Building Blocks of Opportunity?

The Effect of Low-Income Housing Tax Credits on Intergenerational Income Mobility for Disadvantaged Youths

DARTMOUTH

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Abstract

New research reveals substantial variation in intergenerational mobility depending on one's neighborhood of origin. These findings warrant a closer inspection of the characteristics and policies effecting neighborhoods on a child's long-term outcomes. Using new data on economic mobility estimates by census tract for all U.S. children born between 1978 and 1983, I examine the impact of affordable housing created by the Low-Income Housing Tax Credit (LIHTC) program on rates of upward intergenerational income mobility across U.S. neighborhoods. While OLS regression models show a nonsignificant association between the rate of affordable housing in a tract and children's upward absolute income mobility, a two-stage least squares (2SLS) instrumental variable model, which exploits variation in a neighborhood's Qualified Census Tract (QCT) status, reveals a significant positive association between affordable housing and upward intergenerational mobility of low-income neighborhoods. Overall, this paper contributes to the body of literature assessing the effectiveness of this government policy and lays a foundation for examining the effect of a broader range of government housing initiatives on mobility outcomes.

Introduction

The United States has long been championed as the "land of opportunity" with the mantra of "The American Dream" central to the nation's ethos. There is a widespread belief in freedom and equality of opportunity for all citizens regardless of race, gender, or ethnicity. Yet in contemporary American society, it is clear that equality of opportunity is neither distributed equally nor available universally. National trends show that the chances of earning more than your parents have declined substantially over the last half century, and the gap between the rich and poor has widened, increasing the consequences of a child's socioeconomic status at birth (Chetty, Hendren, and Katz 2016; Hout 2018). Recent research on intergenerational mobility reveals significant variation in localized levels of upward mobility across the country (Chetty et al. 2018; Sharkey 2016). Simply put, the place one grows up plays an important role in determining one's outcomes later in life.

At a time when income inequality has been steadily increasing since the 1980s (World Bank 2016) and the quality of opportunity varies substantially by neighborhood, it has become increasingly important to understand the causal mechanisms that determine an individual's chance of success. Research on place-level determinants of upward mobility has focused on the characteristics of people and communities, but less attention has been paid to the local policies impacting these neighborhoods (Chetty, Hendren, and Katz 2016; Chetty et al. 2018; Sharkey 2016). More specifically, it is worth assessing the key policy responses implemented by national and local governments targeted towards low-income and disadvantaged citizens. Of the range of policies available, the U.S. government has continued to emphasize and provide affordable housing as a mechanism to induce community development (Baird et al. 2019).

Housing is both a fundamental necessity and the single largest expenditure of Americans (U.S. Bureau of Labor Statistics 2018). Since housing insecurity is a main driver of inequality and instability (Shapiro, Meschede, and Osoro 2013), providing affordable housing is a pivotal policy focus for the U.S. government. Among the variety of government-led housing initiatives, the Low-Income Housing Tax Credit (LIHTC) program provides the greatest amount of new affordable housing of any program in the U.S. The LIHTC program provides tax incentives for developers to build low-income housing and has been the source of over three million housing units nationwide. And yet, no research has evaluated the impact of this local policy on the long-term outcomes of the communities receiving these developments.

I explore whether the additional low-income housing provided by the LIHTC program is associated with rates of upward income mobility among low income residents across neighborhoods. I utilize data on the stock of LIHTC housing units relative to total housing units and recent mean household income mobility estimates produced from the Opportunity Atlas (Chetty et al. 2018). To calculate upward mobility, I follow previous research in using the rank-rank specification (Chetty et al. 2018, Dahl and DeLeire 2008; O'Brien and Robertson 2019) and compute both absolute mobility, the percentile differential in earnings between children and their parents, and relative mobility, the difference in adult income between children from the top and bottom income families within a neighborhood. I first test the relationship between affordable housing stock and upward mobility, net of a host of neighborhood characteristics, using an ordinary least squares (OLS) regression. I then employ a two-stage least squares (2SLS) instrumental variable model that utilizes variation in LIHTC-induced affordable housing invoked by the Qualified Census Tract (QCT) designation, which identifies certain tracts as low-income and grants developers additional tax credits to build in these areas. Assessing the effectiveness of

government policies on long-term outcomes allows us to improve and revise policy responses beyond our current evaluation methods of short-term changes to neighborhood sociodemographic attributes.

Background

Intergenerational economic mobility is a heavily studied field across a variety of disciplines (Fields and Ok 1999). Although researchers compute mobility in multiple ways, recent research primarily focuses on absolute and relative intergenerational mobility (Chetty et al. 2018, O'Brien and Robertson 2019). As mobility is central to understanding the outcome potentials across different groups of people, relative mobility is commonly used to measure intergenerational elasticity across socioeconomic classes (Fields and Ok 1999; Dahl and DeLeire 2008). However, critics depict relative mobility as a zero-sum game, arguing that mobility between generations is not fully understood by comparing relative positions of people on a distribution (Solon 1999). Put together, the two measures of absolute and relative mobility complement one another, capturing slightly different facets of the question of how children fare in relation to their parents (Chetty et al. 2018).

In addition to analyzing mobility in both absolute and relative terms, there is a growing body of literature that argues for the spatial and geographic importance of understanding economic mobility. American socioeconomic advantage and disadvantage has been found to be organized along spatial boundaries, as is seen through the organization of local governments, zoning laws, public institutions, school districts, and patterns of segregation (Sharkey 2016). Specifically, recent research has found substantial variation in levels of economic mobility across areas within the U.S. For example, Chetty et al. (2014) found that some commuting zones,

such as San Jose, California and Salt Lake City, Utah have mobility rates that match those of the most upwardly mobile countries, such as Denmark and Canada, while other areas like Atlanta, Georgia and Charlotte, North Carolina have rates of mobility lower than any developed country.

Going beyond the commuting zone level, researchers have found that life chances and economic outcomes vary across neighborhoods. Even when comparing neighborhoods just a few miles apart from each other in the same commuting zone, children's outcomes vary drastically. For children with parents earning $27,000 a year, the standard deviation across census tracts within counties is $5,000 (Chetty et al. 2018). Furthermore, researchers have found that moving within commuter zones as a result of housing relocation can significantly alter the long-term outcomes of children (Bergman et al. 2019, Chyn 2018). Overall, neighborhoods expose granular variation in outcomes such as economic mobility, crime, and mortality rates not captured simply by examining broader geographical regions (Chetty et al. 2018; Klinenberg 2003; Sharkey 2016).

Researchers have identified a range of different neighborhood-level mechanisms that are associated with children's social mobility outcomes. The literature on neighborhood effects demonstrates that environmental, structural, and institutional factors are associated with mobility (Chetty et al. 2014; Sharkey and Faber 2014). Research on environmental factors shows that most basic features of a neighborhood's physical environment, from air and water quality to noise and pollution, have an effect on children's cognitive development as well as their social and economic outcomes (Currie et al. 2011; Sharkey and Faber 2014). Structural factors such as the composition and relations of people within a neighborhood are also important mechanisms for understanding local mobility. Lower income inequality and less racial segregation are both associated with higher opportunity neighborhoods (Chetty et al. 2014). Additionally, certain social capital and family composition measures including the number of parents in a household,

the strength of peer groups, and social networks are relevant for assessing the long-term outcomes of communities (Chetty et al. 2014; Putnam 1995).

The prevalence and quality of nearby institutions also play a role in community development. The caliber of schools is commonly studied as a potential characteristic driving neighborhood differences because of the immense localized variation of American educational opportunity at the level of school districts (Reardon 2018; Sastry 2012). Analyses of the Tennessee STAR experiment demonstrate that individuals in school districts with smaller classrooms and more experienced teachers at early ages are more likely to achieve higher levels of educational attainment and earnings (Chetty et al. 2011; Finn, Gerber, and Boyd-Zaharias 2005; Krueger and Whitmore 2001). Other local institutions, such as nonprofits targeted at reducing crime, have been found to strengthen communities and decrease violence (Sharkey, Torrats-Espinosa, and Takyar 2017) although there is little empirical literature on the long-term effects of these organizations (Allard and Small 2013). Overall, there are a multitude of intersecting and overlapping local level factors that contribute to children's prospects of upward mobility (Chetty et al. 2014; Sharkey and Faber 2014; Sharkey 2016).

While researchers have focused on a range of neighborhood-level factors that are associated with children's socioeconomic mobility, the importance of housing has been largely overlooked. Policymakers often look to housing programs and strategies as a policy lever to induce community change and promote community welfare (Baird et al. 2019). Housing is a key determinant of both the type of neighborhood someone is able to live in and the extent to which individuals are able to contribute to the community (Shapiro, Meschede, and Osoro 2013). Both the quality and affordability of housing is closely tied to many of the environmental, structural, and institutional neighborhood characteristics associated with upward mobility (Pollack, Griffin,

and Lynch 2010; Walker 2010). Thus, affordable housing is often targeted by the government as a central policy to create higher opportunity neighborhoods (Baird et al. 2019).

Affordable housing may improve the prospects of upward mobility for three key reasons: providing greater family stability, enabling families to access neighborhoods with improved institutions and resources, and creating positive social and economic externalities to the broader community (Anderson et al. 2003; Chyn 2018; DeLuca and Dayton 2009; Harkness and Newman 2005).

Affordable housing is a critical component of family stability, thus positively impacting both immediate and long-term quality of life metrics. As housing represents the largest portion of a family's expenses (U.S. Bureau of Labor Statistics 2019), too much money spent on housing diverts a family's income away from food, health care, and other necessities (Anderson et al. 2003; Harkness and Newman 2005). In addition to providing greater economic security, affordable housing can improve health for low-income children by reducing the long-term stress associated with housing instability as well as asthma and other health risks that are more common in low quality homes (Rog, Holupka, and Patton 2007; Takaro et al. 2011). The stability and reduction in the number of home relocations as a result of affordable housing contributes to better educational outcomes for vulnerable children (Brennan 2011; Voight, Shinn, and Nation 2012).

Along with the positive association with family stability and security, affordable housing can provide families access to higher quality institutions and resources. Subsidized housing allows families to move into higher opportunity communities that would have otherwise been out of reach due to the unaffordability of local rents (Chetty, Hendren, and Katz 2016). Certain affordable housing programs offer access to high-performing schools and transit routes to job

centers (Ellen and Horn 2012**;** Harrell, Brooks, and Nedwick 2009). Thus, affordable housing can offer families resources and benefits of improved neighborhoods that give rise to better long-term outcomes for children (Chetty, Hendren, and Katz 2016).

Both family stability and access to better neighborhoods as a result of affordable housing should theoretically improve relative mobility by increasing the opportunities for low-income children while having little to no impact on higher-income children within a neighborhood. Additionally, these mechanisms should lead to higher rates of absolute mobility for low-income children, as new affordable housing creates benefits for these children that may not have been available to their parents a generation ago. While family stability and access to improved resources more directly apply to the lower-income population that is eligible for affordable housing, children across the income distribution should enjoy higher rates of absolute mobility from the advantages affordable housing generates for the entire neighborhood.

Affordable housing not only positively impacts the residents but also generates positive externalities throughout the neighborhood (Sweaney and Dorfman 2006). The creation of affordable housing has been linked to neighborhood revitalization and greater investment in community renovation projects (Walker 2010). Low-income housing developments are also associated with reductions in violent crime in the surrounding community (Freedman and Owens 2011). Furthermore, research on affordable housing documents a variety of economic improvements, including job creation due to construction and greater levels of commercial activity from the increased spending of affordable housing residents (Wardrip, Williams, and Hague 2011). Lastly, numerous studies show that affordable housing has neutral to positive effects on nearby property values (Sweaney and Dorfman 2006; Walker 2010). Therefore, there are community-wide benefits from affordable housing even for individuals who do not live in

government-subsidized housing units that are likely to create higher opportunity neighborhoods (Wardrip, Williams, and Hague 2011).

Current Study: Low-Income Housing Tax Credits

The U.S. government provides affordable housing to citizens in two primary ways: subsidizing market rents through vouchers, and by creating below-market rent housing for qualified low-income individuals. While public housing used to be the primary policy through which new affordable housing was built, the LIHTC program is now the predominant source of new affordable housing in the U.S. (Baum-Snow and Marion 2009).

The LIHTC program is the largest federal based housing program in the United States and was first instituted in 1987 as part of the Tax Reform Act (1986). The LITHC program provides tax credits to states, who then allocate these credits to selected developers. Developers must apply for these credits and state housing agencies award developers based on their applications and the state's unique Qualified Action Plan (QAP). Developers can propose to build new housing units or rehabilitate existing housing. LIHTC developments are required to have at least 20% of the units occupied by individuals below 50% of Area Median Income (AMI) or at least 40% of the units occupied by individuals below 60% of AMI. Rents are required to stay at or below 30% AMI (HUD 2019). Since its inception, this program is responsible for approximately 90% of all new affordable housing projects in the U.S. and is estimated to have created or preserved ~3.2 million housing units to date (HUD 2019).

In 1989, Congress passed legislation to create an additional 30% tax credit to developers building in particularly low-income neighborhoods, termed Qualified Census Tracts (QCT), or in high construction cost areas, known as Difficult Development Areas (DDA) (Baum-Snow and Marion 2009). Developer choice of neighborhood is strongly influenced by the QCT and DDA

designated cutoffs, which provide an additional tax credit to builders in certain low-income census tracts (Freedman and Owens 2011; Lang 2012). Given these designations, developers are more likely to select these qualified areas compared to similar non-qualified neighborhoods (Baum-Snow and Marion 2009; Sweaney and Dorfman 2006; Walker 2010).

Literature analyzing the effectiveness of the LIHTC program presents mixed findings for short-term metrics such as schools, crime, and property values, depending on the type of neighborhood that a developer chooses to build in (Baum-Snow and Marion 2009; Cummings and DiPasquale 1999). Di and Murdoch (2013) find that new LIHTC housing developments do not negatively impact local schools and that rehabilitated units improve nearby school performance. Freedman and Owens (2011) examine the association between LIHTC and crime, finding diminished violent crime in lower-income neighborhoods but no significant effects on property crime. Lastly, a variety of research assesses the impact of the LIHTC program on local property values, finding no discernable increase in gentrifying areas yet modestly higher property values in lower-income neighborhoods (Baum-Snow and Marion 2009; Walker 2010). While past studies have documented the short-term local impact of LIHTC units, there is a lack of research examining the long-run effectiveness of the program on a neighborhood's socioeconomic mobility.

Based on previous research and theory above, I hypothesize that the addition of affordable housing invoked by the construction of LIHTC units is associated with an increase in the rate of intergenerational income mobility. More specifically, I expect higher rates of absolute and relative income mobility. This is because research has shown that affordable housing plays a crucial role in childhood development through family stability, access to higher quality resources, and improvements to the community as a whole (Anderson et al. 2003; Brennan 2011;

Wardrip, Williams, and Hague 2011). By increasing the amount of LIHTC housing in a neighborhood, low-income families should benefit from greater stability and an improved quality of life with the ability to reallocate income towards other basic necessities. Additionally, while the neighborhood as a whole should benefit from increased purchasing power and enhanced community well-being, affordable housing more directly serves the low-income population of a neighborhood. Therefore, lower-income children should benefit the most, resulting in a higher rate of relative mobility as low-income children would gain more relative to higher-income children from this policy. For low-income children within neighborhoods, the low-income housing should also positively influence their adult earning potential relative to their parents.

Methods

Data

To test the study hypothesis, I use census tract-level data from the Department of Housing and Urban Development's (HUD) data library that I linked to the Opportunity Insights team's Opportunity Atlas (LIHTC Database; Opportunity Insights). Census tracts were first defined nationwide in 2000 and subsequently updated at the decennial Census in 2010. Tracts are statistical subdivisions of a county that contain approximately 4,000 people. There were 66,304 tracts in 2000 and 74,002 tracts in 2010 (U.S. Census Bureau).[1] All datasets in my analysis are crosswalked to 2010 tract boundaries for standardization across variables.

I use census tracts as my unit of analysis because tracts resemble a neighborhood, covering a small, compact geographical area. Rather than examining county or commuter zone data—which capture patterns across larger geographical areas—I argue that the impact of new,

[1] The number of census tracts increased due to U.S. population growth.

affordable housing will be seen at local units of geography. This is because local policies and tract-level characteristics have limited predictive power of other nearby neighborhoods (Chetty et al. 2018). Therefore, affordable housing construction in one location is unlikely to have wide-ranging spillover effects across large geographical regions.

The Opportunity Atlas dataset contains estimates of intergenerational income mobility across 73,278 census tracts in the United States for a cohort born between 1978 and 1983.[2] These estimates are based on a sample of all individuals in the 1978 to 1983 birth cohorts who were either U.S. citizens or authorized immigrants and whose parents were also citizens or authorized immigrants. Each of these 20.5 million children are traced back to the census tract where they lived up until the age of 23.[3] Chetty et al. (2018) combine these individuals born between 1978 and 1983 into one birth cohort and aggregate individual level estimates to the census tract level. Since children often move between census tracts throughout their youth, Chetty et al. (2018) allocate children into tracts based on the weighted proportion of years up to age 23 that an individual spent living in a given tract.

I use data from the HUD data library to measure affordable housing. The HUD dataset contains project-level data, listing each unique housing project developed as a result of the LIHTC program from 1987, the year it was implemented, to 2017. In this 31-year span, there were 46,554 housing developments constructed or rehabilitated using the tax credits, producing a total of 3,042,210 housing units, for an average of approximately 65 units per LIHTC project. Housing projects are geographically sorted by census tract, with some tracts qualifying for additional tax credits for developers. 2,858,867 (94%) of all units constructed and redeveloped

[2] Using 2010 census tract boundaries.
[3] 3.8% of the sample is excluded due to missing address information, resulting in a sample which consists of ~96% of the target population.

through the LIHTC program are set aside for low-income renters. I first exclude all LIHTC developments built after 2000 to limit the analysis to only the 871,775 LIHTC low-income designated units that could have impacted the cohort of interest during their childhood years. Then, I aggregate the remaining low-income units developed between 1987 and 2000 to the census tract level in order to link the housing and mobility data. Overall, by 2000, 11,052 tracts housed at least one LIHTC low-income unit.[4]

Furthermore, I incorporate three additional datasets to provide supplemental tract-level information and combine the various datasets. I collect data on tract characteristics from the Opportunity Insights website, which contains 33 tract-level sociodemographic statistics for all tracts nationwide using 2010 census tract boundaries (Opportunity Insights). While the LIHTC database contains QCT information in the 11,052 tracts with LIHTC developments, I use HUD's nationwide QCT designations from 2000 to account for the qualified tracts without LIHTC developments (Qualified Census Tracts). This dataset lists the 7,686 tracts designated as QCTs in 2000, using 1990 census tract boundaries.[5] Finally, I use the U.S. Census' relationship files to crosswalk the datasets using 1990 and 2000 tracts to 2010 census tract boundaries, weighting the 1990 and 2000 tract-level statistics by the fraction of the 1990 and 2000 tract areas that make up the 2010 tract specifications.

Of all the 74,002 tracts in the U.S. in 2010, I subset the data to include only lower-income tracts. I keep the 35,719 tracts averaging below median household income in 1990 relative to all tracts within a given county, resulting in a dataset containing just under 50% of all

[4] Using 2010 census tract boundaries.
[5] Although tracts were defined nationwide starting in 2000, the 1990 Census had a combination of census tracts and block numbering areas that covered the entire nation which can be crosswalked to 2000 tract boundaries.

census tracts nationwide.[6] Lower income tracts have over three times more LIHTC housing units than excluded tracts and contain a greater share of the low-income population of interest. Lastly, 982 of the remaining tracts are excluded for missingness, leaving a final sample of 34,737 census tracts. Of the tracts removed for missingness, 462 are missing observations for one of the dependent variables (intergenerational income mobility), whereas the remaining 520 excluded observations do not have complete data related to neighborhood covariates. While missing tracts only represent ~2.7% of all lower-income tracts in the U.S., excluded tracts tend to have lower rates of affordable housing, rank higher on economic mobility measures, and have lower employment and median income compared to non-excluded tracts. Appendix Table A1 displays the difference between tracts with and without missing observations across the various neighborhood characteristics.

Variables

Affordable Housing Stock: The main independent variable of interest, "affordable housing stock," is the percent of all housing units per tract built as a result of the LIHTC program by the year 2000. To calculate this percentage for each tract, I divide the cumulative number of LIHTC low-income units from 1987 to 2000 by the overall number of housing units in a tract in 2000. For example, in tract 950900 in Barbour County, Alabama, there were 53 units built by the LIHTC program in 1987, 17 units in 1990, and 40 units built in 2000. All 110 of these units were low-income housing units. In the year 2000, there were 1,953 total housing units in that tract. Therefore, the affordable housing stock brought on by the LIHTC program was ~5.63% in tract

[6] Tracts with below median household income in a county are removed rather than tracts below the national median due to the substantial variation in regional incomes nationwide. Supplementary models including all tracts in the U.S. yield similar results (Appendix Tables A3 and A4).

950900. Since the affordable housing stock variable is heavily left-skewed (as most tracts have a value of 0), in my regression analysis, I take the natural log of affordable housing stock to account for nonlinearities in the data and counter problems of heteroskedasticity.

The affordable housing stock measure assumes that all LIHTC housing units built from the inception of the program through 2000, remain by the year 2000. This seems reasonable given that the oldest LIHTC units in 2000 are only 13 years old and that developers are required to meet LIHTC rent thresholds for at least 15 years. LIHTC designated low-income units are chosen rather than all LIHTC units because low-income units more directly serve the population of interest. However, using the total number of LIHTC units compared to only low-income units does not significantly affect the results (See Appendix Tables A3 and A4), as low-income units make up ~94% of all LIHTC developments built before 2000. Although LIHTC housing stock data is available through 2017, 2000 was used as a cutoff to align with the years of "childhood" from the birth cohort in Chetty's dataset.

I choose to solely focus on the LIHTC program and not include other types of affordable housing in my analysis to be able to examine the causal effect of a specific program on upward mobility. Including additional affordable housing programs would complicate the ability to determine a causal link with mobility, as various policies have their own unique criteria and qualifications, were implemented at inconsistent points in time, and target slightly different populations.

Intergenerational Income Mobility: For my dependent variable, upward mobility, I focus on intergenerational income mobility. Consistent with previous literature (Solon 1999; Black and Devereux 2011; Chetty, Hendren, and Katz 2016), I create two measures of upward mobility: *absolute mobility* and *relative mobility*. Absolute upward income mobility calculates the

difference in mean percentile rank in the national income distribution in adulthood (measured in 2014-2015, when observed individuals were between the ages of 31 and 37) between children and their parents. Children's adult incomes reflect a predicted estimate of children with parents that average around the 25th percentile of the national income distribution, thus limiting the focus of the study to low-income individuals. On average, children with parents at the 25th percentile rank at the 40th percentile of the national income distribution as adults, resulting in a 15 percentile point increase in economic mobility.

Relative income mobility captures the difference in outcomes between children born to high and low-income parents. Tracts with large disparities between the income ranks of children from high and low-income families have low rates of relative mobility, whereas tracts where high and low-income children end up with similar earnings as adults have high levels of relative mobility. Increases in relative mobility could be driven by either improved outcomes for the poor or worse outcomes for the wealthy, making the interpretations more difficult. However, relative mobility is able to capture within-cohort and tract differences. Additionally, if LIHTC-based housing is supposedly a mechanism which promotes opportunity, then it is useful to compare the lower-income children that are eligible for the affordable housing to children from higher-income families who would not reside in the low-income housing developments. Therefore, relative mobility is important to include alongside the absolute mobility measure to understand how the additions to affordable housing are impacting the low-income individuals more directly affected by affordable housing construction relative to the higher-income individuals in a tract.

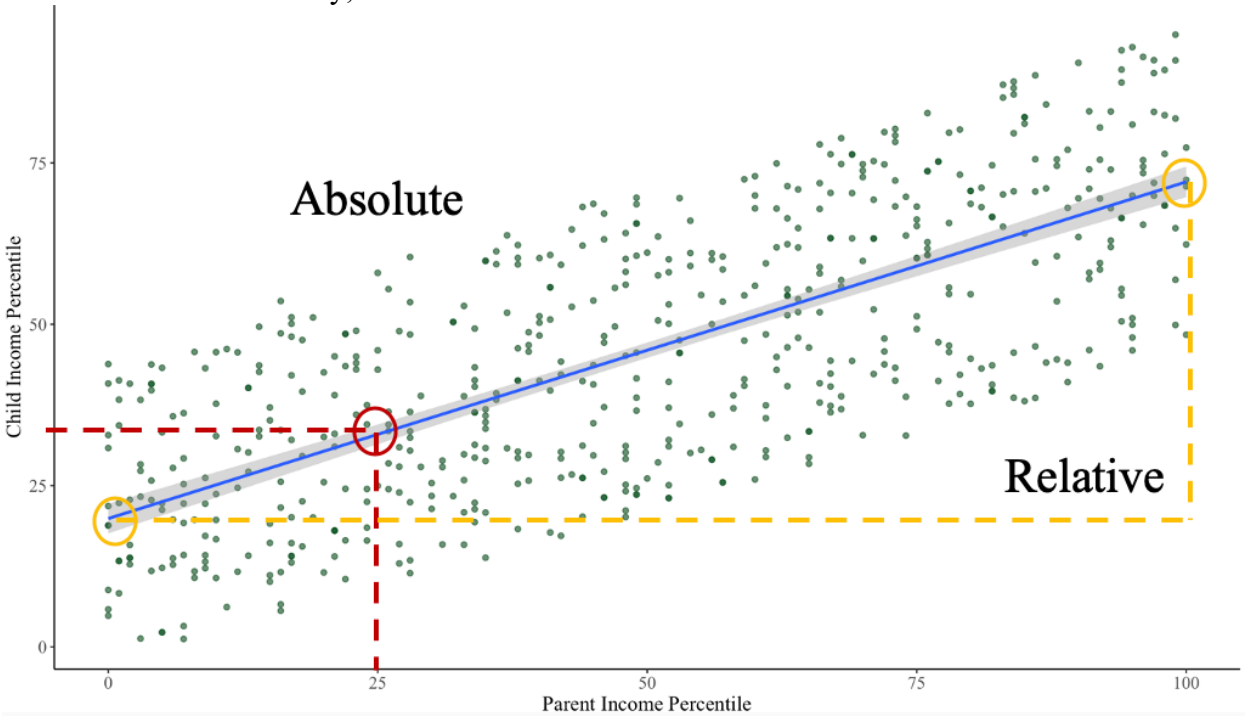
Figure 1 displays the conceptual difference between absolute and relative mobility. This chart illustrates the statistical regression model used to predict the outcomes for children at certain parental income percentiles. Each dot represents a hypothetical family in tract 950900

with a child born between the years 1978 and 1983.[7] For example, while there might not be any parents at the 25th percentile of the national income distribution in every tract, there are parents at nearby percentiles that are used to estimate the hypothetical outcomes of children with parents at the 25th percentile. In addition to using within tract estimates to fill income percentile gaps, Chetty et al. 2018 uses national income statistics to guide the projection of the 25th percentile. Income data from other tracts are used to determine whether estimations for the 25th percentile are closer to the 24th or 26th percentile or halfway in between.

As shown in Figure 1, the relative mobility measure captures the slope of the regression line for each tract, whereas absolute mobility is calculated as the difference between the predicted child income percentile based on the regression line and the parent's income percentile. In this tract, the predicted child income percentile for parents at the 25th percentile is approximately the 33rd percentile, yielding an 8 percentile point gain in absolute mobility.

[7] Actual individual parental and child income percentiles are not publicly available. Hypothetical estimates shown in Figure 1 were constructed using the number of families in the sample for tract 950900 as well as the slope of the regression line as reported by Chetty et al. 2018. Using this information, I calculated a randomized normal distribution of parental income percentiles and used the intercept and slope coefficient of the reported regression equation to predict children income percentiles. Lastly noise was added to each of the estimates to depict a wider array of child outcomes. These hypothetical estimates are only calculated for purposes of illustration.

Figure 1: Illustrative Relationship Between Absolute and Relative Mobility for Census Tract 950900 in Barbour County, Alabama



Controls: A variety of tract-level covariates are included in the analysis to account for sociodemographic characteristics which are likely to confound the association between affordable housing stock and economic mobility. The various covariates used in this analysis attempt to control for the heterogeneity between census tracts. In particular, these variables capture the factors that are highly correlated with geographical variation in upward mobility, including income, quality of education, racial segregation, and family stability (Chetty et al. 2018). Although it would be ideal to measure all of these variables during the observation period of interest (1987-2000), neighborhood characteristics remain fairly stable over time (Chetty et al. 2018). Therefore, the chosen sociodemographic measures, while imperfect, remain useful for capturing structural differences between neighborhoods.

The four categories of controls are economic, educational, racial/ethnic, and other demographic characteristics. Economic covariates include logged median household income

(1990), the poverty rate (1990-2000 average), the employment rate (2000), and the logged number of high-paying (>$40,000 annually) jobs within 5 miles (2015). The local strength of the job market is often considered a strong predictor of upward mobility (Case and Katz 1991, Chetty et al. 2018) and income measures are also highly correlated with the income mobility outcome of interest. Educational factors include the fraction of residents with a college degree or more (2000), and the average school district level standardized test scores in 3rd grade (2013). Racial and ethnic controls include the proportion of white, black, and Hispanic residents (2000) as well as the share of the population born outside the U.S. (2006-2010 ACS). The last category encapsulates other potential confounding neighborhood characteristics, such as the logged population density (per square mile) (2000), the share of single-headed households with children (1990-2000 average), and the Census Form Return Rate (2010).

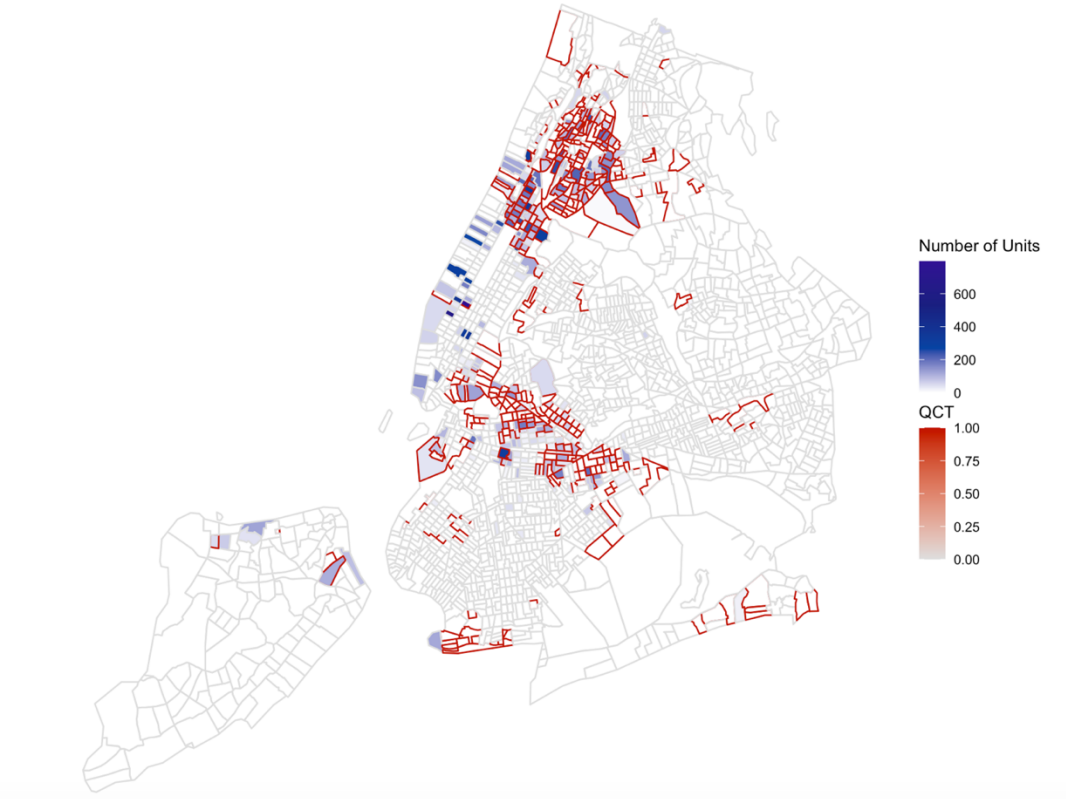
Qualified Census Tracts: I use the qualified designation of census tracts as an instrument in the 2SLS instrumental variable model. QCTs are HUD designations specific to the LIHTC program which offer additional tax incentives to developers. QCTs apply to tracts with a poverty rate above 25% or where more than 50% of households have incomes below 60% of Area Median Gross Income (AMGI). Developers receive 30% higher tax credits in these qualified tracts, and thus their development choices are strongly influenced by this additional tax incentive (Baum-Snow and Marion 2009; Freedman and Owens 2011). Of the 8,283 QCTs in the sample, 2,683 had at least one LIHTC unit by 2000.[8] Therefore, there is a significantly higher proportion of qualified tracts with LIHTC units than non-qualified tracts (Appendix Table A2, Figure 2). Additionally, qualified tracts receive significantly more LIHTC units than non-qualified tracts,

[8] The number of QCTs includes 2010 tracts that are partially qualified due to the changing tract boundaries over time. 4,358 of the 8,283 qualified tracts did not change between 1990 (the year in which tract boundaries were used to determine QCTs) and 2010. The remaining 3,925 tracts in 2010 are "partially qualified," containing a portion of the area of a previously qualified tract.

on average. Although only about 12% of all tracts in the U.S. qualify for additional tax credits, there is a positive association between the qualified status and amount of LIHTC housing, as the tax incentive in these tracts are greater for developers.[9]

Figure 2 illustrates the relationship between the tracts designated as qualified and the tracts in which developers choose to build LIHTC units in New York City. Red outlines delineate census tracts that are designated as QCTs by the year 2000. The fill of tracts indicates the total number of LIHTC units accumulated between 1987 and 2000, with white-colored tracts not receiving any units. As shown by Figure 2, LIHTC units are strongly influenced by the QCT designation, as many of the units built by 2000 are developed within QCTs.

Figure 2: Number of LIHTC Units by Census Tract for New York City 1987—2000[10]



[9] Calculated as the proportion of QCTs designated by 2000 according to 1990 boundaries (7,686) over the total number of 1990 tracts (61,974).

[10] Each tract contains a QCT value of either 0 or 1 for simplicity of illustration. Tracts that are "partially qualified" due to changing census tract boundaries have been assigned a QCT value of 1 in the figure.

Analytic Strategy

I first estimate the basic bivariate relationship of LIHTC housing stock and the income mobility measures using an OLS regression model. Since census tracts differ across a variety of local sociodemographic characteristics, the second model incorporates a vector of potential confounders in an attempt to control for some of the heterogeneity across tracts. The OLS regression model takes the following form:

$$Mobility_T = \alpha + \beta_1 \, log(Affordable\_Housing)_T + \gamma_1 X_T + \varepsilon_T$$

Where the outcome, $Mobility_T$, is the absolute and relative mobility measurements for census tract, *T*. $log(Affordable\_Housing)_T$ is the natural log of the percent of housing units in a tract created by the LIHTC program by the year 2000, X_T is a vector of the observed sociodemographic controls mentioned above, and ε_T is the error term. The parameter of interest, β_1, captures the change in mean household income percentile rank associated with a one percentage point increase in the affordable housing stock induced by LIHTC developments.

Despite the set of confounders that are adjusted for in the OLS regression models, there is the potential for omitted variable bias that complicates the causal link between affordable housing and upward mobility. One possible source of bias is the choice of which tracts receive LIHTC housing units. Affordable housing creation through the LIHTC program is not randomly assigned across census tracts. Instead, developers' choice of particular tracts and the likelihood that their proposals are approved by states is likely based on certain expectations of changes to a variety of neighborhood factors that cannot be fully captured by the observed covariates. Therefore, the choice of tracts that receive LIHTC units is likely to be associated with unobserved measures that also impact upward mobility.

To account for this omitted variable bias, I use a 2SLS instrumental variable approach. Following previous literature which closely examines the impact of QCTs on LIHTC construction (Baum-Snow and Marion 2009; Freedman and Owens 2011), I use the QCT designation to exploit plausibly exogenous variation in the location of LIHTC units. I argue that the qualification status of census tracts strongly influences the development of LIHTC based affordable housing (See Figure 2). This occurs for two reasons. First, developers receive additional tax credits (up to 30%) from these qualified tracts, so for financial reasons, they are strongly incentivized to build in qualified tracts. Additionally, many states prioritize qualified tracts in their Qualified Action Plans, so locating a development proposal in a QCT increases the probability of approval (Freedman and Owens 2011). However, the nomination of QCTs are unlikely to have a direct effect on upward mobility once the factors that impact both QCTs and upward mobility are controlled for.

In order for QCTs to be a valid instrument, it must meet three assumptions: the relevance condition, the exclusion restriction, and the exogeneity assumption. First, the relevance condition is that the instrument must be associated with the independent variable. Consistent with previous research (Baum-Snow and Marion 2009; Bree 2012), QCTs are strongly correlated with affordable housing units. Since developers strategically locate in QCTs because of the additional tax credits and the preferences given to QCTs by housing authorities, the level of LIHTC construction is highly influenced by the QCT designation. Approximately 18 more LIHTC units per tract are built in qualified compared to non-qualified tracts. The first stage F-statistic for the 2SLS model is 29.81, above the suggested cutoff of 10 (Angrist and Pischke 2009), indicating that the instrument is robust. Second, the exclusion restriction condition assumes that the instrumental variable can only affect mobility rates (the dependent variable) via its effect on the

treatment variable, affordable housing. Net of measured covariates, particularly net of mean household income and the poverty rate of a tract, it seems safe to assume that QCTs do not have a direct causal effect on the outcome. This is because QCTs are determined solely by income cutoffs (if >50% of a tract is below 60% of AMI or if >25% is below the poverty line). The designation of QCT only applies to the LIHTC program and thus does not provide qualifications or incentives for any other government policy. QCTs only provide tax incentives to developers building LIHTC residential housing units and cannot be used for commercial housing construction or other types of housing. Thus, net of measurable economic controls and affordable housing, I would expect tracts' qualified status to have no impact on upward mobility. Third, the exogeneity assumption requires that the instrumental variable is uncorrelated with a lagged measure of the dependent variable (prior mobility rates). Put differently, "the values that the instrument takes on should be allocated as if they were randomly assigned, conditional on other variables included in the model" (Sharkey, Torrats-Espinosa, and Takyar 2017:1225). Here, it seems unreasonable to expect sorting of unobservables across tracts because of the QCT designation. Again, QCTs only apply to the LIHTC program and are not used for any other programs or policies. Since QCTs are specific to LIHTCs, and it is unlikely residents are aware of the designation, I would not expect individuals to move census tracts or change their behavior based on the QCT qualification. The designation is out of the control of members living in tracts and demographic shifts as a result of the designation seems unlikely. Therefore, I would argue that the exogeneity assumption holds and QCTs are "as if" randomly assigned across tracts conditional on covariates.

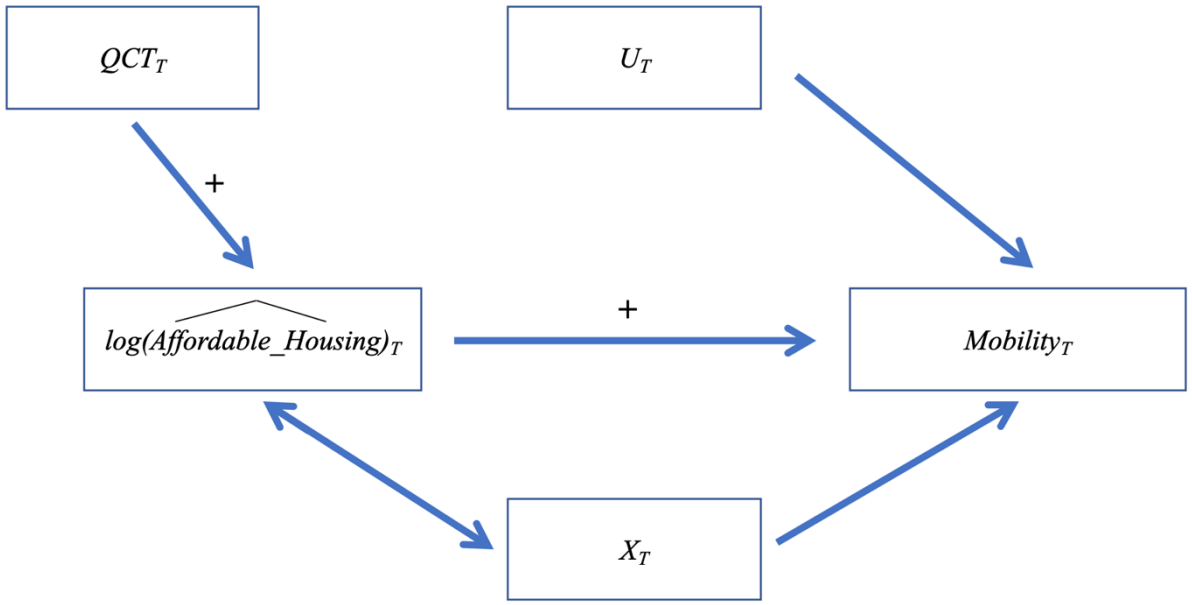
The two stages of the instrumental variable model are given by the following equations:

(1) $log(Affordable\_Housing)_T = \alpha + \delta_1 QCT_T + \gamma_1 X_T + \varepsilon_T$

(2) $Mobility_T = \alpha + \hat{\beta}_1 \, log(Affordable\_Housing)_T + \gamma_1 X_T + \varepsilon_T$

In equation (1), $log(Affordable\_Housing)_T$ is the natural log of the percent of housing units in a tract created by the LIHTC program by the year 2000, *QCT* is a variable which indicates whether or not a tract is qualified, and δ_1 captures the impact of the QCT designation on affordable housing stock for a given tract. In equation (2), $\hat{\beta}_1$ captures the exogeneous difference in affordable housing stock on mobility. This $\hat{\beta}_1$ estimate yields the local average treatment effect of LIHTC housing stock induced by the qualified tract incentive on absolute and relative upward income mobility rates. Figure 3 displays the directed acyclic graph (DAG) associated with the 2SLS instrumental variable model. In Figure 3, the variable names align with the notation used in the two stage equations above, and U_T represents a host of potential omitted variables, such as developer choice, location, and availability of construction sites.

Figure 3: 2SLS Instrumental Variable Directed Acyclic Graph



Results

Table 1 presents descriptive statistics across measures of housing stock, economic mobility, and neighborhood covariates. On average, census tracts have approximately 19 LIHTC units and 18 LIHTC low-income units by 2000, making up ~1.1% of the total tract's housing stock. However, this varies significantly by tract, as ~78% of tracts in the sample do not have any LIHTC units. Tracts with LIHTC projects have an average of 82 low-income units, with approximately 45 units built per project. There is considerable variation in the number of LIHTC units across neighborhoods as the standard deviation between tracts is 63.32 units.

Table 1: Descriptive Statistics

VARIABLES	(1) mean	(2) sd	(3) min	(4) max
Housing				
Number of LIHTC Units	18.77	63.32	0	1,507
Number of LIHTC low-income Units	17.54	59.01	0	1,439
Proportion of LIHTC units to total housing units	1.103	3.903	0	100
Proportion of LIHTC low-income units to total housing units	1.033	3.674	0	100
Logged Proportion of LIHTC units	1.307	0.701	1	5.615
Logged Proportion of LIHTC low-income units	1.299	0.682	1	5.615
Rate of LIHTC housing unit accumulation	10.45	23.50	0	100
Rate of LIHTC low-income housing unit accumulation	10.44	23.49	0	100
Did the tract have any LIHTC units?	0.215	0.411	0	1
Did the tract have any LIHTC low-income units?	0.215	0.411	0	1
Quartile of LIHTC housing stock	0.220	0.430	0	4
Quartile of LIHTC low-income housing stock	0.220	0.427	0	4
Intergenerational Income Mobility				
Absolute Mobility (2014-15)	15.08	6.513	-7.808	75
Relative Mobility (2014-15)	32.60	12.51	-56.04	91.30
Mean Household Income Percentile Rank (2014-15)	40.08	6.513	17.19	100
Absolute Mobility for top 20% of Household Income distr. (2014-15)	9.606	6.356	-17.79	111.9
Relative Mobility for top 20% of Household Income distr. (2014-15)	36.80	21.14	-65.57	247.7
Absolute Mobility (Individuals in childhood CZ)	14.07	6.884	-13.63	57.73
Relative Mobility (Individuals in childhood CZ)	29.75	14.10	-124.8	128.6
Mean Household Income Percentile Rank (Individuals in childhood CZ)	39.07	6.884	11.37	82.73
Instrument				
Qualified Census Tract?	0.185	0.376	0	1

Controls				
Economic				
Logged Median Household Income (1990)	10.04	0.374	8.517	11.44
Poverty Rate (1990-2000 Avg)	0.187	0.122	0	0.894
Employment Rate (2000)	0.560	0.113	0.0201	0.950
Logged Number of High-Paying Jobs within 5 miles (2015)	9.426	2.405	0	14.40
Educational				
Fraction with a College Degree or More (2000)	0.172	0.131	0	0.949
Average School District Standardized Test Scores Grade 3 (2013)	2.990	0.894	-2.706	6.786
Racial/Ethnic				
Share white (2000)	0.595	0.329	0	0.998
Share black (2000)	0.189	0.271	0	0.997
Share Hispanic (2000)	0.162	0.232	0	0.992
Share of Population Born Outside the U.S. (2006-2010)	0.140	0.156	0	0.897
Other				
Logged Population Density (2000)	6.434	2.180	-4.183	12.23
Share of Single-Headed Households (1990-2000 Avg)	0.341	0.164	0	1
Census Form Return Rate (2010)	0.762	0.0759	0	1

Note: A total of 34,737 tracts. Source: Opportunity Insights, LIHTC Database

Children with parents at the 25th percentile of the national income distribution reach an average of the 40th percentile of the national income distribution of adults, indicating an average rise of 15 percentile points on the income distribution for children who grew up at low levels of income. While the 15 percentile point jump for children compared to their parents may seem substantial, this increase should be interpreted with caution. Absolute mobility rates have declined between the two generations – a larger share of the parents was upwardly mobile compared to the children in the sample (Chetty et al. 2014). The 15 percentile point increase instead reflects the regression to the mean effect given that the children studied have parents at the low end of the income spectrum. Furthermore, the prospects for significant upward income mobility are low, as these children only have a 9.6% chance of reaching the top quintile of the income distribution. The high standard deviations across the various controls reinforces the findings from previous research of significant sociodemographic variation between tracts.

Table 2: Regression Estimates Predicting Absolute Upward Income Mobility based on LIHTC Housing Stock

VARIABLES	(1) OLS	(2) OLS + Controls	(3) 2SLS IV
Logged LIHTC low-income units	-1.569***	-0.010	9.856***
	(0.051)	(0.034)	(2.153)
Economic			
Logged Median Household Income (1990)		2.078***	3.187***
		(0.138)	(0.351)
Poverty Rate (1990-2000 Avg)		2.093***	0.763
		(0.470)	(0.913)
Employment Rate (2000)		-3.273***	-5.568***
		(0.281)	(0.720)
Logged Number of High-Paying Jobs within 5 miles (2015)		0.088***	0.182***
		(0.021)	(0.043)
Educational			
Fraction with a College Degree or More (2000)		9.519***	9.725***
		(0.225)	(0.416)
Average School District Standardized Test Scores Grade 3 (2013)		0.596***	0.214**
		(0.030)	(0.100)
Racial/Ethnic			
Share white (2000)		-5.346***	-5.779***
		(0.317)	(0.592)
Share black (2000)		-12.729***	-12.782***
		(0.317)	(0.583)
Share Hispanic (2000)		-7.970***	-7.976***
		(0.299)	(0.551)
Share of Population Born Outside the U.S. (2006-2010)		7.552***	5.496***
		(0.268)	(0.667)
Other			
Logged Population Density (2000)		-0.201***	-0.164***
		(0.022)	(0.041)
Share of Single-Headed Households (1990-2000 Avg)		-10.975***	-21.721***
		(0.301)	(2.409)
Census Form Return Rate (2010)		5.454***	6.052***
		(0.377)	(0.707)
Constant	17.115***	-1.873	-20.544***
	(0.074)	(1.532)	(4.955)
Observations	34,737	34,737	34,737
R-squared	0.027	0.585	

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10
Source: LIHTC Database and Opportunity Insights

Table 2 presents the key findings across the OLS and IV models for absolute income mobility measures. Across the three absolute mobility models, the LIHTC low-income housing

stock coefficient can be interpreted as the percentile change in the absolute mobility of the neighborhood associated with a 1% increase in the log of LIHTC low-income housing stock. Thus, positive coefficients imply an increase in absolute income mobility, whereas negative coefficients indicate a decrease.

The basic bivariate OLS regression model shows a negative statistically significant association between affordable housing stock and absolute mobility. A 1% increase in the amount of affordable housing stock created by the LIHTC program is associated with a .016 decrease in the mean household income percentile rank of a given tract. Model 2 controls for a variety of neighborhood covariates to better estimate the association using an OLS model. While the coefficient remains negative in Model 2, it is extremely small and nonsignificant at all standard alpha levels. However, model 3, which uses the QCT designation as an instrument, shows a reversal in sign compared to the OLS regressions. From the 2SLS instrumental variable model, a 1% increase in the LIHTC affordable housing stock is associated with a .099 increase in absolute mobility for a given census tract. This finding is statistically significant at all standard alpha levels.

Table 3 displays the results of the three regression models using relative mobility as the dependent variable. For relative income mobility, negative coefficients indicate that the gap between the mean household income percentile ranks of high and low-income individuals in a tract has narrowed, whereas positive coefficients represent a widening of that mobility gap. Thus, higher rates of relative mobility are shown by a negative affordable housing stock coefficient.

Table 3: Regression Estimates Predicting Relative Upward Income Mobility based on LIHTC Housing Stock

VARIABLES	(1) OLS	(2) OLS + Controls	(3) 2SLS IV
Logged LIHTC low-income units	0.303**	0.659***	-42.076***
	(0.098)	(0.094)	(8.466)
Economic			
Logged Median Household Income (1990)		-6.525***	-11.329***
		(0.379)	(1.378)
Poverty Rate (1990-2000 Avg)		-4.466***	1.294
		(1.292)	(3.590)
Employment Rate (2000)		7.694***	17.636***
		(0.773)	(2.833)
Logged Number of High-Paying Jobs within 5 miles (2015)		-0.662***	-1.071***
		(0.057)	(0.170)
Educational			
Fraction with a College Degree or More (2000)		-1.346**	-2.241
		(0.618)	(1.637)
Average School District Standardized Test Scores Grade 3 (2013)		-0.660***	0.995**
		(0.081)	(0.392)
Racial/Ethnic			
Share white (2000)		18.696***	20.570***
		(0.872)	(2.328)
Share black (2000)		9.721***	9.948***
		(0.870)	(2.294)
Share Hispanic (2000)		14.397***	14.421***
		(0.823)	(2.168)
Share of Population Born Outside the U.S. (2006-2010)		-8.413***	0.491
		(0.738)	(2.624)
Other			
Logged Population Density (2000)		0.071	-0.089
		(0.061)	(0.163)
Share of Single-Headed Households (1990-2000 Avg)		-3.001***	43.546***
		(0.827)	(9.472)
Census Form Return Rate (2010)		-5.605***	-8.194***
		(1.037)	(2.780)
Constant	32.211***	92.916***	173.793***
	(0.144)	(4.210)	(19.482)
Observations	34,737	34,737	34,737
R-squared	0.000	0.151	

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10
Source: LIHTC Database and Opportunity Insights

In models 1 and 2, LIHTC housing stock is associated with a wider relative mobility gap between high and low-income children. The estimates suggest about a .003 and .007 lower rate of relative mobility with a 1% increase in the affordable housing stock for models 1 and 2, respectively. Alternatively, the 2SLS instrumental variable model shows that affordable housing stock is associated with substantially higher rates of relative mobility. For model 3, a 1% increase in LIHTC housing stock suggests a .42 percentile reduction in the adult income gap between high and low-income children within the same tract.

The sign of the coefficients flips across between models in tables 2 and 3. However, the results across the two tables are similar. In the OLS models, increases in LIHTC housing stock are associated with decreases in both absolute and relative mobility. On the contrary, in both 2SLS instrumental variable models, higher rates of affordable housing stock are associated with higher rates of absolute and relative mobility. The coefficients change drastically between the OLS and IV models because the OLS models are biased by potential omitted variables, and thus the IV models more closely estimate the causal effect.

To better understand the effect size of the 2SLS instrumental variable estimates, I calculate the additional percent of affordable housing stock necessary to raise mobility rates by one percentile point. Roughly an 11% and 2.5% increase in LIHTC housing stock is sufficient to increase absolute and relative mobility by 1 percentile point. Since tracts in the sample contain an average of 1,725 total housing units[11] by the year 2000, the average tract would require an additional 213 LIHTC units to increase absolute mobility by one percentile point and would need an additional 44 LIHTC units to raise relative mobility by the same amount.[12] At the median, a 1

[11] Net of LIHTC housing units. With LIHTC housing units, tracts in the sample average 1,742 total housing units.
[12] Since the average tract has 1,725 housing units and does not have any LIHTC units, increasing the LIHTC housing stock of the tract from 0 to 11% would require 213 LIHTC units, since the tract would then have 1,938 total units, 213 of which were from the LIHTC program.

percentile point increase in mean household income translates to roughly $660 of additional annual earnings.[13]

Overall, increases in a neighborhood's housing stock as a result of LIHTC projects induced by the QCT designation have a strong positive impact on the average adult incomes for low-income individuals who grew up in those neighborhoods. While the OLS regression models do not reveal a positive association between affordable housing stock and upward income mobility, the 2SLS instrumental variable models show substantial local average treatment effects for both absolute and relative mobility.

Tests of Robustness

I conducted seven additional analyses to test the robustness of the results in Tables 2 and 3. Appendix Tables A3 and A4 display the results of the alternative model specifications and sample sizes. Row (1) shows the coefficients for the original analysis across the three models. Rows (2), (3), and (4) test alternative independent variables. Row (2) measures all LIHTC housing, not just LIHTC low-income housing. The independent variable in row (3) is the non-logged measure of LIHTC low-income housing. Finally, row (4) uses an integral measure, which captures the rate of LIHTC housing accumulation from 1987-2000.[14] Across both absolute and relative mobility, the direction of the coefficients for Models 2 and 3 remain the same when using the alternative independent variable measures, although the magnitudes differ slightly.

The fifth row adds tracts that are located in DDAs to the QCT instrument. I chose not to include DDAs as part of the instrument in the main model because nationwide data on DDAs is

[13] Calculated using Chetty et al.'s Opportunity Atlas. At the median, children with parents at the 25th percentile of the national income distribution have mean household incomes of ~$33,000 in 2014-15. At the 51st percentile, their incomes are ~$33,660.

[14] The integral measure is calculated as the area under the curve of LIHTC housing accumulation from 1987-2000. Since tracts that received LIHTC tracts at the beginning of the time period could have different outcomes than tracts receiving the majority of tracts close to 2000, the integral measure accounts for differences in the rates of LIHTC housing accumulation over time.

sparse and incomplete, and the designations of DDAs are more subjective, which would weaken the validity of the instrument. Similar to rows 2-4, the sign of the coefficients in row 5 remains the same as the original model. Row (6) includes a falsification test which measures the association of LIHTC housing stock from 2000-2017 on upward income mobility. In theory, affordable housing stock in these years should have little to no impact because the children in the sample's cohort have already grown up. While the coefficients from row (6) remain statistically significant and have the same sign as the baseline model, the size of the estimates are much more muted. The final row expands the sample to all tracts in the U.S., also displaying similar estimates to the original model. Overall, the results from Appendix Tables A3 and A4 show the findings above are robust to alternative modeling specifications between LIHTC housing stock and upward income mobility.

Conclusion

In this paper, I examine the effect of LIHTC housing stock on a neighborhood's intergenerational income mobility to try to understand how the largest federal based affordable housing program impacts long-run outcomes. I estimate three models in this analysis, the first two using OLS regressions between LIHTC housing stock and both absolute and relative income mobility. The third model estimates the local average treatment effect using a neighborhood's QCT status as an instrument. The bivariate and multivariate OLS regressions ran contrary to my hypothesis: that affordable housing stock would be positively associated with upward mobility. However, it is possible that there are other unobserved characteristics present in neighborhoods and omitted variables associated with the selection of LIHTC unit location by developers that bias the absolute and relative mobility estimates of the OLS regressions. In contrast, the 2SLS

instrumental variable model shows a strong positive association with absolute mobility and a significant association with higher rates of relative mobility. In other words, increases to a neighborhood's affordable housing stock induced by the QCT designation of the LIHTC program results in higher adult earnings for low-income children and smaller gaps between the adult earnings of high and low-income children within a tract. Thus, I find support for my hypothesis indicating that the LIHTC program could plausibly significantly benefit the neighborhoods not just by increasing the amount of affordable housing stock, but also by creating stability and opportunity for lower-income individuals in the long run.

Although the LIHTC program has received bipartisan support over time, political debates over whether to expand or rollback the degree of tax incentives persist (NYU Furman). To date, research over the effectiveness of the program has been inconclusive, as much of the literature on the policy is devoted to examining the relationship between nearby housing prices and construction rates (Baum-Snow and Marion 2009; Cummings and DiPasquale 1999). My study contributes to existing research by analyzing the LIHTC program with respect to the long-run outcomes of children in neighborhoods. The creation of opportunity and upward mobility should be a key objective of any affordable housing program. By looking at the LIHTC policy from this angle, I shed light on the extent to which the program is effective towards advancing the essential policy goal of improving upward mobility. While my findings suggest this policy has a modest impact on the income mobility of low-income children, the results are far from groundbreaking.

Currently, LIHTC tax incentives and QCT designations are structured to target individuals and families based on their level of income. However, this program would benefit from also creating incentives in areas with lower rates of mobility. Rather than solely subsidizing

housing costs for low income individuals, affordable housing policies like the LIHTC program should be designed to improve opportunity and outcomes. Since my findings and other recent research on upward mobility argues that opportunity is not synonymous with income (Chetty et al. 2016), it may be worth realigning LIHTC tax credits and QCT designations based on opportunity, rather than income.

More broadly, my study furthers the literature on production-based affordable housing, which is relatively unexplored compared to the various supply-side housing policies. My analysis also contributes to the research exploring the neighborhood characteristics that effect upward mobility by examining the impact of local policies. While local policies are often designed to target a specific subset of the population, my research provides support for the idea that targeted policies can indirectly have a positive impact on individuals who are not directly taking advantage of the government programs. Going forward, affordable housing should be more consistently included in the discussion of the neighborhood determinants of upward mobility.

The findings also reveal the importance of considering both absolute and relative mobility when analyzing intergenerational mobility. While absolute mobility is the central metric to assess the validity of the American Dream, relative mobility offers a useful within-tract comparison, which is especially important when looking at affordable housing, which disproportionately impacts lower-income individuals. Even though relative mobility has ambiguous normative implications, it is critical for understanding whether affordable housing can be viewed as a mechanism to level the playing field between people of different income brackets.

In my findings, the relative effects of LIHTC housing stock are larger than the absolute effects. As relative mobility compares very low and high-income families within a neighborhood, gains in relative mobility could be driven by improved outcomes for the poor or worse outcomes for wealthy individuals. Since my measure of absolute mobility solely assesses individuals with parents at one point of the income distribution, absolute mobility gains are more modest. Therefore, because of the way in which absolute and relative mobility are measured, less affordable housing is needed to flatten the distribution of outcomes between high and low-income children than is needed to raise the income percentile of low-income children relative to parents and irrespective of other children in the neighborhood.

There are a number of limitations in my analysis. To begin with, since the LIHTC program was first instituted in 1987, I am unable to examine how LIHTC housing stock impacts children at the very early years of development. Children in the sample are between four and ten years of age by the time the LIHTC program incentivizes builders to break ground on housing units in tracts. Given that previous research has found that mobility gains decline steadily with age (Chetty, Hendren, and Katz 2016), it would be beneficial to be able to study children who were impacted by LIHTC housing at very young ages. Ideally, I would also be able to distinguish between children who lived in LIHTC developments and those that did not. Since individual level data is not available, my tract-level unit of analysis captures a mixture of individuals who directly received the treatment of LIHTC housing and those that resided in other types of housing. Based on these two limitations, I would expect the degree of the positive association on absolute and relative income mobility to be slightly understated. In other words, the addition of LIHTC housing stock might have a stronger positive effect for LIHTC housing residents themselves and especially for children who move into these housing units at young ages.

In addition, the birth cohorts of 1978 to 1983 have been combined into one cohort, so that it is impossible to study how the treatment differs across different birth years. Furthermore, it would be more precise to have time-variant neighborhood covariates that matched the period of LIHTC housing accumulation (1987-2000). While some characteristics such as the poverty rate and the share of single parent households cover the majority of the time period of interest, others, such as test scores and high-paying jobs could only be measured outside of the 1987-2000 range. One final limitation is the nature of the QCT designation. Although the QCT status has a large influence on developers' choice and only directly applies to the LIHTC housing policy, QCTs in the sample are statistically correlated with both absolute and relative income mobility net of the neighborhood covariates. Theoretically, QCTs should not be correlated with mobility measures net of the income cutoffs used in the QCT designation. However, it is possible that the economic covariates used in my analysis do not fully control for the income and poverty rate limits used to distinguish QCTs from non-QCTs.

Despite the limitations, my study presents further evidence of the benefits of affordable housing programs for low-income children. While advantages incurred from affordable housing are often studied at the level of the individual using short-term outcome metrics, my analysis shows that affordable housing induced by the LIHTC program can provide moderate sustained benefits at the level of the neighborhood.

My study can serve as a model for future research that wants to look at the intersection of a particular policy at the local level with upward mobility using the Opportunity Insights' publicly available administrative data. Thus far, researchers have analyzed the effect of Medicaid, U.S. Immigrants, and now Low-Income Housing Tax Credits on the intergenerational mobility at the local level. From here, future research should examine other housing policies

such as public housing projects, Section 8 housing assistance, and alternative housing voucher programs to assess the impact of these programs on upward mobility. A comparison of various housing programs on upward mobility across a wider variety of outcome metrics including employment, incarceration rates, and college graduation rates, would provide further evaluation of the effectiveness of LIHTCs as a government policy. Subsequent research may also want to measure the effect of a variety of other policies, from welfare assistance programs to education reform measures, on intergenerational mobility.

As prevailing political ideologies often determine the level of support and resistance to affordable housing programs, it is crucial to better discern the economic impact of these policies on both the population they intend to serve as well as the broader surrounding communities. The presence of reliable, thorough data and research provides an important complement to political theories in deciding the expansion or reduction of such housing policies. If the impact of affordable housing programs on upward mobility varies substantially, it may be time to consider reallocating housing funds towards the policies that, in the long-run, help disadvantaged Americans the most.

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Appendix

Table A1: Comparison of Tracts with and without Missing Data

	(1) Full Sample	(2) Missing = 1	(3) Missing = 0	(4) t-test
Number of LIHTC Units	18.34	3.153	18.77	***
	(62.54)	(15.52)	(63.32)	
Number of LIHTC low-income Units	17.14	3.053	17.54	***
	(58.30)	(15.09)	(59.01)	
Proportion of LIHTC units to total housing units	1.080	0.270	1.103	***
	(3.867)	(2.089)	(3.903)	
Proportion of LIHTC low-income units to total	1.011	0.251	1.033	***
housing units	(3.639)	(1.904)	(3.674)	
Logged Proportion of LIHTC units	1.301	1.083	1.307	***
	(0.695)	(0.363)	(0.701)	
Logged Proportion of LIHTC low-income units	1.293	1.082	1.299	***
	(0.677)	(0.355)	(0.683)	
Rate of LIHTC housing unit accumulation	10.24	2.658	10.45	***
	(23.30)	(11.73)	(23.50)	
Rate of LIHTC low-income housing unit	10.23	2.656	10.44	***
Accumulation	(23.28)	(11.72)	(23.49)	
Did the tract have any LIHTC units?	0.211	0.0682	0.215	***
	(0.408)	(0.252)	(0.411)	
Did the tract have any LIHTC low-income units?	0.211	0.0682	0.215	***
	(0.408)	(0.252)	(0.411)	
Quartile of LIHTC housing stock	0.216	0.0713	0.220	***
	(0.427)	(0.269)	(0.430)	
Quartile of LIHTC low-income housing stock	0.215	0.0703	0.220	***
	(0.424)	(0.264)	(0.427)	
Absolute Mobility (2014-15)	15.11	16.59	15.08	***
	(6.581)	(9.330)	(6.513)	
Relative Mobility (2014-15)	32.57	30.85	32.60	***
	(12.69)	(20.07)	(12.51)	
Mean Household Income Percentile Rank (2014-15)	40.11	41.59	40.08	***
	(6.581)	(9.330)	(6.513)	
Relative Mobility for top 20% of Household Income	36.78	35.99	36.80	
distr. (2014-15)	(21.50)	(35.17)	(21.14)	
Prob. of reaching top 20% of Household Income	9.639	11.39	9.606	***
distr. (2014-15)	(6.445)	(9.882)	(6.356)	
Absolute Mobility (Individuals who Stayed in CZ)	14.06	13.87	14.07	
	(6.907)	(8.304)	(6.884)	
Relative Mobility (Individuals who Stayed in CZ)	29.72	27.31	29.75	***
	(14.17)	(18.24)	(14.10)	
Mean Household Income Rank (Individuals who	39.06	38.87	39.07	
Stayed in CZ)	(6.907)	(8.304)	(6.884)	
Qualified Census Tract?	0.187	0.224	0.185	**
	(0.376)	(0.381)	(0.376)	
Logged Median Household Income (1990)	10.03	9.873	10.04	***
	(0.378)	(0.470)	(0.374)	
Logged Mean Household Income (2000)	11.00	10.89	11.01	***

	(0.313)	(0.484)	(0.306)	
Poverty Rate (1990-2000 Avg)	0.189	0.255	0.187	***
	(0.125)	(0.195)	(0.122)	
Employment Rate (2000)	0.557	0.452	0.560	***
	(0.117)	(0.195)	(0.113)	
Logged Number of High-Paying Jobs within 5 miles (2015)	9.386	7.873	9.426	***
	(2.431)	(2.905)	(2.405)	
Fraction with a College Degree or More (2000)	0.173	0.218	0.172	***
	(0.134)	(0.197)	(0.131)	
Average School District Standardized Test Scores Grade 3 (2013)	2.989	2.917	2.990	*
	(0.897)	(1.042)	(0.894)	
Share white (2000)	0.595	0.604	0.595	
	(0.329)	(0.335)	(0.329)	
Share black (2000)	0.187	0.100	0.189	***
	(0.269)	(0.183)	(0.271)	
Share Hispanic (2000)	0.162	0.127	0.162	***
	(0.232)	(0.214)	(0.232)	
Share of Population Born Outside the U.S. (2006-2010)	0.139	0.0879	0.140	***
	(0.155)	(0.118)	(0.156)	
Logged Population Density (2000)	6.367	3.993	6.434	***
	(2.251)	(3.239)	(2.180)	
Share of Single-Headed Households (1990-2000 Avg)	0.339	0.273	0.341	***
	(0.165)	(0.158)	(0.164)	
Census Form Return Rate (2010)	0.762	0.755	0.762	*
	(0.0786)	(0.175)	(0.0759)	
Observations	35,719	982	34,737	35,719

Mean coefficients; Standard deviation in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Source: LIHTC Database and Opportunity Insights

Table A2: Comparison of Qualified and Non-Qualified Census Tracts

	(1) Full Sample	(2) QCT = 1	(3) QCT = 0	(4) t-test
Number of LIHTC Units	18.77	31.59	14.75	***
	(63.32)	(84.93)	(54.21)	
Number of LIHTC low-income Units	17.54	29.60	13.76	***
	(59.01)	(79.96)	(50.12)	
Proportion of LIHTC units to total housing units	1.103	2.164	0.770	***
	(3.903)	(6.014)	(2.867)	
Proportion of LIHTC low-income units to total housing units	1.033	2.031	0.720	***
	(3.674)	(5.690)	(2.679)	
Logged Proportion of LIHTC units	1.307	1.518	1.242	***
	(0.701)	(0.913)	(0.606)	
Logged Proportion of LIHTC low-income units	1.299	1.504	1.234	***
	(0.683)	(0.891)	(0.588)	
Rate of LIHTC housing unit accumulation	10.45	15.85	8.759	***
	(23.50)	(27.58)	(21.80)	
Rate of LIHTC low-income housing unit Accumulation	10.44	15.84	8.755	***
	(23.49)	(27.56)	(21.79)	
Did the tract have any LIHTC units?	0.215	0.324	0.181	***
	(0.411)	(0.468)	(0.385)	
Did the tract have any LIHTC low-income units?	0.215	0.324	0.181	***
	(0.411)	(0.468)	(0.385)	
Quartile of LIHTC housing stock	0.220	0.339	0.183	***
	(0.430)	(0.511)	(0.394)	
Quartile of LIHTC low-income housing stock	0.220	0.337	0.183	***
	(0.427)	(0.505)	(0.393)	
Absolute Mobility (2014-15)	15.08	10.70	16.45	***
	(6.513)	(6.024)	(6.038)	
Relative Mobility (2014-15)	32.60	30.36	33.31	***
	(12.51)	(13.99)	(11.92)	
Mean Household Income Percentile Rank (2014-15)	40.08	35.70	41.45	***
	(6.513)	(6.024)	(6.038)	
Prob. of reaching top 20% of the national Household income distr. (2014-15)	9.606	6.490	10.58	***
	(6.356)	(4.968)	(6.429)	
Relative Mobility for top 20% of the national Household income distr. (2014-15)	36.80	31.92	38.32	***
	(21.14)	(24.81)	(19.61)	
Absolute Mobility (Individuals in childhood CZ)	14.07	10.11	15.30	***
	(6.884)	(6.498)	(6.525)	
Relative Mobility (Individuals in childhood CZ)	29.75	27.61	30.42	***
	(14.10)	(15.55)	(13.54)	
Mean Household Income Percentile Rank (Individuals in childhood CZ)	39.07	35.11	40.30	***
	(6.884)	(6.498)	(6.525)	
Logged Median Household Income (1990)	10.04	9.650	10.16	***
	(0.374)	(0.377)	(0.279)	
Poverty Rate (1990-2000 Avg)	0.187	0.326	0.143	***
	(0.122)	(0.127)	(0.0801)	
Employment Rate (2000)	0.560	0.477	0.586	***
	(0.113)	(0.107)	(0.101)	
Logged # of High-Paying Jobs within 5 miles (2015)	9.426	10.58	9.064	***
	(2.405)	(1.978)	(2.412)	

Fraction with a College Degree or More (2000)	0.172	0.125	0.187	***
	(0.131)	(0.125)	(0.130)	
Average School District Standardized Test Scores	2.990	2.565	3.124	***
Grade 3 (2013)	(0.894)	(0.864)	(0.861)	
Share white (2000)	0.595	0.325	0.679	***
	(0.329)	(0.316)	(0.284)	
Share black (2000)	0.189	0.380	0.129	***
	(0.271)	(0.357)	(0.203)	
Share Hispanic (2000)	0.162	0.242	0.138	***
	(0.232)	(0.299)	(0.201)	
Share of Population Born Outside the U.S.	0.140	0.166	0.133	***
(2006-2010)	(0.156)	(0.177)	(0.148)	
Logged Population Density (2000)	6.434	7.432	6.121	***
	(2.180)	(1.757)	(2.206)	
Share of Single-Headed Households (1990-2000	0.341	0.501	0.290	***
Avg)	(0.164)	(0.191)	(0.116)	
Census Form Return Rate (2010)	0.762	0.717	0.776	***
	(0.0759)	(0.0730)	(0.0713)	
Observations	34,737	8,283	26,454	34,737

Mean coefficients; Standard deviation in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Source: LIHTC Database and Opportunity Insights

Table A3: Robustness to Alternative Model Specifications and Sample Choices
Dependent Variable: Absolute Mobility

VARIABLES	(1) OLS	(2) OLS + Controls	(3) 2SLS IV
(1) Baseline	-1.569***	-0.010	9.856***
	(0.051)	(0.034)	(2.153)
(2) All LIHTC units (not just low-income)	-1.503***	-0.001	9.832***
	(0.049)	(0.033)	(2.185)
(3) LIHTC Housing Stock (no natural log)	-0.245***	0.001	2.355***
	(0.009)	(0.006)	(0.626)
(4) Rate of LIHTC low-income housing unit accumulation	-0.047***	-0.001	0.509***
	(0.001)	(0.001)	(0.178)
(5) Alternative instrument including DDA	-1.569***	-0.010	2.205***
	(0.051)	(0.034)	(0.281)
(6) Years 2000 – 2017	-1.541***	-0.047**	0.774***
	(0.033)	(0.024)	(0.151)
Observations	34,737	34,737	34,737
(7) All tracts in U.S.	-2.237***	-0.011	8.163***
	(0.046)	(0.031)	(1.032)
Observations	70,782	70,782	70,782
Covariates?	No	Yes	Yes

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10
Source: HUD and Opportunity Insights

Table A4: Robustness to Alternative Model Specifications and Sample Choices
Dependent Variable: Relative Mobility

VARIABLES	(1) OLS	(2) OLS + Controls	(3) 2SLS IV
(1) Baseline	0.303**	0.659***	-42.076***
	(0.098)	(0.094)	(8.466)
(2) All LIHTC units (not just low-income)	0.249**	0.613***	-41.975***
	(0.096)	(0.092)	(8.619)
(3) LIHTC Housing Stock (no natural log)	-0.074***	0.032*	-10.054***
	(0.018)	(0.017)	(2.519)
(4) Rate of LIHTC low-income housing unit accumulation	0.034***	0.028***	-2.172***
	(0.003)	(0.003)	(0.739)
(5) Alternative instrument including DDA	0.303**	0.659***	-9.974***
	(0.098)	(0.094)	(0.852)
(6) Years 2000 – 2017	-0.266***	0.348***	-3.161***
	(0.065)	(0.066)	(0.426)
Observations	34,737	34,737	34,737
(7) All tracts in U.S.	0.983***	0.727***	-28.225***
	(0.077)	(0.074)	(3.093)
Observations	70,782	70,782	70,782
Covariates?	No	Yes	Yes

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10
Source: HUD and Opportunity Insights

Figure A1: Number of LIHTC Units by County 1987–2000

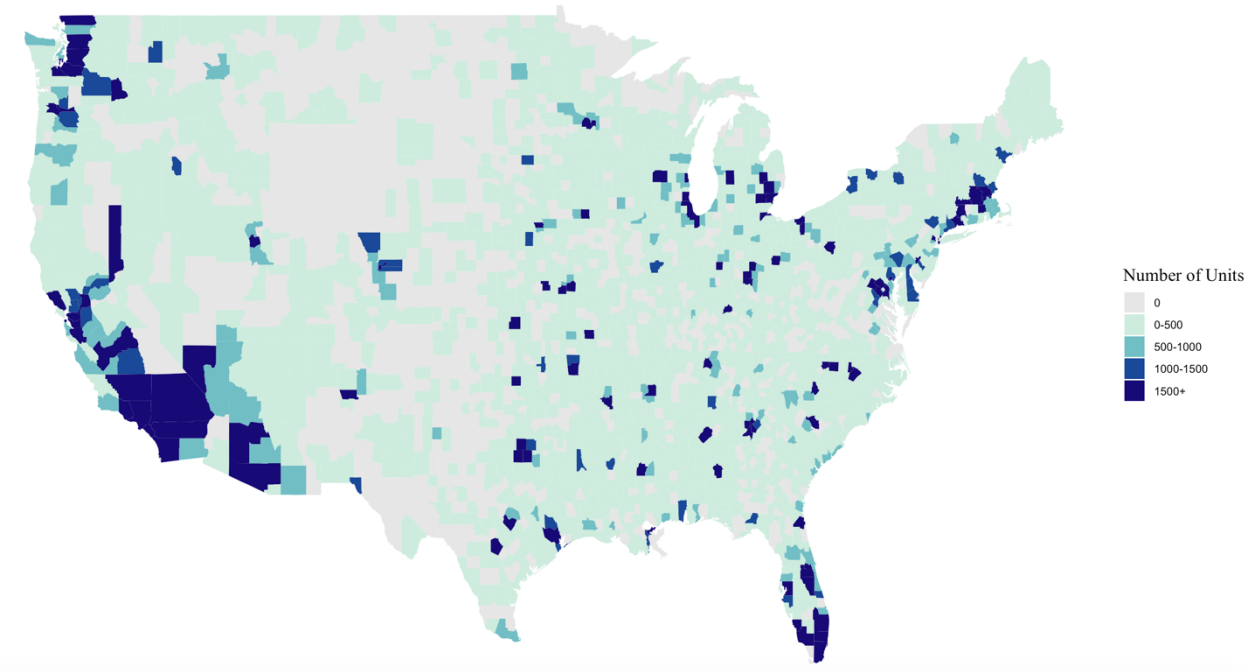
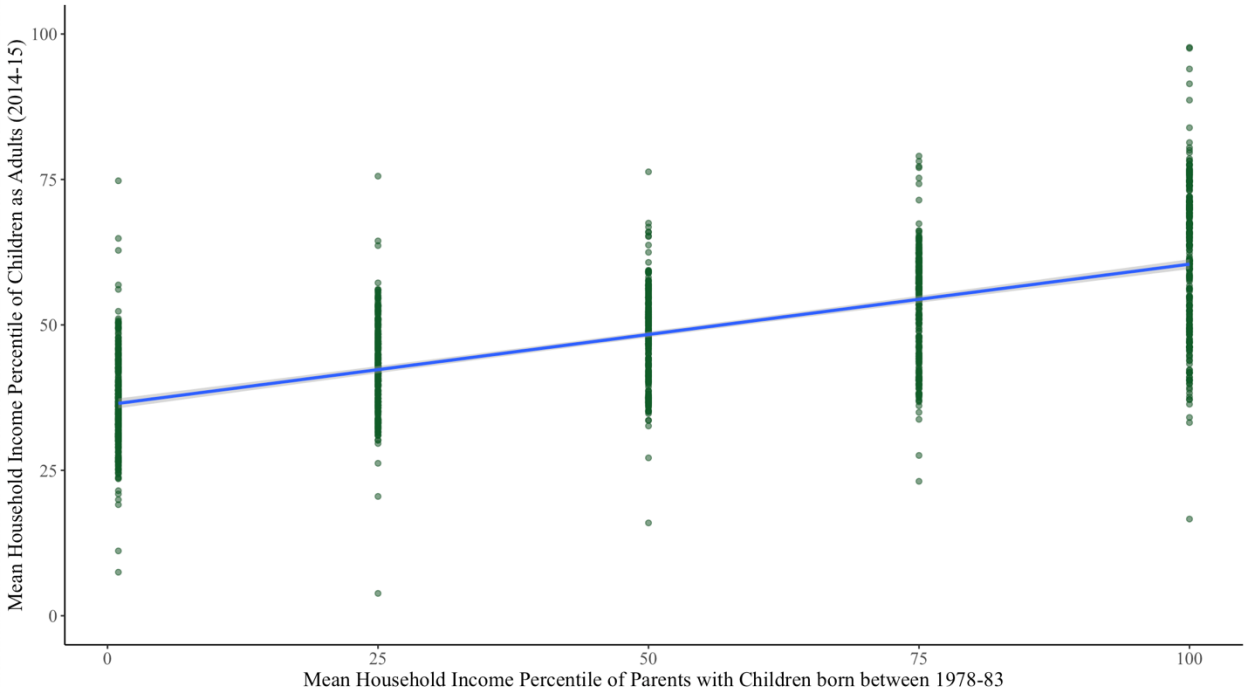


Figure A2: Comparison of Parent and Children Household Income Percentiles for New York County by Census Tract



Note: Each dot represents a different census tract observation. Observations are available from the Opportunity Insights data at the 1st, 25th, 50th, 75th, and 100th income percentiles for parents for each tract.