend to set expectations for and support other families in emulating those family structures (Wasserman, 2020). A large body of causal research further documents a myriad of ways in which places causally shape resident outcomes including physical and mental health, criminal behavior, educational achievement, and more (Kling et al., 2007; Damm and Dustmann, 2014; Laliberte, 2021; Chyn and Shenhav, 2022; Deryugina and Molitor, 2021). Many of these outcomes are likely direct inputs toward achieving upward mobility.

We also provide novel, tenant-level insights to a literature on the LIHTC which has predominantly focused on place-based impacts. The LIHTC has quickly become the largest federal low-income federal housing production program (Collinson et al., 2016). Despite this, research on tenants who live in LIHTC housing remains exceedingly scarce. This knowledge gap persists in large part because of data constraints: administrative data on tenants from HUD provides limited information on policy-relevant outcomes, and outside administrative data cannot be reliably linked to LIHTC tenancy. Experimental and quasi-experimental variation at the tenant level is difficult to obtain, particularly since tenant application and waitlist data are typically managed by individual properties. Because of this, existing studies of the LIHTC have been limited to analyzing the program's spillover impacts on neighborhoods instead of individuals, focusing on outcomes such as crime (Freedman and Owens, 2011; Diamond and McQuade, 2019), demographic composition (McGuire and Seegert, 2023; Davis et al., 2019; Diamond and McQuade, 2019), housing construction (Soltas, 2023; Eriksen and Rosenthal, 2010; Baum-Snow and Marion, 2009), and home prices (Baum-Snow and Marion, 2009; Davis et al., 2019; Diamond and McQuade, 2019).

Several recent working papers now link federal tax data to publicly available LIHTC address data. Derby (2021) finds that each additional year spent in LIHTC housing as a child is associated with increases in college attendance and future earnings. Cook (2023) estimates a residential choice model to estimate the welfare implications of the composition of LIHTC residents. However, obtaining causal estimates with tenant-level outcomes remains a substantial challenge due to unobserved selection into LIHTC housing. Our primary contribution to this growing body of work is the use of developer application data to construct counterfactual outcomes that allow for causal inference.

2 The Low Income Housing Tax Credit (LIHTC)

2.1 How do the subsidies work?

The LIHTC was established as part of the Tax Reform Act of 1986 to expand the supply of affordable housing via developer subsidies. Since its passage, the program has become a bedrock of the U.S. housing landscape with over 3.5 million units placed in service between 1987-2021. Today, the program costs an estimated $13.5 billion annually (Keightley, 2023). Figure 1 shows that the LIHTC is both the largest and fastest-growing housing affordability program operated by HUD. Program funding has been used in the construction of more than 20% of all multi-family housing development over the past two decades (Diamond and McQuade, 2019).

The LIHTC differs from other HUD programs in that it provides developers with incentives (in the form of tax credits) to build rent-restricted housing that is set aside for low-income tenants.[1] The program subsidizes up to 70 percent of a project's development costs for low-income units.[2] Prospective developers choose from a menu of options for rent-restricted units set aside for low-income residents, including: 1) ≥20% of units occupied by tenants earning below 50% of the Area Median Income (AMI), or 2) ≥40% of units occupied by tenants earning below 60% of AMI.[3] Rents for these units cannot exceed 30% of the corresponding AMI threshold. The low-income requirements bind for 15 years, and properties can gradually phase out of the LIHTC program over the course of the subsequent 15 years.

[1] Developers sell tax credits to investors, who in turn receive a dollar-for-dollar credit against their federal tax liability for a period of 10 years if the property continues to comply with program requirements.

[2] The 30 percent subsidy, covers either the acquisition cost of existing buildings or the construction of new buildings when paired with other subsidies. The 70 percent subsidy supports only new construction and does not allow additional federal subsidies to be used.

[3] There is a third criteria added in 2018 which allows developers to set aside 40% of units such that the average AMI threshold among these units does not exceed 60%. The units contributing to this average must range between 20% and 80% AMI.

2.2 How does the LIHTC affect mobility to high-opportunity places?

The LIHTC provides a fixed set of locations where low-income families can exclusively access rent-restricted housing. These locations are highly influenced by state-specific LIHTC policies. Despite being a federal program, each state determines how to allocate its share of tax credits through its own competitive scoring process. Each state discloses its scoring criteria through an annual "Qualified Allocation Plan" (QAP). Project location plays a central role in scoring, and many states have incorporated opportunity-based criteria into their QAPs, including access to education, economic vitality, health care access, and access to transportation (Freddie Mac, 2023).

Currently, housing vouchers remain the predominant approach for promoting housing mobility. The landmark Moving to Opportunity (MTO) experiment demonstrated that housing vouchers tied to moving to a low-poverty neighborhood increased the future incomes and social outcomes of young children (Chetty et al., 2016). Three decades later, voucher-based housing mobility programs still remain limited in size and prevalence (Mumphery et al., 2023). The broader housing voucher system also faces significant constraints. Just one quarter of housing voucher applicants are selected by lottery, only to be placed on waitlists averaging two and a half years in length (and as long as eight years in some areas) before ultimately receiving their vouchers (Acosta and Gartland 2021). Widely-documented landlord discrimination against voucher holders has also negatively impacted housing mobility among low-income households (Sard et al. 2018).

In theory, the LIHTC could provide an attractive complement to housing vouchers by aligning financial incentives of private developers with the ever-growing need for more affordable housing. From a mobility perspective, LIHTC units constructed in high-opportunity locations could provide similar benefits as a housing mobility voucher. However, the LIHTC's role in promoting economic mobility crucially depends on state-specific QAP incentives to build in high-opportunity places. Some state QAPs reward points to projects located in low-cost areas where access to amenities and economic opportunities may be limited. On top of state-specific scoring incentives, any project built within qualified low-income census tracts is eligible for a federally-mandated 30% increase in tax credit generosity, further incentivizing development in high-poverty neighborhoods. The misalignment of federal and state incentives potentially offsets the overall mobility benefits of the LIHTC, though the extent to which this occurs remains unknown.

3 Data

Due to the highly decentralized nature of the LIHTC program, there is no national individual-level dataset that identifies residents of LIHTC-funded housing.[4] Moreover, existing large microdatasets that capture outcomes of interest (e.g., ACS, CPS) do not capture whether an individual is living in a LIHTC-funded unit (Collinson et al., 2016). Some very recent work has made progress in this area by linking known locations of LIHTC-funded properties to administrative records (Derby, 2021; Cook, 2023). However, such linkages are unable to identify *applicants* to LIHTC-funded units, who form a natural comparison group at the individual-level for placed tenants. Since government agencies do not collect administrative data on applicants to LIHTC-funded properties, it is only possible to identify applicants by accessing proprietary data maintained by developers.

Our key empirical innovation in this paper is to link proprietary application, waitlist, and tenant data from a large private developer of LIHTC-funded housing to individual-level outcomes. These novel data allow us to surmount the obstacles that have impeded previous work by identifying plausible counterfactual outcomes for LIHTC tenants. In this section, we provide background information on the private developer who supplied the applicant and tenant data, including institutional details relating to the application and placement processes. We discuss salient features of the applicant and tenant data, and provide summary statistics. Finally, we detail the various other datasets that we link to the applicant and tenant sample.

[4]In fact, HUD only began collecting project-level demographic and economic information on tenants in LIHTC units in 2008. The annual "tenant reports" produced from these aggregated data are limited by incomplete coverage and the lack of uniform reporting requirements. Most of the data collection is carried out by the respective state housing finance agencies (HFAs), and per HUD documentation: "although income and rent information was collected across HFAs using fairly uniform standards and definitions, the demographic information was not standardized and, for some HFAs, not collected at all."

3.1 Applicant and Tenant Data

We obtain applicant and tenant data from Woda Cooper Companies, a large private developer of affordable housing based in Columbus, OH. With a development portfolio of $1.5 billion and more than 350 LIHTC-funded properties spanning 16 states, Woda Cooper ranks as one of the top 20 largest developers of newly constructed low-income LIHTC units in the U.S. (HUD, 2023). More than 30,000 individuals currently reside in a Woda Cooper property, and more than 100,000 have been tenants since the company's founding in 1990. Woda Cooper specializes in multi-family apartments, single-family dwellings, and senior communities. Among large private LIHTC developers, Woda Cooper is notable for being fully vertically integrated – the development, design, construction, and management of each property is all conducted in-house. As a result, applicant and tenant data for all properties is subject to uniform internal standards of reporting and stewardship, which is a key advantage in our setting.

Figure 2 depicts the geographic distribution of units associated with all LIHTC-funded properties managed by Woda Cooper. Extending from its base in the Midwest, Woda Cooper also has a significant presence in parts of Appalachia and the Southeast. While Woda Cooper's portfolio includes developments in several large cities (e.g., Columbus, Cincinnati, and Cleveland, OH; Atlanta, GA; Charleston, SC; Norfolk, VA), the majority of their LIHTC-funded units are located in suburban or exurban counties. This distribution highlights an important feature of LIHTC more broadly: while much of the literature on other supply-side affordable housing programs tends to focus on dynamics in urban areas, LIHTC is embedded in the housing landscape across a wide variety of neighborhood types and locations, often including suburban and rural areas. In this context, migration to LIHTC-subsidized units may look quite different than migration to public housing or project-based Section 8 units. In particular, migration to LIHTC units likely occurs over longer distances on average, and thus may imply even greater changes in neighborhood characteristics such as school district quality and access to jobs.

Since 2012, Woda Cooper has tracked all interactions with prospective applicants, applicants, and tenants at each property using Yardi, an internal client management database. Figure 3 depicts the end-to-end flow for the application and placement processes. Prospective applicants ("prospects") can initiate the process by contacting the property manager directly or by expressing interest through one of several online listing platforms (e.g., Zillow, Apartments.com). At this stage, prospects supply basic contact information and wait for the property staff to follow up with details on how to apply.[5] The application collects additional information including family size, unit preferences (e.g., # bedrooms, special needs), current address, and self-reported income. Once the application is submitted and the application fee is paid,[6] the application is forwarded for processing. In general, applications are reviewed on a first come, first served basis. Property staff use observed characteristics including unit preferences and income to match applicants to suitable units. Income is especially important, since units within each property have varying income restrictions in order to ensure compliance with HUD affordability rules. If no suitable unit is currently available, the applicant is assigned to a wait list for units of that type. If a suitable unit is available, the applicant progresses to the eligibility screening, which involves criminal background and credit checks as well as a third-party verification of income. If an applicant is determined to be eligible, they can accept the offered unit and begin planning their move-in. At any point after an application is submitted (but before a unit is accepted), an applicant may cancel their application, which would remove them from any waitlist.

For all applicants, we observe the applicant's full name, the address they applied from, unit preferences, self-reported income, the application date, the outcome of their application, and a contact log which details all interactions with the property. For placed tenants, we observe all of the applicant characteristics as well as race,[7] verified income, unit characteristics, and move date.

We observe a variety of property-level characteristics from Woda Cooper, including each property's name, date placed-in-service,[8] funding sources, tax credit details, and affordability rules. We

[5]Alternatively, an interested individual can simply submit a full application without first expressing interest.

[6]Application fees at Woda Cooper properties are typically low (less than $25). They are used to cover administrative costs as well as costs associated with background checks used for eligiblity screening.

[7]Properties are not permitted to record the race of non-residents.

[8]The LIHTC "placed-in-service" date corresponds to the date that a property is certified as ready for occupancy. For new construction, this date generally corresponds to the inspector's certification. LIHTC-funded properties can begin earning tax credits for investors only after the units are placed-in-service and occupied.

also observe all unit-level addresses associated with each property in our sample. Since some properties are "scattered sites" with units spread across multiple locations, this allows us to identify the exact location to which placed residents move. Finally, we observe several unit-level characteristics, including unit size (sq ft), number of bedrooms, rent and utility allowance, and whether the unit is designated as subsidized or market rate. For all subsidized units, we observe the income restriction rule associated with the unit.

3.2 Supplementary Data

We supplement the applicant and tenant data from Woda Cooper with data from various sources:

- **LIHTC Placed-In-Service Database** (HUD, 2023). HUD maintains a publicly available database of all LIHTC-funded projects placed-in-service since the program's founding in 1986. These data include developer identifiers, property names and addresses, placed-in-service and credit allocation dates, whether the property targets specific populations (e.g., families, elderly, disabled, homeless), unit counts (total and subsidized), funding sources, and several variables related to the siting of properties. We use these data to compare Woda Cooper properties to other LIHTC properties. We also fuzzy match the Woda Cooper sample of properties to the HUD database to supplement the set of property-level variables available from Woda Cooper.

- **Opportunity Atlas**. The Opportunity Atlas is constructed collaboratively by researchers at the Census Bureau and Opportunity Insights, a research and policy group based at Harvard University. The Opportunity Atlas builds upon the literature spawned by Chetty et al. (2014) in providing Census tract-level data for a wide array of observed and predicted socioeconomic mobility indicators. We use these data to construct tract-level measures of "opportunity." We follow previous work in selecting a diverse set of measures intended to proxy for various dimensions of neighborhood opportunity. We include two measures which relate to generational mobility, a key focus of the place-based opportunity literature: (1) the predicted probability of incarceration as an adult conditional on having parents in the bottom quartile of the national income distribution as a child, and (2) the predicted probability of reaching the top quintile of the national income distribution as an adult conditional on having parents in the bottom quartile of the national income distribution as a child. A drawback of these mobility measures is that they represent neighborhood opportunity lagged by several decades, since they are constructed based on the childhood locations of current adults. Therefore, we supplement the generational mobility measures using several contemporaneous measures of opportunity, including: the poverty rate, standardized 3rd grade math scores (at the district-level), the single parent share, average wage growth of high school graduates, jobs within five miles, and the average annualized job growth rate.

- **Infutor Consumer Reference Database**. In future work, we will use personally-identifiable information available from the Woda Cooper applicant and tenant data to link individuals to migration histories compiled by Infutor Data Solutions. Infutor contains over 375 million individual-level records linked with nearly 1 billion address and name histories. Each address record in Infutor is associated with an 'effective date", interpretable as a move-in date, allowing us to sequence an individual's move history over time. Because Infutor provides name histories, we can further link records for individuals associated with multiple aliases and for those whose surname changes over time. We also observe date of birth, gender, and (for about 40% of records) SSN, which further improves the quality of probabilistic record linking. Previous work finds that Infutor is highly representative of the U.S. adult population,[9] especially since the 1990s.[10] Infutor data has been previously used by economists to study immigration

[9] Infutor aggregates information from numerous private and public record sources, including USPS change of address forms, county assessor records, magazine subscriptions, and phonebooks. Due to the nature of the source data, Infutor is generally unable to detect individuals who do not have a "paper trail", such as minors, undocumented immigrants, or homeless populations. Given that our population consists of adults who are able to afford LIHTC-subsidized housing, we believe that Infutor is well-suited to measure migration-related outcomes in our context.

[10] Using 2017 ACS 5-year estimates, Asquith et al. (2023) finds a median of 0.88 Infutor observations per Census individual aged 25+ across all Census tracts. Bernstein et al. (2022) find that variation in county populations estimated from Infutor can account for 99% of the variation observed in county populations in the 2000 Census. Phillips (2020) shows that Infutor move dates can detect highly-localized migration shocks, including out-migration from Hurricane Katrina and closures of public housing projects in Chicago.

(Bernstein et al., 2022), rent control (Diamond et al., 2019), housing markets (Pennington, 2021; Asquith et al., 2023; Mast, 2023), and housing stability (Phillips, 2020; Collinson et al., 2022). Linking is on-going as of this writing, and the resulting analyses will be reported in future versions of this paper.

3.3 Summary Statistics

We construct our main sample of LIHTC-funded Woda Cooper properties by applying two sample restrictions. First, we exclude all properties placed-in-service in 2012 or later, since we cannot identify initial lease up activity for properties that predate the Yardi database. Second, given this paper's focus on neighborhood opportunity for low-income families, we exclude senior communities. The resulting sample includes 135 LIHTC-funded properties.

Table 1 provides summary statistics at the property level. Several features are notable from panel A (Property Characteristics). First, both for Woda Cooper properties and LIHTC properties more broadly, over 90% of total units are set-aside for low-income families and have applicable income restrictions. This greatly exceeds the compliance standards imposed by HUD, but is consistent with a competitive credit allocation process which forces developers to commit to building more subsidized units than is minimally required. Second, Woda Cooper properties are characterized by low vacancy rates – point-in-time measurement from 2023 shows that only 5.5% of all subsidized units are vacant.[11] High occupancy rates reflect the fact that HUD compliance requires all subsidized units to be occupied within one year of the placed-in-service data, absent extenuating circumstances. We also find that each unit receives about 3.4 applications during the first year of lease up which, together with low vacancy rates, implies that units are moderately oversubscribed. We will leverage this oversubscription of units and the first come, first-served nature of the waitlist in our empirical design.

In order to characterize the types of neighborhoods in which LIHTC properties are located, we geocode each property-level address, attribute Census tracts, and merge in 2010 tract-level observ-

[11]For comparison, the vacancy rate for all LIHTC two-bedroom units from 2010-2020 was approximately 4%.

ables from the Opportunity Atlas data. The results are presented in panel B. Consistent with the geographic distribution of Woda Cooper properties, we find that Woda Cooper tends to develop in areas that have lower population density, higher White shares of population, and higher homeownership rates relative to other LIHTC-funded properties. However, in terms of the three measures that we interpret as proxies for neighborhood-level opportunity – share with a bachelor's degree or higher, poverty rate, and single parent share – neighborhoods with Woda Cooper properties are comparable to the average neighborhood with LIHTC properties. The average neighborhood with LIHTC-funded housing (Woda Cooper or otherwise) is near the national 75$^{\text{th}}$ percentile in terms of the poverty rate and single parent share, which suggests that LIHTC development is concentrated in areas of relatively low opportunity.[12]

We also fuzzy match Woda Cooper properties to the HUD LIHTC Placed-in-Service Database to analyze additional property-level characteristics (panel C). We successfully match 82/135 main sample properties (60%) to the HUD data. From this sub-sample, we are particularly interested in the proportion of properties that are built in Qualified Census Tracts, or "QCTs". QCTs are tracts that have (1) $>$ 50% of households with incomes below 60% of the Area Median Gross Income and/or (2) a poverty rate of 25% of more. Since 1990, federal statute has stipulated that properties in QCTs are to be afforded a 30% tax credit boost, which incentivizes additional development.[13] Many state QAPs also encode special preferences for development in QCTs (Ellen et al., 2015). However, as QCTs are defined to be the most economically disadvantaged neighborhoods in an area, they may play a role in further entrenching LIHTC families in low opportunity neighborhoods. We find that while Woda Cooper properties in our sample are less likely to be sited in QCTs than other LIHTC properties, a non-trivial proportion – approximately 24% – are located in a QCT.

We also present additional unit-level summary statistics for subsidized units only in Table 2, and highlight several features. First, the vast majority of subsidized units (82%) have two or three bedrooms, which is consistent with a tenant population consisting mostly of families. Second, we

[12]This is consistent with Ellen et al. (2018), who find that LIHTC units are located in neighborhoods with higher poverty rates, lower quality schools, and more polluted environments relative to other rental units.

[13]The impact of the QCT rule on the local supply of LIHTC units has been exploited by Baum-Snow and Marion (2009) and subsequent literature.

find that the current income of tenants in subsidized units (33% of AMGI) is slightly higher than the income reported by those tenants at move-in (32% of AMGI). Unlike other project- or tenant-based rental assistance programs, the rent subsidy that LIHTC tenants receive is not a function of own income. So while a LIHTC tenant must be income-eligible for their unit at the time of placement, any future increases in earnings do not impact eligibility or rents. Insofar as LIHTC does not "tax" post-placement earnings and therefore does not generate labor supply disincentives, local prospects for income mobility may be even more salient for applicants to LIHTC-subsidized units relative to applicants to other rental assistance programs. Finally, while various other affordability thresholds have been used since income averaging was introduced in 2018 (see footnote 3) we observe that about three-quarters of subsidized units are restricted at the 50% or 60% AMI thresholds. This implies that the original LIHTC income affordability rules still provide a reasonable approximation for the composition of tenants in subsidized units.

4 Preliminary Descriptive Results

4.1 Sample Construction

We construct our applicant-level sample for analysis by applying several restrictions. We exclude any individuals associated with properties outside our main property-level sample (i.e., those that target the elderly population, and/or were placed-in-service prior to the adoption of Yardi in 2012). We drop all individuals who did not advance far enough in the process to submit an application ("prospects"), for whom key observables are unavailable. We drop commercial applicants (e.g., retail stores on the bottom floor of an apartment building), and any records that are missing address at application or application date. We also limit the sample based on previous application history. Individuals may apply to a property multiple times after cancelling a previous application. Placement from subsequent applications may not be exogenous if people who apply multiple times have different underlying characteristics or housing situations than those who apply once. We therefore restrict our sample to only include those who have at most one application per property.

Finally, we drop applications from individuals who we identify as applying to a new unit within the same Woda Cooper property in which they currently reside.

Table 3 provides a breakdown of of applicants by status type in our main sample for analysis. These statuses correspond to the "terminal status" for each applicant; i.e., the ultimate outcome of their application. For example, if an individual is admitted into a unit after spending several months on the waitlist, we observe this individual as a "Resident". We find that most individuals who apply are not placed as tenants – 21% are still on the waitlist as of last measurement, 28% canceled at some point after applying, and 17% were denied due to ineligibility. There is a relatively small group of applicants (2.5%) whose eligibility was approved at last measurement, but who are not yet placed in a unit. The remaining 31% of the sample is comprised of residents. Overall the sample includes approximately 16,000 applicants, the vast majority of which are applicants to subsidized units.

4.2 Baseline Balance

In future work, our basic comparison will be that of residents (treatment group) versus non-placed applicants (control group). To test whether these groups are similar at the time of application, we analyze baseline balance in Table 4. For this analysis, we further restrict the sample to exclude "Denied" individuals, since these ineligible applicants are unlikely to serve as a suitable comparison group for residents. We also drop individuals whose eligibility has been approved but have not yet been placed in a unit, since their ultimate status is to be determined.

Columns (1) and (2) present unconditional means for residents and non-residents, respectively. We test for differences at baseline using the following regression equation, estimated by OLS:

$$X_i = \beta_0 + \beta_1 Resident_i + \theta_p + \varepsilon_i \tag{1}$$

where the dependent variable X_i is an observable characteristic at baseline, $Resident_i$ is a treatment indicator equal to 1 if the applicant is a placed resident, and θ_p is a property-level fixed effect. Column (3) reports the β_1 coefficient for each baseline characteristic X_i, which is interpretable as the "regression-adjusted" difference in means from columns (1) and (2). $\beta_1 > 0$ therefore implies that the non-resident group mean is greater than the resident group mean when using only within-property variation. To contextualize the results within the broader housing landscape, column (4) reports the national (2010) mean for each tract-level characteristic.

In panel A, we characterize applicants based on their geographic proximity to the property to which they are applying. In both groups, applicants are predominantly from the local area – a clear majority are applying from within-county and about half are applying from the same city. But a considerable proportion are coming from outside the local area, including about 10% who apply from out-of-state. For any geographic level, we find that applicants who become residents are less likely to be "local" compared to applicants who do not. Conditional on submitting an application, individuals from outside the local area may have a higher probability of placement if they had to overcome greater search and information frictions compared to local applicants, a signal of their seriousness and strong interest in a particular property. As a result, non-local applicants may be more likely to follow through at each step of the application process, and/or may be willing to wait longer on wait lists for units to open up.

In panels B-D, we geocode the application address of each applicant, attribute 2010 Census tracts, and merge in tract-level characteristics from Opportunity Atlas. Group differences at baseline are often statistically significant, but small in magnitude for most tract-level observables. There is some evidence that successful applicants apply from tracts that are more dense (10% difference relative to the non-resident mean) and have slightly higher incomes (3% difference relative to the non-resident mean) compared to unsuccessful applicants. Most importantly for the focus of this paper, however, we find that residents and non-residents look very similar in terms of the opportunity level of their application neighborhoods (panel D). Group differences are statistically insignificant for 3/8 opportunity measures, and 4 of the statistically significant adjusted differences are within +/- 5% of the corresponding non-resident group mean. A notable exception is the tract-level annual job growth rate: residents tend to come from tracts that have considerably higher job growth rates than non-residents. Moreover, the within-property (regression-adjusted) difference is much larger than the difference in unconditional means, which suggests that applicants from high growth areas disproportionately apply to more competitive properties (i.e., those with less favorable resident : non-resident ratios) compared to applicants from low growth areas. This result is consistent with greater demand for affordable housing in hot job markets.

The results of these baseline balance tests highlight the need to control for relevant characteristics of applicants' sending neighborhoods in future work, in order to ensure comparability between the treatment and control groups.

4.3 Main Results

As of this writing, we have not completed linking Woda Cooper applicants to address histories from the Infutor database, which precludes us from tracking the migration outcomes of non-placed applicants. However, since we observe the application address and the unit address for placed applicants, it is possible to characterize the moves made by applicants who become residents in Woda Cooper's LIHTC-funded properties. In this section, we present preliminary results on the degree to which those moves to LIHTC properties are opportunity-improving at the neighborhood level. While we are cautious to draw strong conclusions from analyses that lack a valid counterfactual, these descriptive results nonetheless provide useful insights by supplying the first evidence on the migration of LIHTC tenants using information from both sending and receiving locations.

From our main analysis sample of applicants, we drop individuals with statuses of "Denied" and "Eligibility Approved" as in Section 4.2. We also limit attention here to individuals who moved to subsidized units, yielding a final sample of 4945 residents. We then construct a panel at the applicant-period level. Periods are defined by the move date to a LIHTC-funded property: the "pre" period corresponds to the pre-move period (and thus the address at time of application), and the "post" period corresponds to the post-move period (and thus the Woda Cooper unit address), such that each applicant is associated with two observations. To identify the average difference in neighborhood characteristics between receiving (LIHTC property) and sending (application) tracts, we estimate the following regression using OLS:

$$y_{it} = \beta_0 + \beta_1 Post_t + \delta_i + \varepsilon_{it} \tag{2}$$

where the outcome y_{it} is a tract-level measure of opportunity for individual i's address in period t, $Post_t$ is a period indicator equal to 1 for the post-move LIHTC address and equal to 0 for the pre-move application address, and δ_i is an individual-level fixed effect.

We report the regression results in Table 5. Column (3) reports the β_1 coefficient for each outcome y_{it}, which is interpretable as the difference in means between receiving and sending tracts. $\beta_1 > 0$ implies that the receiving tract mean is greater than the sending tract mean, using within-individual variation. To aid in interpretability, we bin the neighborhood opportunity outcomes into measures of low vs. high opportunity. For measures of low opportunity, $\beta_1 > 0$ signifies that the move to LIHTC was opportunity *reducing*; for measures of high opportunity, $\beta_1 > 0$ signifies that the move to LIHTC was opportunity *improving*.

The results suggest that moving to LIHTC provides low-income families with a mixed bag in terms of neighborhood-level opportunity. Migrants to LIHTC tend to end up in neighborhoods that have a higher poverty rate (+3pp, about a 12% increase over the application tract mean), but stronger job markets as measured by proximity to jobs (10% increase) and average annualized job growth rates (+1 pp). These results are consistent with findings from the previous literature on neighborhood opportunity that show a negative correlation between job concentrations and upward mobility in metro areas (Chetty et al., 2018). For the other opportunity measures, the change from sending to receiving tract is small and/or statistically insignificant.

4.4 Heterogeneity

Our results from Table 5 suggest a relatively limited impact of moving to LIHTC on neighborhood quality. However, average differences between sending and receiving tracts may mask underlying heterogeneity. From a policy perspective, it is critically important to understand whether moving to

LIHTC results in differential outcomes across various subgroups of migrants. To get a sense for the degree to which heterogeneous effects may be important in our setting, we plot the full distribution of applicant-level data for each outcome measure in Figure 4. Each scatterplot corresponds to a different measure, and shows the relationship between the application tract value (x) and the LIHTC property tract value (y) for that measure. To make the graphs legible, we use Stata's *binscatter* program to non-parametrically group applicant-level data into bins of equal observations. The 45 degree line provides a reference level: intuitively, the further away a data point is from the 45 degree line, the greater is the implied change in neighborhood-level opportunity that results from the move to LIHTC. For measures of low opportunity (4a, 4b, and 4c) data points below the line correspond to opportunity-reducing moves, while those above the line correspond to opportunity-improving moves. For measures of high opportunity (4d-h), the interpretation flips.

The plots from Figure 4 are suggestive of a high degree of heterogeneity, and a similar pattern emerges across most measures: applicants from relatively low opportunity tracts tend to upgrade in terms of neighborhood quality after moving to LIHTC-funded properties, while applicants from relatively high opportunity tracts tend to do worse. 3rd grade math scores appear to be an exception, and this may be due to the fact that these scores are measured at the district-level, which would tend to attenuate any differences between sending and receiving tracts. The impact of moving to LIHTC on access to jobs within 5 miles also appears to be close to zero for most applicants – with the major exception of applicants from tracts with very few jobs, for whom moving to LIHTC appears to greatly improves job access. Overall, the results from Figure 4 are consistent with a view of LIHTC as a "leveler" of neighborhood quality, providing a ladder up to better neighborhoods for those from the lowest opportunity areas while simultaneously inducing applicants from the highest opportunity areas to move to more socioeconomically disadvantaged tracts. Since LIHTC is fundamentally a project-based rental assistance program and applicants take the set of possible subsidized locations as given, it therefore matters a great deal for aggregate effects where the "level" is set – i.e., where developers are incentivized and awarded credits to build. The impact of moving to LIHTC for low-income families is indeed an equilibrium outcome, influenced by the interaction of incentives at both the applicant and developer levels. While other recent work focuses on modelling the developer side (Cook, 2023; Soltas, 2023), in this paper we seek to shed light specifically on how moving to LIHTC impacts tenants, taking the supply of LIHTC-funded housing as given.

In our final set of descriptive results, we estimate heterogeneous effects across various subgroups more systematically using the following regression equation:

$$y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Char_i + \beta_3 Post_t \times Char_i + \delta_i + \varepsilon_{it} \tag{3}$$

where $Char_i$ is an indicator for belonging to a subgroup with a specified characteristic, and other variables are as in Equation 2. β_1 is interpretable as the mean change in opportunity for tenants who do not belong to the specified subgroup, and β_3 corresponds to the mean change in opportunity for tenants who belong to the specified subgroup.[14]

We present the results from the subgroup analysis in Table 6. For each outcome, we report both β_1 ("Post") and β_3 ("Post × Char"). We report results separately for various subgroups by column. We again group measures of low vs high opportunity together for ease of interpretation. And, as before: a positive coefficient signifies that the move to LIHTC was opportunity *reducing* for measures of low opportunity, while a positive coefficient signifies that the move to LIHTC was opportunity *improving* for measures of high opportunity.

The results from Table 6 present a complicated story and should be interpreted conservatively. However, these results are suggestive of certain dynamics that are in alignment with our previous findings and which are worth highlighting here. First, from column (1), we again find evidence of heterogeneity by the poverty level of the sending tract. Across most measures, moves to LIHTC are opportunity-improving for those from high poverty tracts, while moves to LIHTC are opportunity-reducing for those from low poverty tracts. In column (2), we split the sample according to whether the sending tract was majority non-White. We find that those applying from majority non-White tracts consistently do better by moving to LIHTC, while those from majority white tracts do worse.

[14]Note that the main effect for each outcome can be recovered by taking the weighted sums of β_1 and β_3, where the weights correspond to the proportion of the sample that do/do not belong to each subgroup.

Insofar as tract-level racial composition is positively correlated with applicant race, this suggests that LIHTC may be especially effective at providing an entry point to better neighborhoods for minority applicants. In both columns (1) and (2), however, the opportunity measures related to the job market again tell a different story: for these measures, applicants from high poverty and majority non-White tracts do *worse* in terms of neighborhood quality after moving to LIHTC. These results underline the importance of thinking about "opportunity" in a multi-faceted, non-monolithic manner, and imply that policies designed to improve outcomes along one margin may trade-off worse outcomes along another.

In column (4), we find some evidence that moves to the most income-restricted units (income restriction $<$ 60% AMGI) are opportunity-reducing relative to moves to less restricted units. This is consistent with highly restricted units being more competitive, such that applicants are willing to trade off desirable neighborhoods in exchange for highly subsidized rents. Indeed, we would expect that applicants to subsidized units seek to optimize their housing situation across several dimensions, of which neighborhood quality is one – but certainly not the only (and perhaps not the most important) one.

Finally, in column (5), we split the sample based on moves to LIHTC properties in Qualified Census Tracts (QCTs). As expected, moves to QCT tracts tend to be opportunity-reducing by nearly every measure. This descriptive result points strongly to an important role for the design of developer incentives at both the federal and state levels in mediating the impacts of moving to LIHTC on neighborhood opportunity.

5 Discussion

Although neighborhoods heavily shape upward mobility prospects for low-income families, low-income renters are frequently priced out of living in high-opportunity neighborhoods. Many of these households, particularly those living in high-cost regions, face prohibitively high rent burdens even while living in low-opportunity places. This project aims to showcase the potential of the LIHTC—

the nation's largest and fastest-growing housing affordability program—as a policy complement to existing voucher-based housing mobility programs.

Preliminary descriptive findings from LIHTC tenant-level application data show that on average, successful applicants move to neighborhoods which are higher-quality on average along certain dimensions (e.g., job growth) but lower-quality along others (e.g., poverty rate). When comparing the quality of sending and receiving tracts, we find that applicants from low-opportunity neighborhoods typically experience increases in neighborhood quality, and applicants from high-opportunity neighborhoods experience decreases in neighborhood quality. For certain opportunity measures such as job density, applicants from low-opportunity tracts experience improvements whereas applicants from high-opportunity tracts remain unaffected. Future updates to this work will incorporate quasi-experimental features of the applicant waitlist in order to compare outcomes of successful applicants against comparable applicants who did not receive offers for LIHTC housing.

The heterogeneity we observe in our findings underscore the importance of policies which influence the locations where LIHTC housing is located. Regardless of where it is built, LIHTC housing attracts low-income tenants from across a spectrum of neighborhoods. State policies which incentivize specific neighborhood features therefore have an outsized impact on the mobility impacts of the program.

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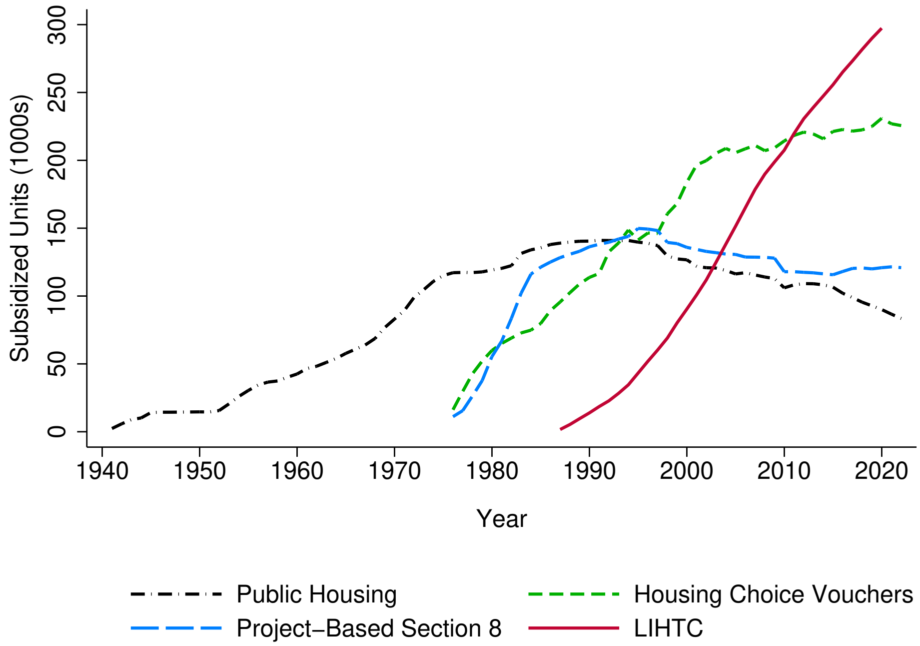
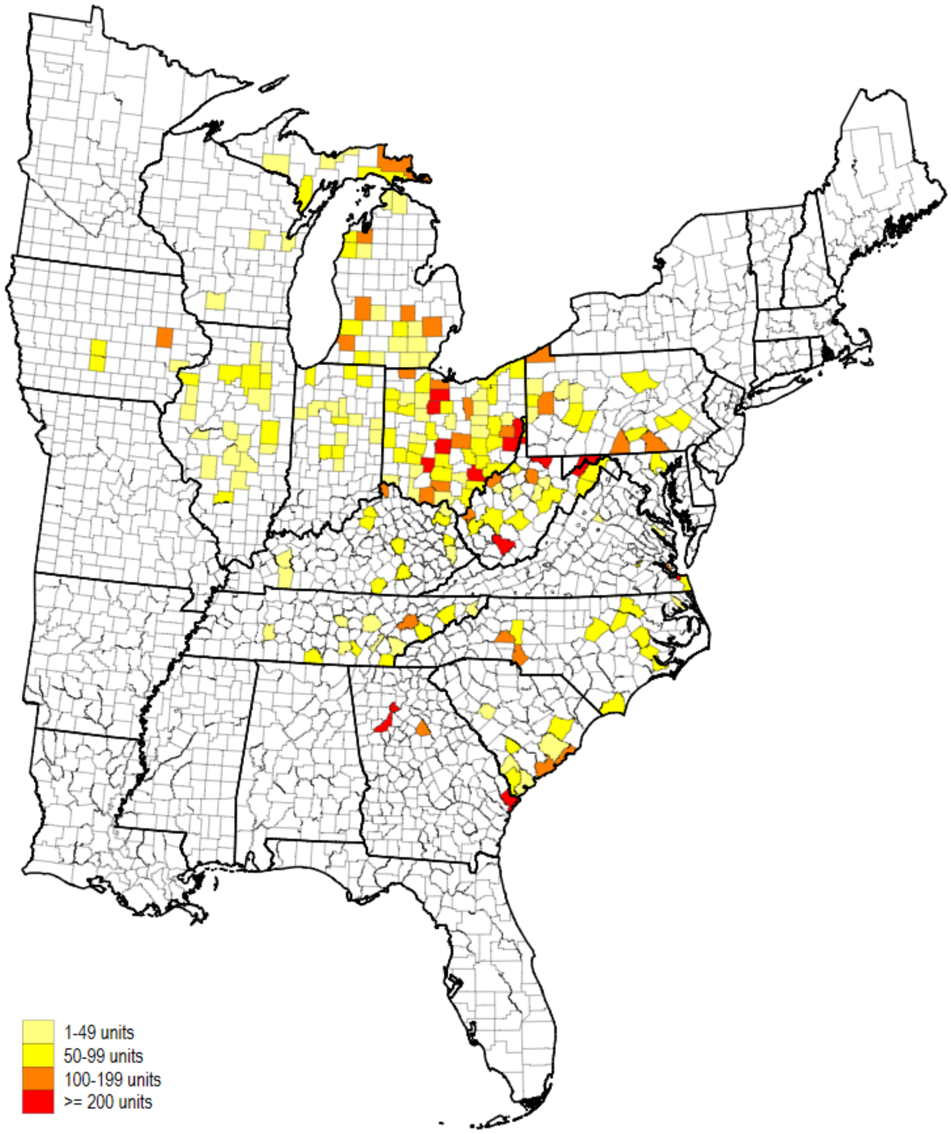
Figure 1. Subsidized Units per Year, by HUD Program



Notes: LIHTC series data are from HUD's database of all LIHTC units placed in service 1987-2021, and reflect all low-income units in LIHTC-subsidized properties. Data on public housing, housing choice voucher, and project-based Section 8 are from Olsen (2003) (pre-1998), HUD Annual Performance Reports (1998-2015), and HUD's "Assisted Housing: National and Local" database (2016-2021).

Figure 2. Map of Woda Cooper LIHTC-Funded Properties



Notes: Sample includes all LIHTC-funded properties managed by Woda Cooper, regardless of target population or year placed-in-service. Unit counts reflect both LIHTC-subsidized units and market rate units.

Figure 3. Applicant Process Flow Diagram

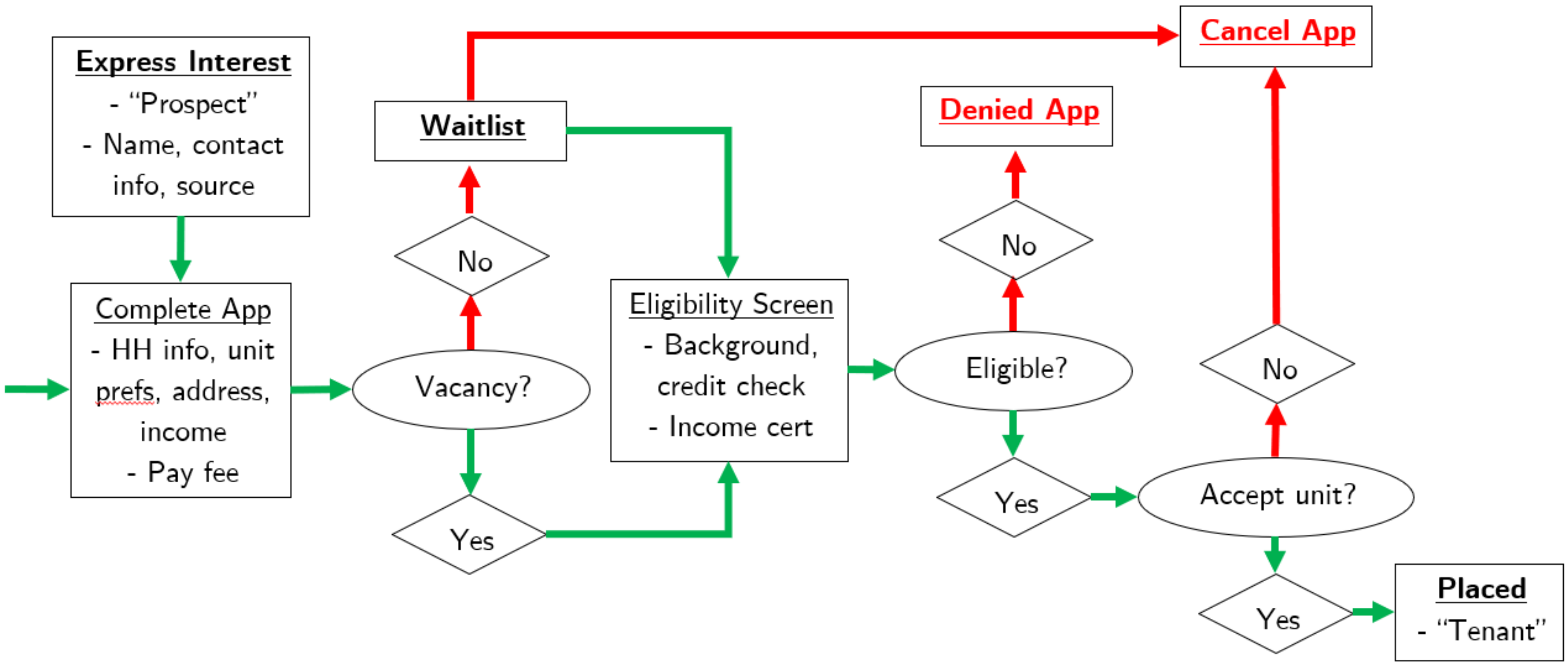
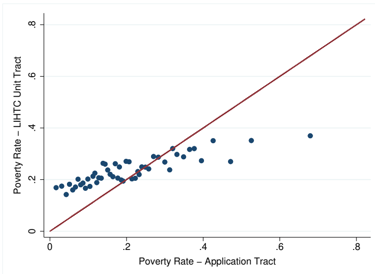
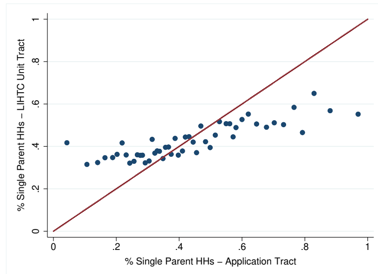


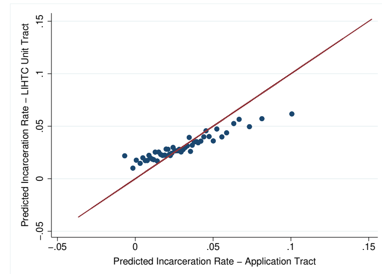
Figure 4. Descriptive Results: Moves to Low-Income LIHTC Units



(a) Poverty Rate

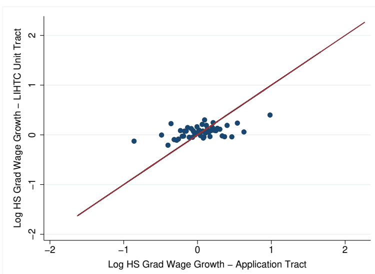


(b) Single Parent HH Share

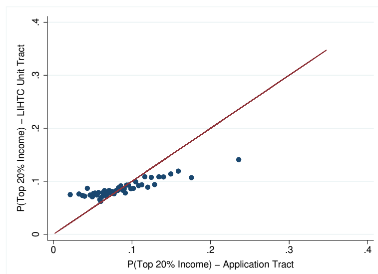


(c) Predicted incarceration rate | parent income 25p

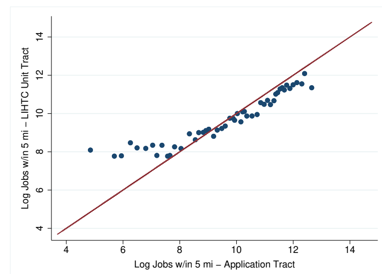
(d) 3rd Grade Math Scores



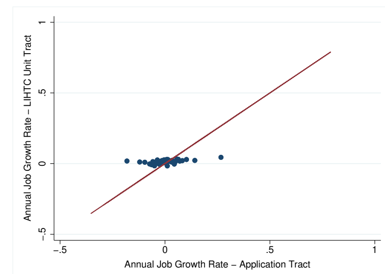
(e) Log HS Grad Wage Growth



(f) P(top 20% income) | parent income 25p



(g) Log Jobs w/in 5 mi



(h) Annual Job Growth Rate

Notes: Filler

Table 1. Woda Cooper Properties: Summary Stats

	Woda Cooper	Other LIHTC
A. Property Characteristics		
# Units	47.4	78.6
# Low Income Units	43.0	72.0
Vacancy Rate, Low Income Units	0.055	.
Applicants per Units	3.44	.
Multiple Buildings	0.52	.
HOME funding	0.32	.
Rural Development funding	0.32	.
Local funding	0.081	.
B. 2010 Census Tract Characteristics		
Pop per sq mi	1348.6	8011.0
% Black	0.17	0.23
% Hispanic	0.041	0.20
% owner occupied units	0.53	0.43
% college plus	0.19	0.22
% in poverty	0.21	0.23
% single parent HHs	0.40	0.45
N	135	8041
C. HUD Characteristics		
New construction	0.55	0.56
QCT	0.24	0.39
Metro	0.95	0.98
Target pop = families	0.59	0.50
N	82	8085

Notes: Sample includes properties PIS 2012 or later that do not target elderly populations. For HUD characteristics, the sample is further restricted to those main sample properties which could be fuzzy matched to HUD's LIHTC Placed-in-Service Database.

Table 2. Woda Cooper Units: Summary Stats

	Mean	% Missing
Unit Characteristics		
Avg Sq Ft	944.5	0.011
1 BR	0.17	0.011
2 BR	0.56	0.011
3 BR	0.26	0.011
4 BR	0.014	0.011
Move-in Income % AMGI	0.32	0.011
Current Income % AMGI	0.33	0.011
Income Restrict. = 30%	0.073	0.011
Income Restrict. = 40%	0.052	0.011
Income Restrict. = 50%	0.24	0.011
Income Restrict. = 60%	0.50	0.011
Income Restrict. = 80%	0.075	0.011
N	4387	

Notes: This sample includes all LIHTC-subsidized units in main sample Woda Cooper properties.

Table 3. Applicants by Status Type

	# Applicants	% of Sample
On Waitlist	3416	0.21
Eligiblity Approved	408	0.025
Canceled	4576	0.28
Denied	2799	0.17
Resident	5099	0.31
N	16298	

Notes: Sample is constructed is described in Section 4.

Table 4. Baseline Balance in the Applicant Sample

	(1) Resident Mean	(2) Non-Resident Mean	(3) Adj. Diff	(4) Natl Mean
A. Move Characteristics				
Applied from same state	0.90	0.93	0.028***	
Applied from same county	0.62	0.70	0.077***	
Applied from same city	0.50	0.54	0.075***	
Applied from same zip	0.24	0.34	0.045***	
Applied from same tract	0.098	0.14	0.029***	
B. Tract Demographic Characteristics				
Pop (2010)	4833.9	4558.5	-44.2	4242.4
Pop per sq mi (2010)	2511.0	2123.8	-195.4**	5181.0
% Black (2010)	0.34	0.26	0.018***	0.14
% Hispanic (2010)	0.056	0.050	-0.0032**	0.15
% College + (2010)	0.20	0.19	-0.0045*	0.27
C. Tract Economic Characteristics				
Median HH income (2016)	43113.6	42107.6	-1247.2***	58810.3
2 BR apt rent (2015)	759.9	722.8	-12.9***	950.3
D. Tract Opportunity Characteristics				
P(incarcerated) | parent income 25p (2010)	0.032	0.030	0.00058	0.022
P(top 20% income) | parent income 25p (2014-2015)	0.088	0.086	-0.0031***	0.14
Poverty rate (2010)	0.21	0.21	0.012***	0.15
% single parent (2010)	0.45	0.44	0.014***	0.33
3^{rd} grade math scores (2010)	3.01	3.04	-0.038***	3.19
Annual job growth rate (2004-2013)	0.0046	0.0036	-0.0040***	0.015
Log HS grad wage growth (2005-2014)	0.039	0.048	-0.0050	0.043
Jobs w/in 5mi (2015)	65077.6	54256.5	2436.5	111949.5
N	7992	5098	13089	

Notes: Sample is constructed is described in Section 4, and we further exclude those with "Denied" and "Approved" applicant statuses.

Table 5. Descriptive Results: Main Effects

	(1) App. Tract Mean	(2) Prop. Tract Mean	(3) Diff
A. Move Characteristics			
Move distance (mi)			33.32
Pop per sq mi (2010)	2169.8	1937.8	-232.0***
B. Measures of Low Opportunity			
Poverty rate (2010)	0.21	0.24	0.026***
% single parent (2010)	0.44	0.43	-0.010**
P(incarcerated) | parent income 25p (2010)	0.030	0.030	-0.000030
C. Measures of High Opportunity			
3^{rd} grade math scores (2010)	3.04	3.03	-0.0099
P(top 20% income) | parent income 25p (2014-2015)	0.086	0.086	-0.000073
Log HS grad wage growth (2005-2014)	0.048	0.055	0.0074
Log jobs w/in 5mi (2015)	9.57	9.67	0.10***
Annual job growth rate (2004-2013)	0.0034	0.014	0.011***
N (residents)	4945	4945	4945

Notes: Sample restricts to the main applicant sample with "Denied" and "Eligibility Approved" individuals dropped, and further restricts to residents of subsidized units.

Table 6. Descriptive Results: Heterogeneity by Subgroup

	(1) App. Tract > Median Poverty	(2) App. Tract ≥ 50% Non-White	(3) App. Tract ≥ 1k Pop	(4) Income Rest. < 60% AMGI	(5) In QCT
A. Measures of Low Opportunity					
Poverty rate (2010)					
Post	0.094***	0.040***	0.030***	0.020***	-0.014***
Post × Char	-0.14***	-0.046***	-0.0083	0.016***	0.11***
% single parent (2010)					
Post	0.059***	0.021***	0.037***	-0.013**	-0.041***
Post × Char	-0.14***	-0.11***	-0.091***	0.0063	0.13***
Predicted incarceration rate | parent income 25p (2010)					
Post	0.0036***	0.0011***	-0.000082	-0.0024***	-0.0042***
Post × Char	-0.0073***	-0.0040***	0.000100	0.0059***	0.014***
B. Measures of High Opportunity					
3^{rd} grade math scores (2010)					
Post	-0.14***	-0.057***	0.00084	0.021	-0.0094
Post × Char	0.26***	0.16***	-0.021	-0.077**	-0.17***
P(top 20% income) | parent income 25p (2014-2015)					
Post	-0.0098***	-0.0049***	-0.0041***	0.00055	0.0077***
Post × Char	0.020***	0.017***	0.0078***	-0.0016	-0.024***
Log HS grad wage growth (2005-2014)					
Post	0.041***	-0.0096	-0.023**	0.014	-0.034***
Post × Char	-0.064***	0.053***	0.056***	-0.017	0.040**
Log jobs w/in 5mi (2015)					
Post	0.27***	0.21***	0.67***	0.098**	0.12**
Post × Char	-0.34***	-0.37***	-1.10***	0.0069	0.015
Annual job growth rate (2004-2013)					
Post	0.0095***	0.0084***	-0.0029*	0.0081***	0.0086***
Post × Char	0.0021	0.0072***	0.026***	0.0060**	-0.016***

Notes: Sample restricts to the main applicant sample with "Denied" and "Eligibility Approved" individuals dropped, and further restricts to residents of subsidized units.