Does Growing Up in Tax-subsidized Housing Lead to Higher Earnings and Educational Attainment?

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February 15, 2021

Abstract

This paper investigates the effects of the Low-Income Housing Tax Credit (LIHTC) on residents of buildings qualifying for the credit. Specifically, it analyzes whether individuals who grow up in LIHTC housing are more likely to enroll in post-secondary education programs and have higher earnings as adults. Using administrative tax records, I find that each additional year spent in LIHTC housing as a child is associated with an average 4.3 percent increase in the likelihood of attending a higher education program for four years or more, and a 5.7 percent increase in future earnings. Furthermore, I find that there are heterogeneous effects when comparing individuals who live in LIHTC housing located in neighborhoods with different characteristics, and among families that have varying income levels and varying levels of housing security prior to moving into a LIHTC building. Based on this analysis, it is likely that the housing subsidy provides some families with a more stable living situation and with more disposable income.

*This research embodies work undertaken for the staff of the Joint Committee on Taxation (JCT), but as members of both parties and both houses of Congress comprise the Joint Committee on Taxation, this work should not be construed to represent the position of any member of the Committee. Many thanks to Arik Levinson, John Rust, and Michael Bailey for their comments and guidance on this project.

1 Summary

The Low-Income Housing Tax Credit (LIHTC) is the largest federal subsidy for the construction of low-income housing in the United States. Since its establishment through the Tax Reform Act of 1986, the LIHTC has helped finance the construction and renovation of over three million units, and currently costs approximately $10 billion per year in forgone tax revenue (JCT, 2020; HUD, 2019). Yet despite the size and importance of the LIHTC we still know relatively little about the people who reside in LIHTC buildings; nor do we know whether access to subsidized housing funded by the LIHTC improves people's lives in measurable ways. The main reason for this is the lack of data available on LIHTC residents and their outcomes. These tax credits are issued directly to developers, who until recently were not required to track or report information on the tenants residing in their buildings.

In this paper I addresses this problem by using a newly created data set of families residing in qualifying LIHTC properties to evaluate the long-run effects of growing up in LIHTC housing. Specifically, I use administrative tax records to estimate whether individuals who grow up in LIHTC housing have higher wages as adults than they would otherwise, and whether they are more likely to enroll in higher education programs. Using administrative tax records, I create a database of families with children under the age of 18 who lived in LIHTC housing between 1999 and 2012. I identify families living in LIHTC housing during these years using the publicly available addresses of LIHTC buildings, matched with parents' addresses listed on their information returns (such as W-2 and 1099 forms), and tax returns. I match parents and children based on the parents' and the children's ages, and whether the children are listed as dependents on their parents' tax returns. I then use the children's Social Security numbers to find their adult wages in 2018, when they are between ages 24 and 36. I also observe how many years they enroll in higher education programs using 1098-T tuition statements, which are filed by American colleges and universities.

In order to estimate the effects of living in LIHTC housing, I exploit variation in the number of years that individuals spend living in these buildings as children. This "dosage" measure of exposure to LIHTC housing helps address potential biases that may arise from comparing the outcomes of individuals whose families made the decision to move into LIHTC housing to those who did not live in subsidized low-income housing during the same time period. By comparing individuals whose families all decided to move into LIHTC housing when they were different ages, I eliminate potential bias from omitted unobserved variables such as parents' motivation to secure affordable housing for their families. However, there may still exist some bias associated with circumstances leading families to leave LIHTC housing, and the timing of families moving into LIHTC housing. To address these issues I use the stratified sampling procedure outlined below.

The first step in my stratified sampling approach is to estimate the effect of spending one additional year in LIHTC housing as a weighted average across groups of individuals who left LIHTC housing at different ages. This should eliminate any bias arising from both negative and positive circumstances that could cause families to leave LIHTC housing, such as eviction or moving in with a family member. This strategy also helps deal with differences in the effect of spending the same amount of time in LIHTC housing at different ages. For example, an individual who lives in LIHTC housing from ages 5 to 10 may experience a different effect than someone who lives in LIHTC housing from ages 13 to 18, despite spending the same number of years living in a LIHTC building. Instead, all variation comes from the age of entry into LIHTC housing.

Second, I further limit my sample population to include only individuals who move into LIHTC housing the same year or one year after the building is placed in service. This helps deal with bias that may arise from families strategically moving into LIHTC housing when their child is a specific age. For example, a family may decide to move into a better school district when their child is 11 years old and about to enter middle school. Using this stratified sampling method, even if parents target their move into a LIHTC building based on the age of their child, it will be purely coincidental that they enter into a building that was put into commission that same year, or the year prior. This approach assumes that parents who want to move into subsidized housing when their child is a particular age do not also favor moving into a newly constructed building. I assume that parents are concerned with moving into a subsidized unit, possibly timing the move according to the age of their child, and they do not care whether the building they move into was built in the last two years (as opposed to buildings that are at least three years old).

Using this strategy, I find that spending a longer amount of time growing up in LIHTC housing has a positive and statistically significant effect on both earnings and education. Under my preferred specification I find that *for every additional year* spent in LIHTC housing as a child, individuals are 4.3 percent more likely to enroll in a higher education program for four or more years, and are 4.2 percent more likely to enroll in two or more years of higher education. Additionally, individuals earn approximately 5.7 percent more as adults for every additional year spent in LIHTC housing. The cumulative effect is large. For example, I find that individuals who stay in LIHTC housing for seven years are 31.8 percent more likely to attend a college, university, or trade school for four or more years than those who live in LIHTC housing for just one year. Those who stay for seven years also earn 27.0 percent more on average in income than their counterparts who stay for one year.

In the following sections I describe these findings in greater detail and explore possible mechanisms that may be driving these results. In particular, I examine differences in the effect of living in LIHTC housing located in neighborhoods with different characteristics, including varying poverty levels, racial composition, median household incomes, high school graduation rates, and measures of opportunity constructed by Chetty, et al. (2018). I also look at heterogeneous effects based on the level of housing security a family has prior to entering into LIHTC housing − measured by the number of times that an individual changes addresses prior to moving into a LIHTC building − and heterogeneous effects based on household income. I find that although there are differences in the "LIHTC effect" based on both neighborhood and family characteristics, the latter appears to play a more important role in explaining my results.

2 Background

2.1 How the Low-Income Housing Tax Credit Works

Congress passed the Low-Income Housing Tax Credit (LIHTC) as part of the 1986 Tax Reform Act, touting the credit as an incentive to encourage private investment in the development and rehabilitation of low-income housing in the United States (Keightley, 2019). During this time period the number of households living in LIHTC units increased from approximately 400,000 in 1993 to roughly 2.6 million households in 2016, nearly equaling the number of households served by all other public housing programs combined (Kingsley, 2017). Yet despite the size and importance of the LIHTC program, we know relatively little about how the tax credit affects the low-income renters it intends to serve.

Unlike other federal low-income housing subsidies, the LIHTC is issued directly to developers − as opposed to individual renters or homeowners − and is used solely to help finance the construction or renovation of low-income housing. The Internal Revenue Service (IRS) and Department of Treasury administer the tax credit at the federal level, but selection of projects eligible for the credit, and administration and oversight of the program, are the responsibilities of state and city governments. Each year the federal government allocates tax credits to each state's Housing Finance Agency (HFA) based on the state's population − or the city's HFA if it is a "home rule" city − with the minimum credit level set at $3.1 million as of fiscal year 2018 (Novogradac, 2018). The HFAs then award tax credits to developers based on federal guidelines, and on criteria that each state or city sets in its Qualified Action Plan (QAP) (Ellen, et al., 2015).

There are two types of Low-Income Housing Tax Credits: nine percent credits, which are capped based on state population, and four percent credits, which are uncapped and typically allocated to projects that are financed in part with tax-exempt bonds (Keightley, 2019). Each credit is awarded for a period of 10 years, and designated LIHTC units must remain affordable to low-income renters − as defined by federal regulations − for a period of 15 years, with additional rent restrictions for a three to 15 year period afterward (Black, 2014; Baum-Snow and Marion, 2009). The recipient of the credit can claim a percentage (either nine or four percent depending on the type of credit) of the building's qualified basis each year. However, the applicable rates are typically lower, as they fluctuate with interest rates. In practice, the total subsidy is equivalent to approximately 30 percent of the initial value of the project's qualified basis in the case of the four percent credit, and 70 percent of the qualified basis in the case of the nine percent credit (Keightley, 2019). The term "qualified basis" has a lengthy legal definition, but is essentially understood to be the total cost of construction or renovation that will ultimately benefit low-income residents.

Developers apply to receive credits by proposing plans directly to state HFAs, who approve a set number of plans each year to receive nine percent credits (with total allocated credits falling below the annual limit), and an unrestricted number of plans to receive four percent credits. Since approval is decided at the state level, there are considerable differences between states when it comes to the location of LIHTC housing, which are driven by the states' Qualified Action Plans (QAPs). Some state QAPs promote economic and racial diversification, so proposals for LIHTC buildings in more affluent or mixed-income neighborhoods are given priority. Other state QAPs place greater emphasis on economic development of impoverished communities, prioritizing proposals for buildings in low-income neighborhoods (Ellen, et al., 2015). In general, although LIHTC developments are typically located in neighborhoods with higher poverty rates compared to national averages, they are also located in relatively more affluent neighborhoods compared to project-based public housing (McClure, 2006). A larger percentage of LIHTC buildings are also built in suburban neighborhoods, compared to public housing projects.

Developers (or more commonly investors) cannot claim the LIHTC on their federal returns until their project is completed and occupied by tenants (Keightley, 2019). In order to fully qualify for the credit, developers must prove that at least 20 percent of units in their building are occupied by families or individuals with incomes lower than 50 percent of the area median income (AMI), or at least 40 percent of the units are occupied by families or individuals with incomes lower than 60 percent of the AMI, with slightly lower or higher income thresholds depending on family size (Keightley, 2019). This is commonly referred to as the 20-50 test, or the 40-60 test. Developers must also prove that the rent level for these units is set no higher than 30 percent of the designated income threshold for the building (also adjusted based on family size). For example, in a building that qualifies based on the 20-50 test, rent for a 4-person family can be set no higher than 30 percent of 50 percent of the area median income (or 15 percent of the AMI).

Since the LIHTC cannot be claimed until buildings are occupied, developers typically sell these tax credits to third party investors − usually banks and other financial institutions − for equity to fund the construction or renovation of their buildings (Keightley, 2019). These partnerships between developers and investors are sometimes brokered by syndicators, who charge an additional fee for processing the transactions (GAO, 2019). On top of benefiting from a generous tax credit, financial institutions in particular have an incentive to purchase Low-Income Housing Tax Credits in order to meet federal requirements for local investment under the Community Reinvestment Act of 1977 (GAO, 2019).

One of the largest differences between the LIHTC and other federally funded housing programs is that income limits are set according to characteristics of the building, unit, and area; not according to the income of the tenant (O'Regan, et al., 2013). Thus, unlike with housing vouchers (for example), families living in LIHTC housing often pay more than 30 percent of their household income towards rent, a rate that is commonly considered the "rent burden" threshold. Yet a 2012 study by the Furman Center at New York University found that over 45 percent of LIHTC residents are considered extremely low-income, meaning that their income is less than 30 percent of the area median income (O'Regan, et al., 2013; Hollar, 2014). These people can afford to live in LIHTC housing in large part because they often also receive additional housing subsidies − both directly through housing vouchers and indirectly through building- or unit-specific subsidies.

The Furman Center found that over one-third of LIHTC households receive some other form of rental assistance, including Section 8 housing vouchers (O'Regan, et al., 2013). This is especially true of extremely low-income tenants, 70 percent of whom receive some other type of rent subsidy in addition to lower LIHTC rents (NYU, 2012). One of the main reasons why a lot of Section 8 voucher recipients reside in LIHTC buildings is that voucher holders face considerable housing discrimination in unregulated markets, especially in high or middle-income neighborhoods (Emple, 2014). Voucher holders often report being ignored by landlords, or turned away when applying for apartments that are not designated as low-income units. In contrast, LIHTC buildings need these tenants in order to qualify for the tax credits and are less likely to turn them away. However, it is also the case that LIHTC developments themselves receive a number of additional subsidies from federal, state, and local organizations, and in return these buildings charge their tenants lower rents (O'Regan, et al., 2013).

This overlap between the LIHTC and other housing subsidies does make it difficult to separate the effect of living in LIHTC housing from that of receiving a Section 8 voucher, for example. However, these programs can be considered complimentary in many ways, since many low-income renters could not afford to live in LIHTC buildings without other housing subsidies, and many voucher recipients are not able to find housing in non-LIHTC buildings. My identification strategy does help isolate the effect of LIHTC housing by restricting my sample to families that move into new LIHTC buildings, essentially measuring the effect of new subsidized housing being introduced to a given area. However, in general I interpret my results as the effect of a combination of housing subsidies, since the estimate would likely change in the absence of having extremely low-income renters comprising almost half of all LIHTC residents.

2.2 Housing Policy and Economic Mobility

There are several reasons why growing up in LIHTC housing might lead to higher educational attainment and higher earnings later in life. First, if LIHTC housing is built in a more affluent neighborhood where low-income families could not otherwise afford to rent an apartment or house, then the children growing up in these buildings might benefit from attending better, well-funded schools, with access to resources and social networks that they would not otherwise have. Previous studies on peer effects show that organizational norms and structures at the high school level − as well as social expectations around college attendance − can have a large effect on the probability of individual students attending college, especially for low-income students (Sokatch, 2006; Roderick, et al., 2011; Falk and Ichino, 2006).

The most famous experiment testing this theory of location effects on adult outcomes is the US Department of Housing and Urban Development's (HUD's) decade-long Moving to Opportunity (MTO) program, which relocated families living in high-poverty neighborhoods to low-poverty neighborhoods through a restricted voucher system (Ludwig, et al., 2013; Leventhal and Brooks-Gunn, 2003; Sanbonmatsu, et al., 2011). The MTO experiment aimed to fix what HUD perceived as a problem with the Section 8 voucher program. In theory, families who received these vouchers had unlimited choice when it came to which neighborhood they could move to. However, the majority of tenants who received Section 8 vouchers remained in high-poverty neighborhoods, both because of personal preference − choosing to remain in a familiar neighborhood where they felt comfortable − and as a result of discriminatory housing practices, with landlords refusing to accept vouchers as a form of rent payment.

As an alternative, MTO required random voucher recipients to move into low-poverty neighborhoods to test the theory that housing policy could go beyond simply providing people with a cheaper place to live, and could help improve the lives of tenants by moving them into areas with better opportunities for education and employment. HUD created local programs in each of the test cities (Baltimore, Boston, Chicago, Los Angeles, and New York) and entered into agreements with local non-profit organizations to provide counseling and assistance to participating families in order to help them navigate different housing markets (Gennetian, et al.,2011). In addition, they worked directly with landlords to encourage their participation in the program and reduce the incidence of discrimination against voucher holders.

The initial results of the MTO experiment were mixed. The data did show improved mental and physical health outcomes for children who moved to low-poverty neighborhoods, such as lower obesity and diabetes rates (Ludwig, et al., 2013; Leventhal and Brooks-Gunn, 2003; Sanbonmatsu, et al., 2011). The study also concluded that outcomes for girls who moved into low-poverty neighborhoods were generally better than they were for boys. However, the experiment revealed no significant effect of moving to a low-poverty neighborhood on students' test scores, or on their future employment and wages (Ludwig, et al., 2013). Thus, the study concluded that moving to a high opportunity neighborhood had no discernible impact on individuals' long-run outcomes.

However, a few years after publication of the initial MTO findings, Chetty, Hendren, and Katz (2016) re-evaluated the MTO data and found that moving to a low-poverty neighborhood actually did lead to improved outcomes, particularly for individuals who moved into these areas before age 13. The reason the initial MTO study missed this pattern is that HUD collected its final round of outcomes data in 2008, when most individuals who participated in the program were not yet old enough to enter the labor market. Furthermore, the participating individuals who had entered the labor market by 2008 had moved into low-income neighborhoods at an older age. So the original conclusions of MTO were based solely on the outcomes of children who had low "exposure" to low-poverty neighborhoods, and who had moved at an age at which the negative disruption in their schooling and personal life may have outweighed the benefits of moving to a more prosperous area.

In general, Chetty, et al. (2016) find that the neighborhood in which a person grows up has a large effect on their outcomes later in life, and that "high opportunity" neighborhoods are not randomly scattered across the country. They are clustered in very specific geographic areas, with significant differences even across adjacent Census tracts (Chetty, et al.,2016). The more time children from low-income families spent in high opportunity neighborhoods − neighborhoods where individuals eventually ended up earning more than other people in their age group on average − the more likely they were to end up in a higher income bracket than their counterparts in low opportunity neighborhoods.

Another reason why living in LIHTC housing may lead to higher earnings and educational achievement may be that the construction of LIHTC housing has a revitalizing effect on low-income neighborhoods themselves. Rebecca Diamond and Tim McQuade (2019) find that the construction of LIHTC housing in low-income areas leads to an increase in housing prices, a decrease in crime rates, and greater racial and economic diversification in these neighborhoods. Baum-Snow and Marion (2009) also find that the construction of LIHTC buildings leads to an increase in property values in declining areas. In the same way that building LIHTC housing in a high-income neighborhood can lead to better resources and opportunities for children growing up in these buildings, improvements to low-income neighborhoods may have similar positive effects on schools and available resources in these communities. Thus, children growing up in LIHTC buildings constructed in high-poverty areas may benefit from a general improvement in the neighborhood where they are constructed, because the buildings themselves bring about changes that affect childhood development.

There are several other possible reasons why moving into subsidized housing might be beneficial to low-income families, and why it might lead to better outcomes later in life for the children who move in at younger ages. Spending less income on rent may give parents more disposable income to spend on other resources for their children. They might be able to afford more nutritious food, or pay for after school programs and tutors, all of which would benefit their children in the long run. Entry into LIHTC housing may also alleviate homelessness for some families, or provide a more stable living situation, especially if the family was moving around a lot prior to securing low-income housing in a LIHTC building. LIHTC housing may also provide a safer environment for families than their previous living situation.

This paper examines three of these possible explanations for why growing up in LIHTC housing may lead to better outcomes: location, housing stability, and household income. To do this I decompose the effect by both neighborhood and household characteristics to determine if the effect differs between children growing up in different neighborhoods or in families facing different financial and housing circumstances. The results from these two analyses suggest that the positive estimated effect of growing up in LIHTC housing is more the result of improved housing stability and higher net household earnings than of moving to a better neighborhood. However, as I explain in greater detail in the following sections, I cannot rule out the importance of location since most families do not move to a higher opportunity neighborhood when they move into LIHTC housing.

3 Data

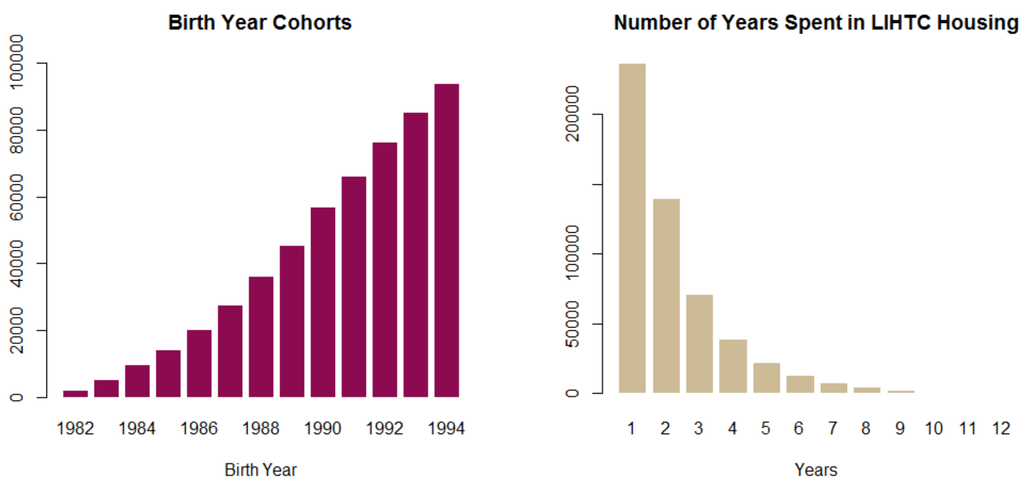
Most of my data come from the population of tax and information returns in the United States, including tax returns filed by individuals, and information returns issued by employers to employees and contractors, such as W-2 and 1099 forms. Using these data I am able to track families' addresses over time, link parents with their children (listed as dependents on tax returns), find earnings information for both the parents and the adult children, and ascertain children's educational achievement using 1098-T tuition statements. These records are limited in some ways. I only have access to data starting in 1999, and I am not able to track families for the oldest cohorts for more than a few years. Some data are also missing from administrative tax records. In particular I find that when it comes to tax returns (as opposed to information returns) the tax years associated with a lot of addresses are missing, which makes it difficult to determine which years each tax filer lived at each address. This seems to be particularly common in earlier years as there is a jump in the number of addresses listed on tax returns filed after 2003. As such, I rely heavily on information returns to locate parents prior to this year.

My second main source of data is the US Department of Housing and Urban Development (HUD) database for buildings constructed under the Low-Income Housing Tax Credit (HUD, 2019). HUD provides a wide range of information on each building, including the building's address and zip code, the year it was placed in service, the total number of units in each building, the number of low-income units in the building, the income threshold rule (20-50 or 40-60), the Census tract number (in both 2000 and 2010) where the building is located, county and state identifiers, and cost information related to the tax credit issued for the building. There are some problems with these data as well, particularly with missing or partially available addresses (for example, a few buildings provide just a zip code). There are some missing data in other fields as well, like the number of LIHTC units in the building compared with the overall number of units. As such, I do exclude a small number (about six percent) of buildings due to missing or incomplete data.

In order to identify families living in LIHTC housing, I match addresses of LIHTC buildings with addresses listed either on parents' information returns or their individual tax returns. I provide a detailed explanation of the matching process I use to identify families in **Appendix A**. The fully merged data set includes 540,839 individuals born between 1982 and 1994 whom I observe living in LIHTC housing between 2000 and 2012. The population includes only dependents that I identify as living in LIHTC units based on their parents' income and on the income thresholds unique to each building. I exclude anyone I observe living in LIHTC housing in 1999 because I cannot tell how long they lived in the building prior to that year. As such, all of the individuals in my data moved into LIHTC housing in 2000 or later.

I observe these individuals moving into LIHTC housing between ages 6 and 18, and approximately one third of them remain in LIHTC housing through age 18. They are between ages 24 and 36 in 2018, when I observe their annual earnings. **Figure 1** below shows the distribution of ages and amounts of time spent in LIHTC housing in the full data set. As shown in the graphs, there are a greater number of individuals in younger cohorts simply because the data only go as far back as 1999, so I observe the families of individuals born in earlier years for a shorter period of time. Since I observe older individuals for a shorter amount of time, the number of years spent in LIHTC housing also tends to be skewed towards the lower end.

Figure 1: Summary Statistics

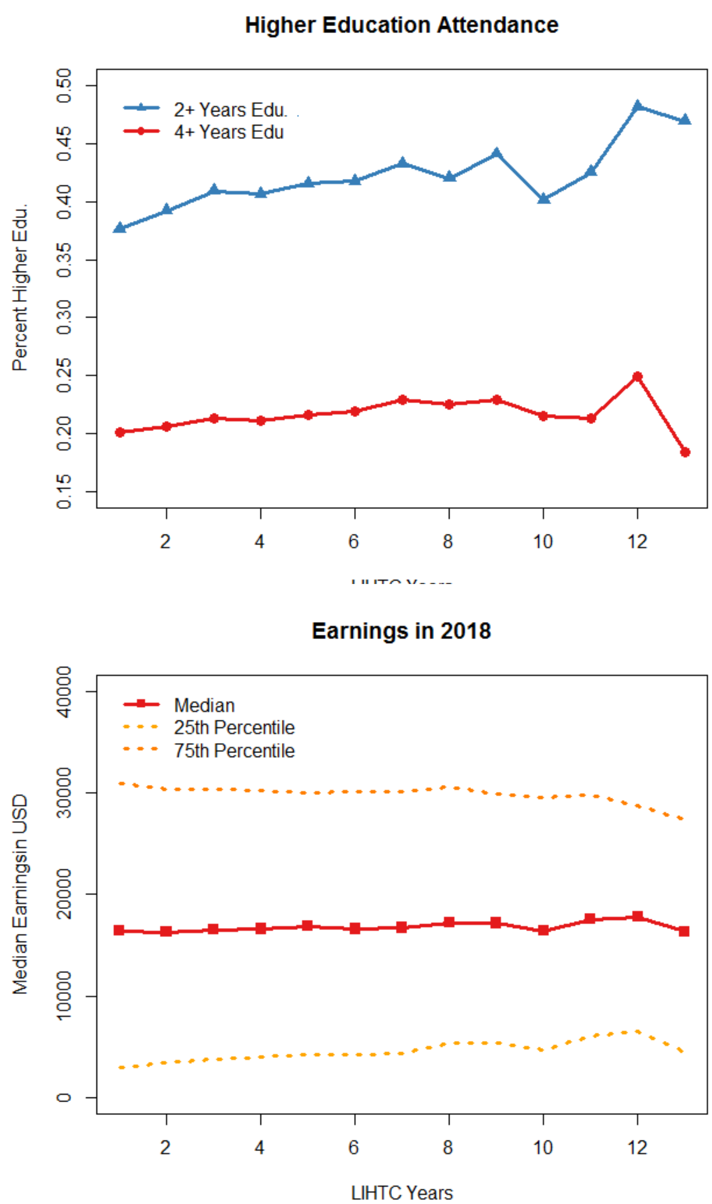


To further examine the mechanisms that may be underlying the effect of growing up in LIHTC housing I also use Census tract data from the US Census Bureau's 2000 Census of Population and Housing to estimate differences in the effect for individuals growing up in LIHTC housing located in neighborhoods with varying characteristics (Census, 2000). I use these data to analyze differences in the estimated effect for buildings constructed in neighborhoods with varying levels of poverty, high school graduation rates, racial composition, and median household incomes. In the following section I provide further details on how I divide my sample into different quantiles based on neighborhood characteristics in order to conduct this analysis.

In addition, I use data from Chetty, et al.'s (2018) Opportunity Atlas (`www.opportunityatlas.org/`) to look at how the LIHTC effect varies among neighborhoods with different opportunity measures. The opportunity measure I use is the fraction of children who grew up in a specific area whose household income in 2014/2015 (when they are in their mid-30s) is in the top 20 percent of the national income distribution for children born in the same year. It is a measure of the average differences in the outcomes of individuals who grow up in different neighborhoods (Chetty, et al., 2018). In other words, the opportunity measure tells us how likely it is that a child who grows up in a particular area will be in a relatively higher or lower income percentile than their peers growing up in other neighborhoods. This provides a more dynamic measure of poverty than more traditional measures that show a snapshot of neighborhood conditions.

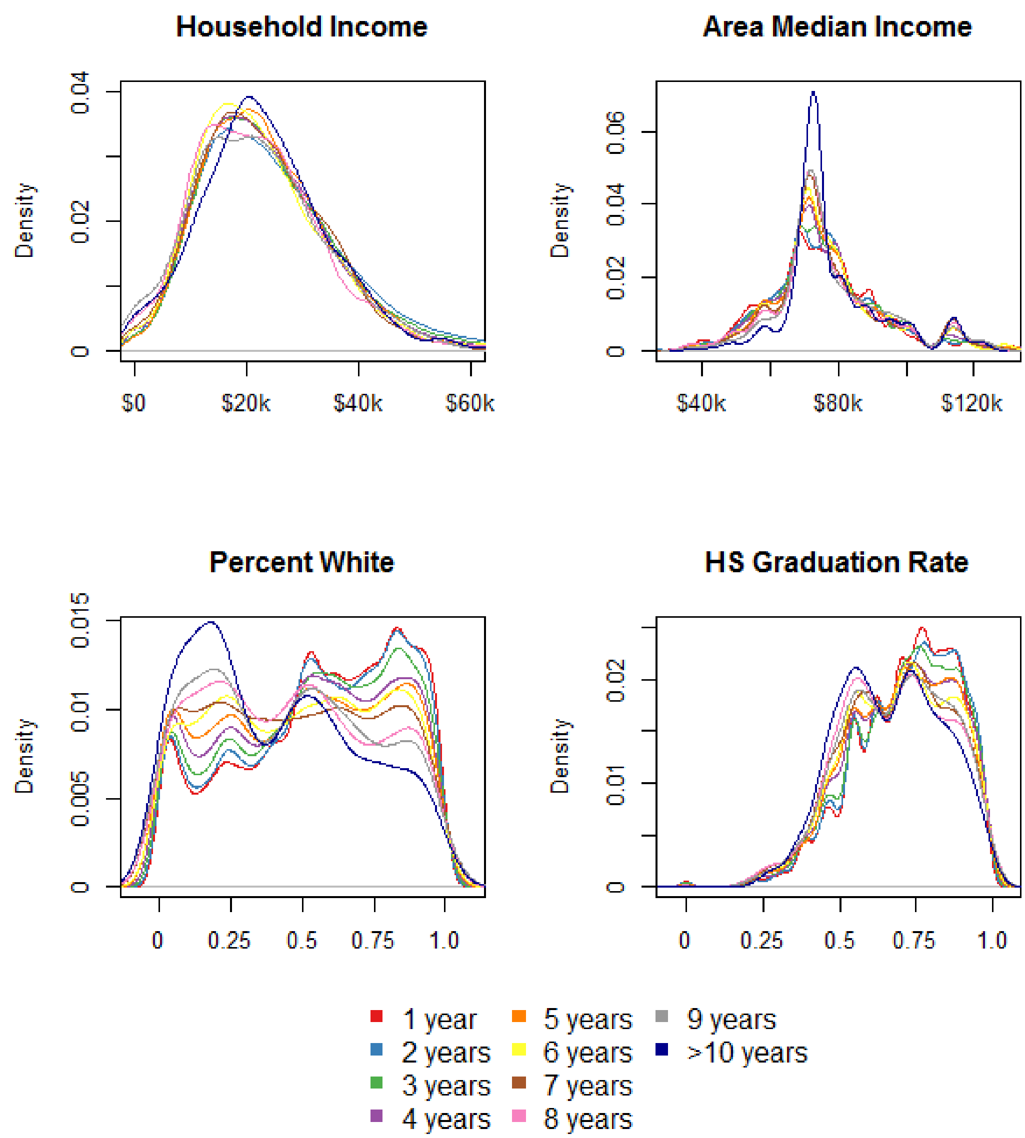
Looking at the raw data, there does appear to be a small positive correlation between the number of years spent in LIHTC housing ("LIHTC Years") and the likelihood of enrolling in a higher education program, without controlling for other variables. However, there does not appear to be as strong of a relationship between earnings and number of years spent in LIHTC housing. The first graph in **Figure 2** below shows the percent of individuals who enrolled in four or two years of post-secondary education, according to the number of years each group spent in LIHTC housing. The second graph shows 2018 earnings at the 25^{th}, 50^{th} and 75^{th} percentiles by group. These raw patterns in the data do not control for several factors that may introduce some bias in the effect of growing up in LIHTC housing on adult outcomes. In the following section I further describe my approach to estimating this effect, which turns out to be larger and more statistically significant than the graphs in **Figure 2** might suggest.

Figure 2: Educational Attainment and Earnings by LIHTC Years



Since I do not use a traditional binary treatment variable in my analysis – but rather a dosage measure of years spent in LIHTC housing – it is difficult to construct balance tables to compare individuals across LIHTC years. As such, I graph distributions of household or neighborhood characteristics by number of years spent in LIHTC housing to see if there are any differences across groups. **Figure 3** below graphs these distributions by LIHTC years for (pre-LIHTC) household income, area median income (measured at the county level), racial composition, and high school graduation rate (both measured at the census tract level). As we can see in the figure, the household income distributions are actually quite similar across groups, although the parents of individuals who stay in LIHTC housing for 10 years or more do have slightly higher incomes on average. The same is true for area median income: the distributions are similar across the board.

Figure 3: Summary Statistics



However, there do appear to be some differences between individuals in each group when it comes to neighborhood racial composition and high school graduation rates. Individuals that spend longer amounts of time in LIHTC housing tend to reside in neighborhoods that are less white and less educated (have lower high school graduation rates among adults 25 years and older). Each of the distributions for these variables is monotonically changing with respect to LIHTC years. This is interesting given that families that stay for very long periods of time (10 years or more) also have higher incomes on average before moving into LIHTC housing, and household income tends to have a negative correlation with average education and percentage of the population that is white.

Since there is at least some correlation between LIHTC housing and these variables, I control for them in my regressions either directly − in the case of household income − or indirectly using a zip code fixed effect. I explain my estimation strategy in greater detail in the following section.

4 Empirical Specification

The focus of this paper is estimating the effect of growing up in LIHTC housing on educational achievement and adult earnings. As such, it may seem natural to compare children growing up in LIHTC housing with similar individuals growing up in non-LIHTC housing. However, this comparison may not be appropriate if parents who secure housing in a LIHTC building are in some way inherently different from parents who do not live in LIHTC housing. In particular, it would not be possible to control for unobservable characteristics like parental ambition, which might affect both the parent's ability and willingness to find a rent-subsidized unit in a LIHTC building, and would also likely affect their children's future outcomes. If parents who rent units in LIHTC buildings are more proactive about securing housing for their families, then they may be proactive in other ways that would help their children succeed, such as enrolling them in free after school programs.

Rather than compare individuals who grow up in LIHTC housing with those who do not, I instead compare individuals who spend different amounts of time in LIHTC housing as children with each other. Instead of estimating the overall effect of growing up in LIHTC housing I measure the effect of spending *one additional year* growing up in LIHTC housing. My main variable of interest, which I call "LIHTC Years" can be considered a kind of dosage or exposure variable, where individuals who spend a longer amount of time living in LIHTC housing as children are considered to have greater exposure or a larger dose of LIHTC housing than their counterparts who spend just one or two years living in a LIHTC building.

I estimate the effect using parametric regressions of adult earnings and educational attainment on the number of years spent growing up in LIHTC housing, controlling for a number of individual, family, and location characteristics. I estimate the effect of growing up in LIHTC housing, $\hat{\theta}$, using the formula in equation (1) below, where $y_{i,b,z}$ is the outcome variable (either educational attainment or adult earnings) for individual i with birth year b growing up in LIHTC housing located in zip code z, regressed on LIHTC years $h_{i,b,z}$, and a vector of control variables $X_{i,b,z}$, with birth year and zip code fixed effects, γ_b and δ_z. Standard errors are robust and clustered at the zip code level.

$$y_{i,b,z} = \theta h_{i,b,z} + \beta X_{i,b,z} + \gamma_b + \delta_z + \epsilon_{i,b,z} \tag{1}$$

I use a logistic regression for both of my binary education outcome variables (the incidence of attending four or more years of higher education and the incidence of attending two or more years of higher education), and I use an ordinary least squares regression for my earnings outcome variable. I control for a number of individual, household and building characteristics including household income (for all years I am able to observe the family before the child turns 18 years old, from 1999 to 2012), gender, parents' ages relative to their children, area median income, family size, the number of units in each building, and parents' filing status (e.g. married or single). Each variable is explained in greater detail in **Appendix B**. One notable control missing from my estimates is race. Race and ethnicity are not reported to the Internal Revenue Service or the Social Security Administration.

4.1 Stratified Sampling

Even after controlling for the variables listed above, there is reason to believe that the estimated LIHTC effect using the full population, $\hat{\theta}_{All}$, may suffer from omitted variable bias on unobserved characteristics. Thus, I employ a stratified sampling approach to deal with the potential sources of bias explained below, and to establish a more convincing level of causal inference for my estimates.

One source of potential bias has to do with the circumstances that may cause a family to leave LIHTC housing. Approximately two thirds of the dependents in my sample leave LIHTC housing before age 18. This could be for positive reasons I cannot observe, like the family moving into a better neighborhood with a relative, or for negative reasons, like eviction. If there is a high incidence of eviction among families who spend just one or two years in LIHTC housing, for example, then my estimates will be positively biased. The positive effect of living in LIHTC housing for a longer period of time will be amplified because the reasons underlying the family leaving LIHTC housing may further disadvantage the children whose families spend a short amount of time in LIHTC housing due to eviction.

Thus, in order to eliminate potential bias coming from families leaving LIHTC housing, I divide my sample into groups based on the last age at which I observe each child in a LIHTC building. I then estimate the effect of spending an additional year in LIHTC housing on each of these sub-groups, stratified by age of exit, and then combine the total effect using weights based on the percent of individuals represented in each group. The regression specification is defined as follows:

$$\hat{\theta}_S = \sum_{k=8}^{18} \hat{\theta}_k w_k \tag{2}$$

$$s.t.\ \ E[y_{i,b,z} \mid i \in \mathcal{S}_k] = E[\theta_k h_{i,b,z} + \beta X_{i,b,z} + \gamma_b + \delta_z \mid i \in \mathcal{S}_k]$$

$$w_k = \frac{\sum_i I\{i \in \mathcal{S}_k\}}{\sum_i I\{i\}} \tag{3}$$

In equations (2) and (3), $\mathcal{S}_k$ represents "stayers", i.e. the group of individuals who stay in LIHTC housing up until age k. All other variables remain as before. By undertaking this procedure, all of the variation in my estimate now comes from the age of entry into LIHTC housing, and compares individuals only to others who exit LIHTC housing at the same age. For example, among individuals who stay in LIHTC housing through age 18, all individuals who spend one year in LIHTC housing enter at age 18, and all individuals who spend seven years in LIHTC housing enter at age 12. The equation assumes a linear effect, meaning the single-year effect of moving in one year earlier is the same from age 12 to 13 as it is from age 17 to 18. I will relax this assumption in the following section.

A second source of potential bias is families timing their move into a different neighborhood or a different rent-subsidized building when their child is a particular age. For example, parents may look for housing in a neighborhood with a good middle school district when their oldest child is about to leave elementary school (around age 10 or 11). Although I do not see any evidence that families are doing this on average − there appears to be a uniform distribution of age of entry within each birth cohort − parents who are generally more ambitious may plan their move into LIHTC building at a "better" age than other parents. There may be less disruption in a child's life, for example, if they move at the same time they were supposed to change schools anyway.

For this reason, I further limit the sample of individuals in my third regression to children who move into a LIHTC building the same year or one year after that building is placed in service. In this series of "New Building" regressions I am still using the stratified sampling procedure based on age of exit. Note that in this specification the leaving age begins at 11 years rather than eight due a low number of individuals leaving new buildings at younger ages in the data. The regression is specified as follows:

$$\hat{\theta}_{NB} = \sum_{k=11}^{18} \hat{\theta}_k w_k \tag{4}$$

$$s.t.\ \ E[y_{i,b,z} \mid i \in \mathcal{S}_k, i \in \mathcal{NB}] = E[\theta_k h_{i,b,z} + \beta X_{i,b,z} + \gamma_b + \delta_z \mid i \in \mathcal{S}_k, i \in \mathcal{NB}]$$

$$w_k = \frac{\sum_i I\{i \in \mathcal{S}_k\}}{\sum_i I\{i\}} \tag{5}$$

In equation (4) above, $\mathcal{NB}$ is the set of individuals who move into a LIHTC building the same year or one year after the building is placed in service. If there are parents who are planning their move based on the age of their child, then it will be purely coincidental that they move into a building that was recently placed in service. Some bias may still exist if parents are planning to move into a new building the same year that their child turns a specific age, but it seems unlikely that such targeting would be successful since there is some uncertainty about when buildings are placed in service, and families would more likely search for a new apartment based on availability and location. Even families with a preference for new buildings would probably not differentiate much between a building constructed three or four years ago and a building constructed one year ago.

By limiting my sample to only families that I observe moving into a new building I also take advantage of the exogenous event of new affordable housing appearing in a given family's local area. The location data I have for parents show that most of these families (85 percent) move less than 10 miles from their previous location when they move into a LIHTC building, and over half (55 percent) do not move out of their current zip code. This is especially true for families in the "New Building" sub-sample. 58 percent of individuals in this subset do not change zip codes when moving into LIHTC housing, and 88 percent travel less than 10 miles to move into LIHTC housing (95 percent travel less than 20 miles). Moreover, there is little correlation between the distance a family moves and the affluence of their new neighborhood (measured by things like poverty level and median income). **Figures 4 and 5** below show the distribution of distances that families travel when they move into LIHTC housing, for the full data set and for the"New Building" sub-sample, respectively. The distributions are graphed by continuous miles and by discrete categories, and have large spikes at zero. This suggests that families move into low-income housing as it becomes available in their area.

Figure 4: Distance between Old and New Addresses (Full Sample)

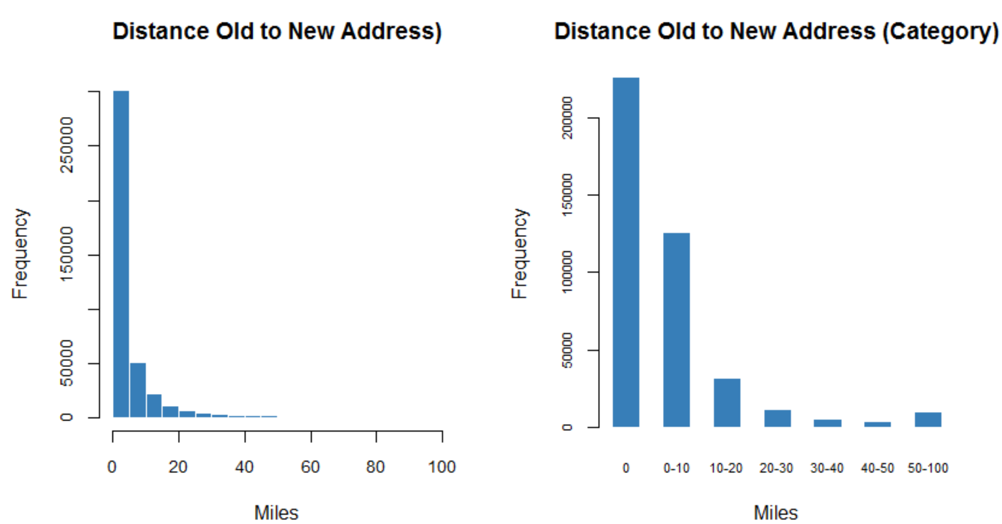
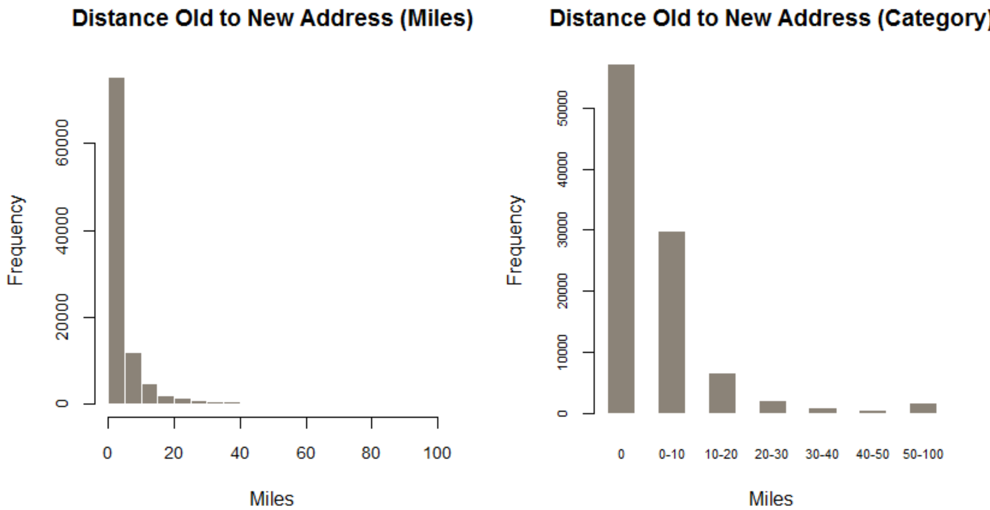


Figure 5: Distance between Old and New Addresses (New Building)



5 Results

5.1 Stratified Sampling Regression Results

As shown in **Table 1** below, the estimated effect of spending one additional year in LIHTC housing on the probability of attending four or more years of post-secondary education is positive, significant, and large. The estimates presented in **Table 1** are the relative odds ratios (minus one). When running the regression on all LIHTC residents, I find that individuals are 4.4 percent more likely to enroll in a four-year program for every additional year they spend in LIHTC housing. When I use the stratified sampling procedure outlined above (a weighted estimate for each sub-sample of "stayers"), the estimate increases slightly to 5.3 percent. The difference in estimates suggests that there may be some negative bias on $\hat{\theta}_{All}$ coming from families leaving LIHTC housing at various ages. However, when limiting the sample further to include only families who move into new buildings, the estimated effect goes back down to 4.3 percent, indicating that there may also be some positive bias coming from families timing their move into LIHTC housing based on the age of their child.

Most of the control variables also have statistically significant estimated effects on adult outcomes. Higher household income and older parental age at birth are both associated with a higher probability of college attendance; as is higher area median income, although this effect disappears when using stratified sampling. This may be because AMI is defined at the county level, and the zip code fixed effect is absorbing most of the effect (though not all since I calculate area median income as an average over all years spent in LIHTC housing).

I also find that males are significantly less likely to attend a four-year program than females. This result is in line with the original Moving to Opportunity (MTO) study, which found that girls who moved to low opportunity neighborhoods fared better than boys (Ludwig, et al., 2013; Clampet-Lundquist, et al., 2006; Kling, et al., 2007). Girls who participated in the experiment did 13.6 percent better across a number of educational measures − including test scores and graduation rates − than girls in the control group. In comparison, boys who moved to low-poverty neighborhoods performed worse than their counterparts in the control group, although the differences were not statistically significant (Kling, et al., 2007). The finding is also in line with gender comparisons of college enrollment rates for low-income students: low-income boys are generally less likely to enroll in a four-year university program than low-income girls (Semuels, 2017).

As shown in **Table 2** below, the estimated effect of growing up in LIHTC housing on attending two or more years of post-secondary education is similar. According to my preferred specification, for every additional year spent growing up in LIHTC housing, individuals are 4.3 percent more likely to attend two or more years of higher education. Differences in the estimate across regressions and the estimated effect of each of the control variables also follow the same patterns as in **Table 1**, with a slightly larger effect measured in the first regression on the full sample. It is important to note that since the results I am presenting in each table are log odds, the results should be understood as a percent increase over the baseline education rates of 23.8 percent (four years) and 42.4 percent (two years). For example, someone who spends seven years in LIHTC housing would be approximately seven percentage points more likely to attend university than someone who spends one year in LIHTC housing (a 4.3 percent increase in enrollment for seven years over a baseline rate of 23.2 percent). Similarly, someone who spends seven years in LIHTC housing would be approximately 12.5 percentage points more likely to enroll in two or more years of higher education compared to someone who spent one year in LIHTC housing.

I am concerned that the positive estimated effect of LIHTC years might simply be explained as the effect of remaining in any given place for a longer period of time (regardless of whether the family is living in a LIHTC building). However, the number of times a family moves is very likely to be impacted by length of stay in LIHTC housing. In other words, number of moves is a post-treatment variable, so including it in my regression would produce biased results. However, for robustness I do include total moves − defined as the total number of times that a family moves over the entire time period that I observe them − as a regressor in the same equation to test whether it absorbs all of the estimated LIHTC effect. As shown in **Tables 5 through 7** in **Appendix C**, including this variable in my regressions does not significantly change the estimated effect of LIHTC years on future education and earnings.

Table 1: Regression Results: 4+ Years Higher Education

	4+ Years Higher Education (Odds Ratios)		
	All LIHTC	Stayers	New Building
LIHTC Years	0.044***	0.053***	0.043**
	(0.002)	(0.011)	(0.018)
Male	-0.541***	-0.542***	-0.539***
	(0.003)	(0.010)	(0.018)
Log Household Income	0.156***	0.240***	0.191***
	(0.005)	(0.022)	(0.035)
Parent's Age at Birth	0.008***	0.010***	0.009***
	(0.000)	(0.002)	(0.003)
Log Area Median Income	1.612***	0.650**	0.001
	(0.169)	(0.267)	(0.323)
Family Size	-0.101***	-0.119***	-0.133***
	(0.004)	(0.011)	(0.020)
Log Units in Building	0.033***	0.038*	0.031
	(0.007)	(0.023)	(0.052)
Filing status fixed effects	✓	✓	✓
Birth year fixed effects	✓	✓	✓
Zip code fixed effects	✓	✓	✓
Observations	540,839	531,088	108,825
Baseline Enroll Rate	0.201	0.201	0.238

Note: *p<0.10, **p<0.05, ***p<0.01

Table 2: Regression Results: 2+ Years Higher Education

	2+ Years Higher Education (Odds Ratios)		
	All LIHTC	Stayers	New Building
LIHTC Years	0.054***	0.058***	0.042***
	(0.002)	(0.009)	(0.015)
Male	-0.538***	-0.540***	-0.546***
	(0.003)	(0.008)	(0.015)
Log Household Income	0.127***	0.195***	0.162***
	(0.004)	(0.017)	(0.028)
Parent's Age at Birth	0.003***	0.004***	0.005**
	(0.000)	(0.001)	(0.002)
Log Area Median Income	1.956***	0.800***	0.338
	(0.161)	(0.244)	(0.393)
Family Size	-0.086***	-0.107***	-0.121***
	(0.003)	(0.009)	(0.017)
Log Units in Building	0.034***	0.035*	0.004
	(0.006)	(0.018)	(0.043)
Filing status fixed effects	✓	✓	✓
Birth year fixed effects	✓	✓	✓
Zip code fixed effects	✓	✓	✓
Observations	540,839	531,088	108,825
Baseline Enroll Rate	0.376	0.373	0.424

Note: *p<0.10, **p<0.05, ***p<0.01

Table 3 below shows results from the same three regressions − the full sample and two stratified sampling regressions − estimating the effect of growing up in LIHTC housing on adult earnings, as observed in 2018. As detailed in the table, the estimated effect of spending one additional year growing up in LIHTC housing on adult earnings is positive and statistically significant at the five percent level in all three regressions, which is not surprising given the positive estimated effect on education (on average, people with greater educational attainment have higher earnings). When looking at the full population, for every additional year spent in LIHTC housing individuals earn approximately 3.6 percent more in income.

This estimate is once again higher when running the regression using the "Stayers" stratified sampling approach, which estimates that on average individuals earn 5.7 percent more for every additional year spent in LIHTC housing. The estimated effect for families moving into new buildings, $\hat{\theta}_{NB}$ is actually close to this estimate: for every additional year spent in LIHTC housing individuals earn approximately 5.7 percent more in income as adults. Since the baseline wage level (the mean wage among individuals who spend one year in LIHTC housing) is $26,337, the estimated effect equates to an increase in earnings of approximately $1,500 as a result of one additional year spent in LIHTC housing. The cumulative effect of spending seven years in LIHTC housing (compared to one year) is equivalent to an increase in earnings of about $10,500.

There are similar patterns in the estimated effect of each control variable as in the regressions on education: males earn less on average compared to females, household income has a positive estimated effect on earnings, and family size has a negative estimated effect on earnings. Variables like area median income, the age of the parent at birth, and the number of units in the LIHTC building do not seem to have as much of an effect on wages as they do on education outcomes. This may be because the individuals I observe are between ages 24 and 36 in 2018, an age range in which the gap in earnings between college- and non-college-educated workers tends to be smaller. The relationship may be stronger if I were to compare incomes at a later age, which I am unable to do at present time due to data restrictions (data are not available before 1999).

Since the estimated effect of spending an additional year in LIHTC housing on earnings is similar to the effect on education, I further test whether higher education is the likely mechanism through which spending additional time in LIHTC housing may affect earnings. In **Table 4** below I test this theory by including the incidence of attending two or more years of education as a control variable in my earnings regressions. In doing so, I find that the effect is lower across the board and is no longer statistically significant at the five percent level when I use the stratified sampling approach. Thus, it appears that the effect of spending an additional year in LIHTC housing on future earnings works primarily through the effect on education: individuals who spend a longer amount of time growing up in a LIHTC building are more likely to enroll in two or more years of higher education, and as a result are more likely to earn higher wages as adults. For this reason, when I decompose the effect based on neighborhood and family characteristics in the following section I focus solely on the effect of LIHTC housing on educational outcomes.

Table 3: Regression Results: Earnings in 2018

	Log Adult Earnings (in 2018)		
	All LIHTC	Stayers	New Building
LIHTC Years	0.040***	0.061***	0.057***
	(0.003)	(0.007)	(0.013)
Male	-0.430***	-0.447***	-0.524***
	(0.021)	(0.020)	(0.032)
Log Household Income	0.139***	0.162***	0.166***
	(0.006)	(0.011)	(0.019)
Age of Parent at Birth	-0.002***	-0.002**	0.001
	(0.001)	(0.001)	(0.002)
Log Area Median Income	0.705***	0.345	0.747**
	(0.113)	(0.213)	(0.401)
Family Size	-0.100***	-0.105***	-0.107***
	(0.007)	(0.010)	(0.018)
Log Units in Building	0.017	0.018	-0.058
	(0.013)	(0.017)	(0.041)
Filing status fixed effects	✓	✓	✓
Birth year fixed effects	✓	✓	✓
Zip code fixed effects	✓	✓	✓
Observations	540,839	179,356	41,989
Baseline Mean Wage	$22,443	$23,322	$26,337
Note:			*p<0.10, **p<0.05, ***p<0.01

Table 4: Regression Results: Earnings in 2018 (Controlling for Education)

	Log Adult Earnings (in 2018)		
	All LIHTC	Stayers	New Building
LIHTC Years	0.017***	0.027	0.039
	(0.003)	(0.017)	(0.022)
2+ Years Education	2.022***	2.041***	2.017***
	(0.019)	(0.019)	(0.030)
Male	-0.083***	-0.097***	-0.160***
	(0.020)	(0.020)	(0.031)
Log Household Income	0.093***	0.102***	0.110***
	(0.006)	(0.010)	(0.018)
Age of Parent at Birth	-0.004***	-0.004**	-0.001
	(0.001)	(0.001)	(0.002)
Log Area Median Income	0.219**	0.242	0.662*
	(0.104)	(0.206)	(0.374)
Family Size	-0.060***	-0.054***	-0.049***
	(0.006)	(0.010)	(0.017)
Log Units in Building	0.002	-0.002	-0.058
	(0.011)	(0.017)	(0.039)
Filing status fixed effects	✓	✓	✓
Birth year fixed effects	✓	✓	✓
Zip code fixed effects	✓	✓	✓
Observations	540,839	531,088	102,476
Baseline Mean Wage	$22,443	$23,322	$26,337

Note: *p<0.10, **p<0.05, ***p<0.01

In sum, spending more time in LIHTC housing does appear to be strongly correlated with both higher educational achievement and higher earnings. Even after controlling for a number of variables including location, family, and individual characteristics, and using stratified sampling techniques to control for unobserved correlates, the estimated effect, $\hat{\theta}$ is positive, significant, and large. Furthermore, when I include education as a control variable in my earnings regression it absorbs most of the estimated LIHTC effect, suggesting that the primary mechanism through which growing up in LIHTC housing affects earnings is through higher education.

In the following sections I will relax assumptions about the functional form relationships between LIHTC Years and education/earnings in order to test if the effect $\hat{\theta}$ is linear in nature. I will also delve into possible explanations as to *why* living in LIHTC housing may have a positive effect on these outcomes by comparing estimates of $\hat{\theta}$ across neighborhoods and families with different characteristics.

5.2 LIHTC Fixed Effects

In the regression results presented above, I make assumptions about the linear or log-linear effect $\hat{\theta}$. In other words, I assume that the effect of spending one additional year in LIHTC housing is the same at any age. For example, the effect of spending one more year in LIHTC housing from ages six to seven is the same as spending an additional year in LIHTC housing from ages 16 to 17. However, this assumption may not be correct, and the effect may be heterogeneous in age of entry. It may be the case that the effect of spending one more year in LIHTC housing at age six has a much greater effect on adult outcomes than spending an additional year in the same housing at age 16.

In order to test the linearity assumption I make in the previous section, I transform the variable "LIHTC years" into a fixed effect to separately estimate the effect of spending different amounts of time in LIHTC housing, relative to one year. In place of $h_{i,b,z}$, I regress outcomes on a vector of 11 binary variables, $H_{i,b,z}$, one for every possible number of years spent in LIHTC housing, from 2 to 12 years. I use the same stratified sampling procedure with this new regression specification. The results from these regressions are presented in **Figures 6 through 8** below. **Figure 6** graphs the estimated difference in the probability of attending a higher education program for four or more years, for individuals who spend different amounts of time growing up in LIHTC housing. Each point represents the estimated effect and the tails are 95 percent confidence intervals. The effect for each group (categorized by LIHTC years) is the estimated percentage change compared to spending one year growing up in LIHTC housing. **Figure 7** graphs the same results for two or more years of education, and **Figure 8** graphs the percent difference in earnings for each group relative to those who spend one year in LIHTC housing as children.

Although the pattern in estimated differences is not perfectly linear, there is little evidence of a non-linear increase in gains from spending one additional year growing up in LIHTC housing at different ages. Rather, the effect is cumulative: the benefit of moving in at an earlier age is that one can potentially spend a longer amount of time living in LIHTC housing, with each additional year associated with a similar increase in future earnings and probability of enrolling in higher education. There does appear to be a small increase in the effect when comparing individuals who spend six versus seven years in LIHTC housing, and this pattern is stronger when you look at individuals who remain in LIHTC housing through age 18, which is equivalent to moving in at age 12 rather than age 13. **Figure 14** in **Appendix D** graphs the results of this analysis, comparing only individuals who stay in LIHTC housing through age 18. As shown in the figure, those who move in prior to age 13 see a jump in the estimated effect of spending one additional year in LIHTC housing compared to those who move in at age 13 or later. This is consistent with previous analysis of the MTO experiment, with greater positive effects for individuals who move into a low-poverty neighborhood before age 13 (Chetty, et al., 2018).

Overall, this analysis suggests that the estimated gains from spending an additional year growing up in LIHTC housing do not vary by age, aside from a small increase in the effect if an individual moves in before high school and remains in LIHTC housing through age 18. As shown in **Figure 6**, the confidence intervals for the effect of LIHTC on earnings are similar, although there is a lot more noise in the estimate, resulting in larger standard errors. As mentioned earlier, this is likely because the individuals in my data are between ages 24 and 36 in 2018, a time at which differences in salaries between college- and non-college-educated workers are smaller and more varied than they are later in life. Regardless, there is also no sign of heterogeneous age effects in these results.

Figure 6: LIHTC Fixed Effects Results: 4+ Years Education

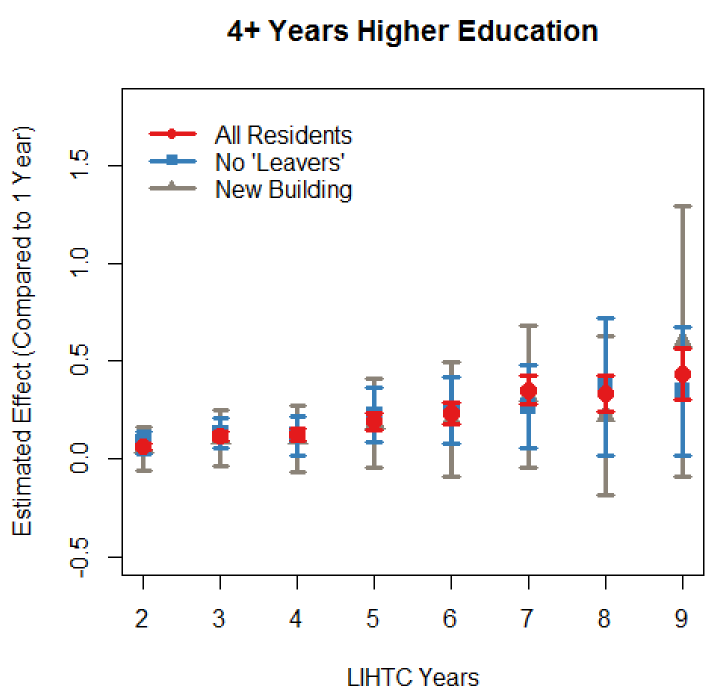


Figure 7: LIHTC Fixed Effects Results: 2+ Years Education

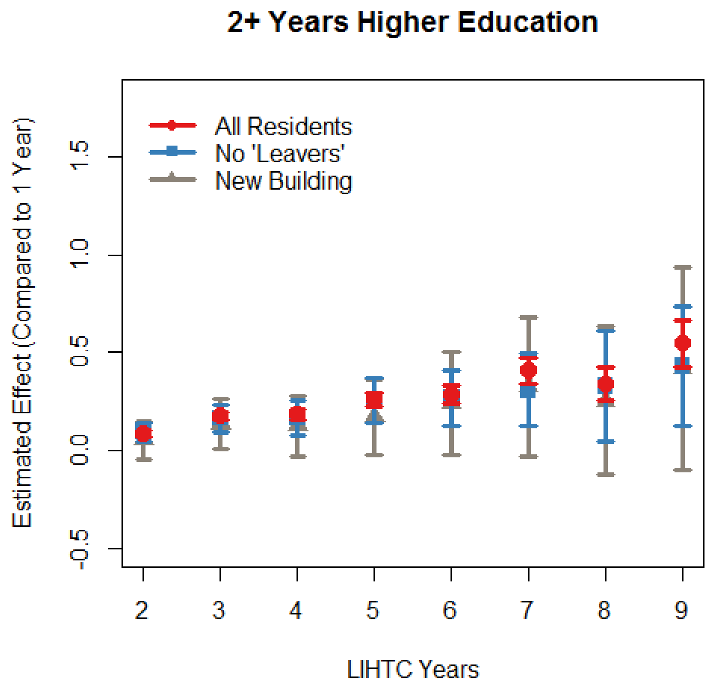
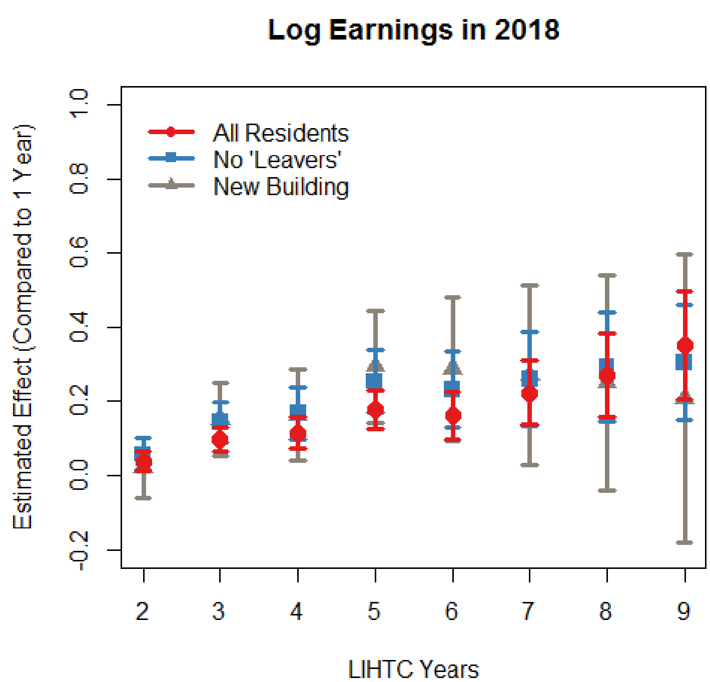


Figure 8: LIHTC Fixed Effects Results: Earnings



All three graphs also illustrate the large cumulative estimated effect of growing up in LI-

HTC housing. According to the "New Building" fixed effect regression results, a person who spends seven years in LIHTC housing as a child is on average 31.8 percent more likely to enroll in four or more years of higher education than someone who spends only one year in LIHTC housing. Similarly, those who spend seven years in LIHTC housing earn 27.0 percent more in income on average than individuals live in LIHTC housing for one year.

There are several possible explanations for the observed effect. Perhaps families are moving into better neighborhoods with higher performing schools, or parents are paying less in rent, which allows them to invest more income in their children's education. It is also possible that the availability of affordable housing simply provides stability for families that previously moved around a lot. In the following section I attempt to answer the question of why spending an additional year in LIHTC housing might affect educational attainment by looking at three possible sources of heterogeneity: building location, housing stability, and household income. First, I look at differences in the LIHTC effect for buildings in neighborhoods with difference characteristics. Second, I look at differences in the effect for families that vary in how many times they change addresses prior to entering LIHTC housing. And third, I look at differences in the effect based on parents' earnings.

6 Heterogeneous Effects

6.1 Heterogeneous Neighborhood Effects

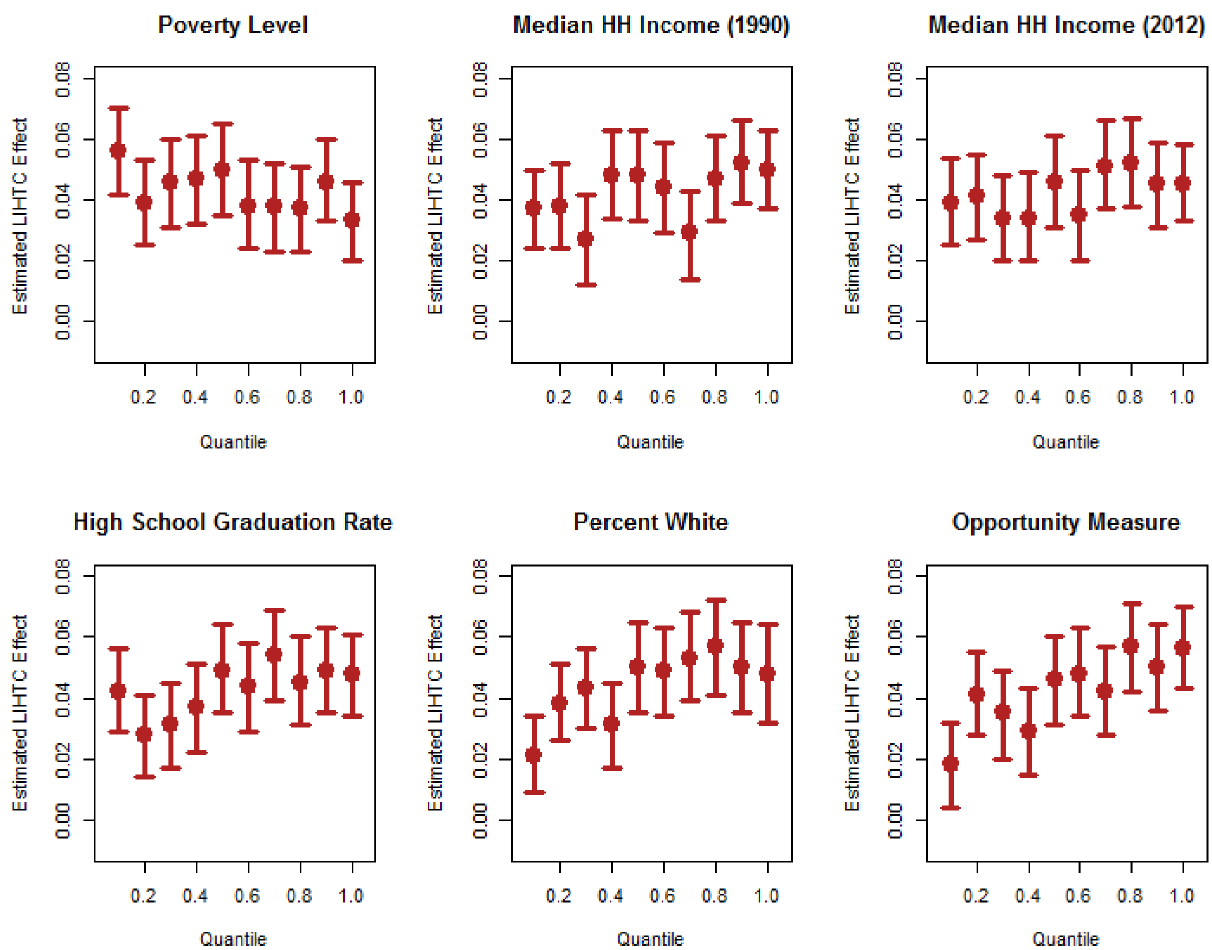
Many characteristics of a neighborhood can affect a child's trajectory in life. Measurable demographic variables like racial composition, median wealth, poverty rates, and education rates can all affect the opportunities that a child has for greater educational attainment or higher wages. Thus, as an extension of my analysis of the effects of the LIHTC on individuals' long-run outcomes, I want to know if the effect of growing up in LIHTC housing is more positive in certain neighborhoods compared to others. In the following analysis I focus on the effect of LIHTC housing on education since this appears to be the driving mechanism behind the effect on earnings.

I first look at differences in the LIHTC effect across neighborhoods with different characteristics. I focus on five observable sources of variation at the Census tract level: poverty rates, median household income (in 1990 and in 2012), high school graduation rates among adults 25 and older in the neighborhood, racial composition (the percent of the population that is white), and opportunity measures from Chetty, et al. (2018), as described in the previous section.

To measure the differences in the estimated effect, $\hat{\theta}$, across neighborhoods with varying characteristics I match each LIHTC building with location data using the Federal Information Processing Standards (FIPS) codes provided by HUD − also known as Census tract codes − and then divide the full data set into 10 evenly divided groups based on quantiles of each neighborhood characteristic. I then run 10 separate regressions for each group and graph the predicted effects, $\hat{\Theta}$, to compare results based on each characteristic. **Table 8** in **Appendix E** provides the cutoff points for each quantile of each variable.

Figure 9 below shows the regression results for the estimated effect $\hat{\theta}$ by neighborhood characteristic on four years of higher education, and **Figure 10** shows differences in the effect on two or more years of education. For the first three characteristics – poverty level, median household income (in 1990 and 2012), and high school graduation rate (of adults over 25) – there do appear to be trends in the direction one would expect, but the differences are not statistically significant. The estimated LIHTC effect decreases slightly as the poverty level rises, and it increases as household income and high school graduation rates increase. However, the confidence intervals are overlapping even when comparing the lowest and highest estimates.

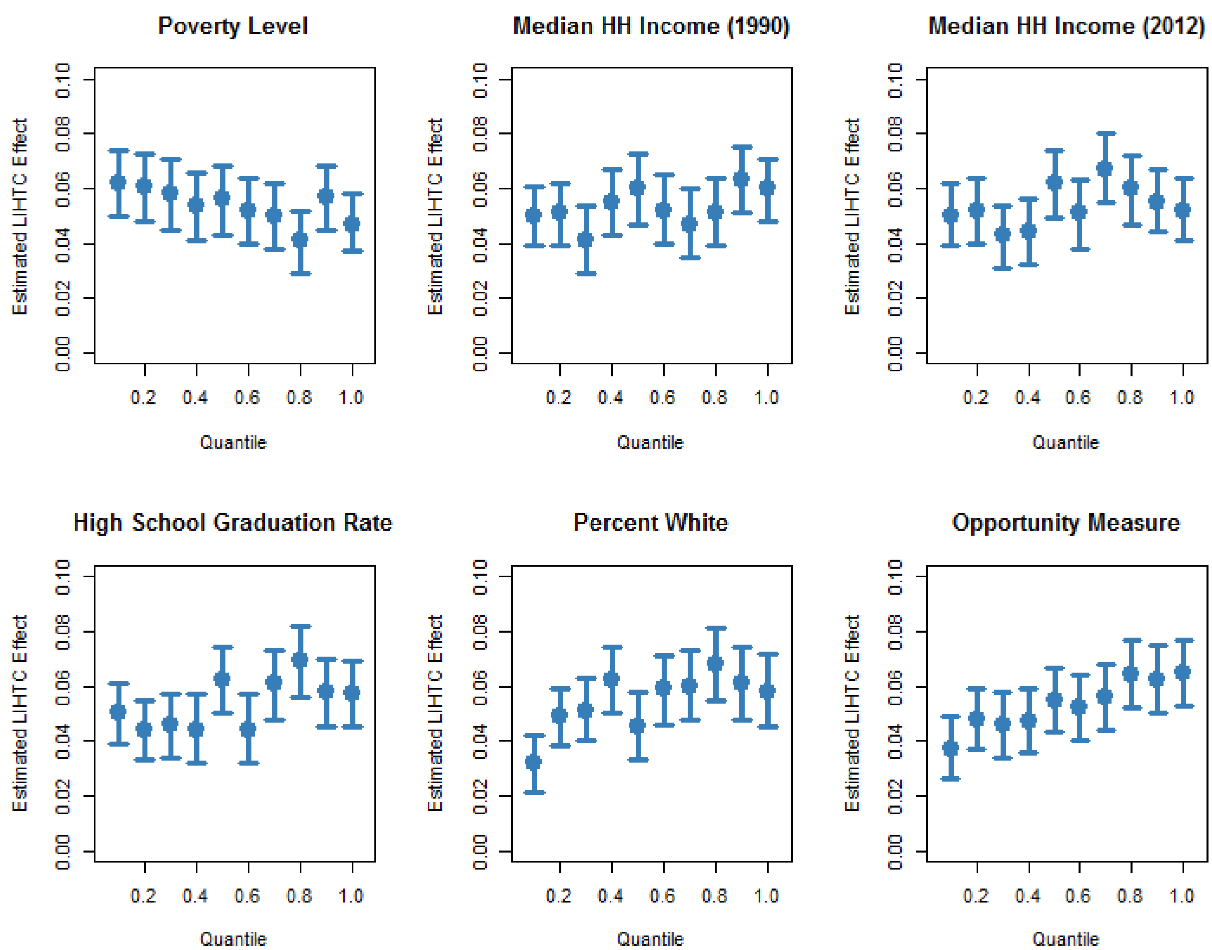
Figure 9: Neighborhood Effects, 4+ Years Higher Education



On the other hand, there are significant differences in the estimated effect when it comes to racial composition and opportunity measures. As shown in **Figure 9**, the estimated effect of spending an additional year in LIHTC housing on the probability of enrolling in four or more years of higher education is 2.1 percent in a neighborhood that is 0-11.3 percent white. In comparison, the estimated effect for individuals who move into a LIHTC building in a neighborhood that is 70.6-79.0 percent white is 5.7 percent.

However, because there is a strong correlation between a neighborhood's racial composition and the racial identities of the individuals that live in that neighborhood, I cannot draw strong conclusions about differences in the LIHTC effect between neighborhoods of varying racial makeup. By construction, people of color are more likely to live in neighborhoods that have fewer white people, and white people are more likely to live in neighborhoods that have fewer people of color. So differences in the LIHTC effect may actually be capturing differences in the benefit that white people get from moving into LIHTC housing for a longer period of time compared to other racial groups. The ability to include race in these regressions would be helpful in determining whether this difference in effect persists when controlling for the race of each individual.

Figure 10: Neighborhood Effects, 2+ Years Higher Education



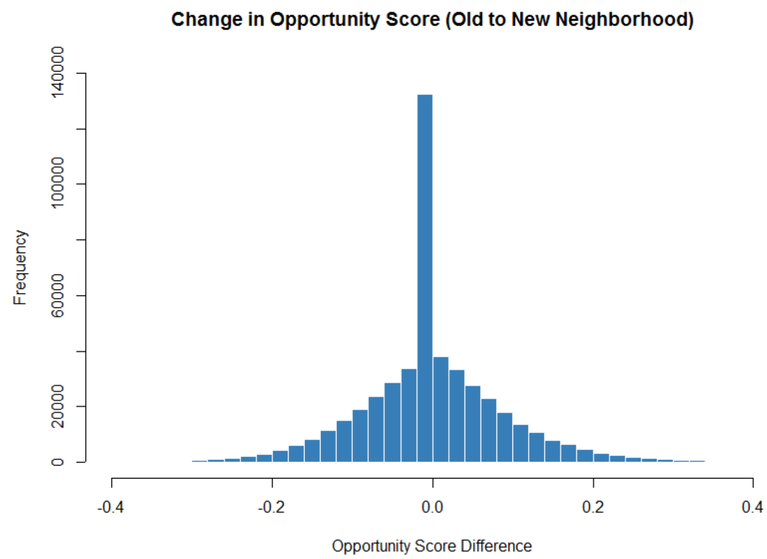
One thing to note when looking at differences in effect across neighborhoods with varying racial composition is that even the lowest estimated LIHTC effect of 2.1 percent is still positive and significant. Moreover, the estimated effect for the second lowest quantile (neighborhoods that are 11.3-28.3 percent white) is 3.8 percent, which is quite high and close to the estimated average effect for the entire population. This suggests that those who spend more time in LIHTC housing as children have better outcomes regardless of what neighborhood they live in. An individual who lives in a neighborhood that is mostly white may benefit slightly more − either because of the neighborhood, because of the individual's race, or a combination of both factors − but spending additional time growing up in LIHTC housing still appears to be generally beneficial across all neighborhoods.

I also see significant differences between neighborhoods with varying opportunity measures. The estimated effect for individuals who grow up in LIHTC housing in neighborhoods with an opportunity measure of 0 to 0.04 is 1.8 percent. In comparison, the estimated effect for individuals growing up in a neighborhood with an opportunity score of 0.22 to 0.27 is 5.6 percent. Once again, I cannot necessarily draw conclusions about these differences as neighborhood opportunity measures and racial composition are highly correlated. Moreover, there is a small correlation between the number of buildings that are constructed in a given area and the opportunity measure, although the correlation is negative at -0.16.

In general, I find that while the location of LIHTC housing appears to matter somewhat when it comes to the size of the LIHTC effect, differences between neighborhoods do not fully explain the positive estimated effect of growing up in LIHTC housing on adult outcomes. Regardless of where the LIHTC housing is located, it appears that individuals benefit from spending additional time living in these buildings as children. Even when I estimate statistically significant differences in the effect between neighborhoods with different racial demographics and opportunity scores, I cannot rule out the possibility that these differences are attributable to individual rather than neighborhood characteristics (in particular the race of the individual).

Furthermore, as I mention earlier, most people do not move very far away from where they are living when they move into LIHTC housing. As shown in **Figure 4** above, most of the families in my data stay in the same zip code or move to a zip code less than 10 miles away when they move into a LIHTC building. Moreover, the families who do change locations do not seem to move to a "higher opportunity" area on average. As shown in **Figure 11** below, when I graph the difference in opportunity scores between old and new neighborhoods − the new neighborhood being where the LIHTC building is located − there appears to be a normal distribution with a large spike at zero, which represents individuals who do not change zip codes. This trend is in line with the original Moving to Opportunity study, which found that people did not generally move to higher opportunity neighborhoods when given the choice (Ludwig, et al., 2013; Sanbonmatsu, et al., 2011). Thus, moving to a "better" neighborhood does not seem to be a very good explanation for why individuals might be better off when they spend more time in LIHTC housing as children.

Figure 11: Differences in Opportunity Measure from Old to New Neighborhood



6.2 Heterogeneous Family Effects

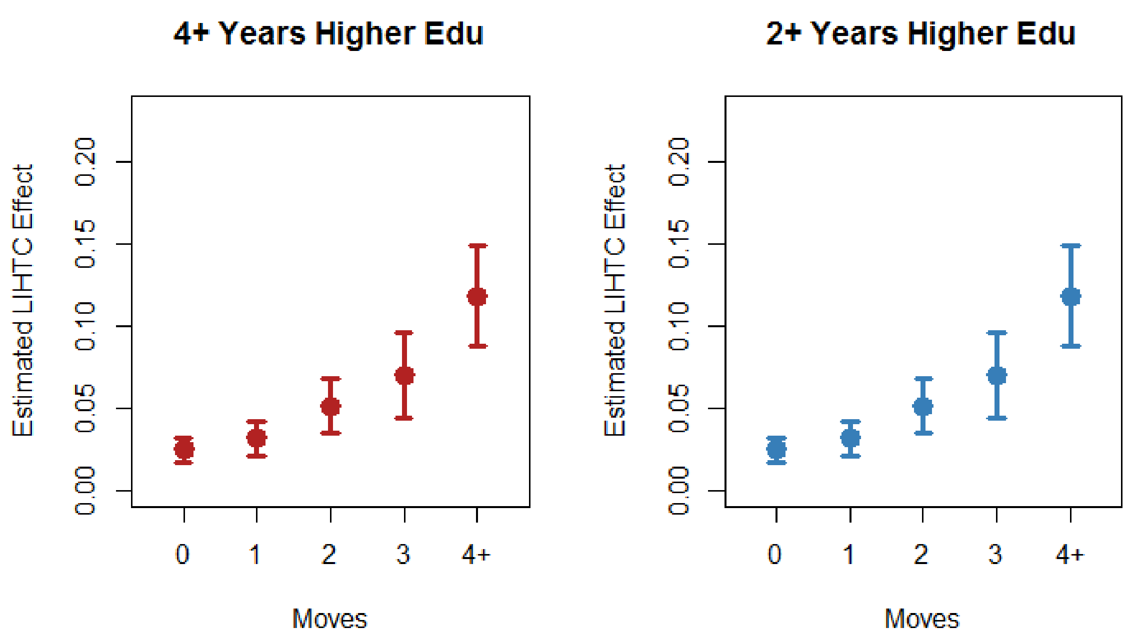
Another possible explanation for why individuals might have better outcomes the longer they spend in LIHTC housing as children is that subsidized housing provides a more stable living situation for families who are suffering from a lack of housing security. Housing insecurity can cause families to move from one living situation to another, disrupting the lives of the children, particularly when it comes to their schooling. When affordable housing becomes available in a family's area – a new LIHTC building is constructed or a subsidized unit becomes available to rent – this might provide a more stable living situation for the family, as they are more likely to be able to afford that housing for a longer period of time.

In order to test to what extent improved housing security is a driver of the estimated LIHTC effect I divide my full sample into five groups based on the number of times that they change addresses *before* entering into LIHTC housing. This provides a relatively good measure of the level of housing stability the family has prior to securing low-income housing in a LIHTC building. Since the number of pre-LIHTC moves is a discrete variable, I group individuals into five categories based on the number of times the family changes addresses: one category each for zero to three moves and one category for four or more moves. I then run the same regression for each group. Since taxpayers sometimes receive information returns at more than one address, I find the most commonly reported address for parents of each child in each year before they move into LIHTC housing, and then sum up the number of moves based on these addresses.

As shown in **Figure 12** below, I find strong evidence of heterogeneous effects in housing stability. I estimate that for a person who did not change addresses prior to entering into LIHTC housing, one additional year spent in LIHTC housing is associated with a 2.5 percent increase in the likelihood of attending four or more years of higher education. In comparison, the estimated effect for someone who moved three times is 7.0 percent, and for someone who moved four or more times the estimated effect is 11.8 percent. Unlike in the neighborhood effects analysis based on opportunity scores, the correlation between the number of pre-LIHTC moves and neighborhood racial composition is low (about 0.036), which suggests that differences in housing stability cannot be attributed to the race of the individual.

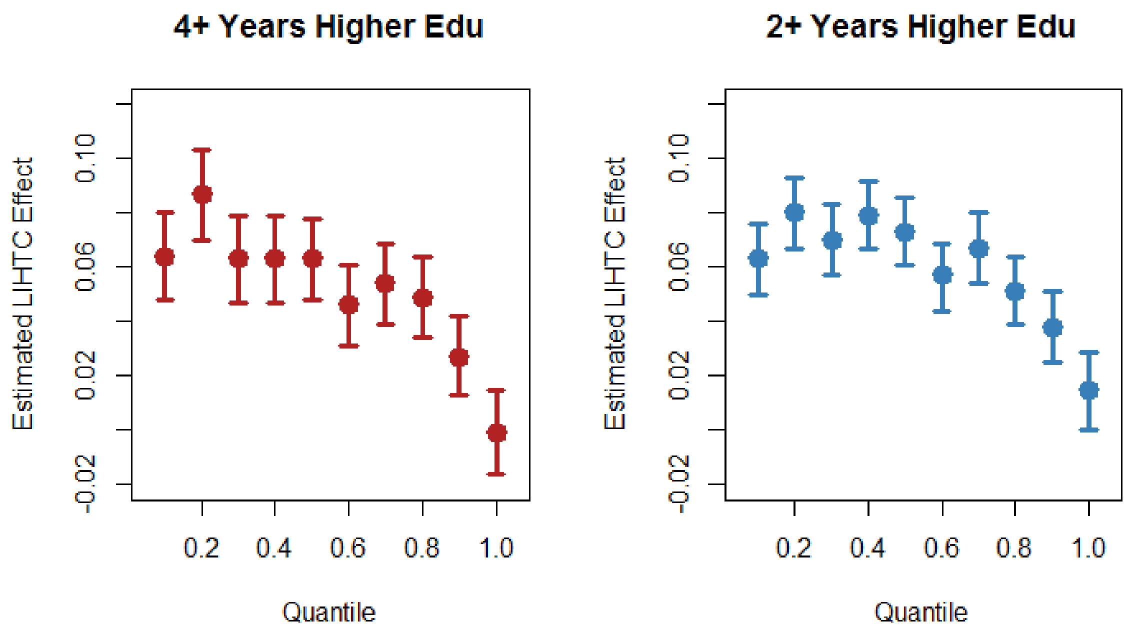
As with the analysis of heterogeneous neighborhood effects, it is encouraging that the estimated effect for the lowest group here is still positive and significant, albeit using the full sample, without implementing the stratified sampling procedures. Nevertheless, the large effect that an additional year in LIHTC housing seems to have on individuals who move around a lot prior to entering into subsidized housing suggests that this is likely one of the main drivers of the overall effect.

Figure 12: Heterogeneous Effects: Housing Stability



Another possible explanation for the positive estimated LIHTC effect is that families have more financial resources to invest in their children. In order to test this theory I once again split my population into ten groups based on average household income (calculated as an average for all years I observe the child from ages 6 to 18). As shown in **Figure 13** below, I see that there are strong patterns in the LIHTC effect based on household income as well. The estimated effect on attending four or more years of higher education for a family in the bottom 10 percent of earnings is 6.4 percent. In comparison, the estimated effect for a family in the top 10 percent of earnings is statistically insignificant (with a point estimate of -0.1 percent). The difference in the effect between these two groups is statistically significant a the one percent level. As shown in **Figure 13**, the same pattern also is evident in regressions estimating the effect on the incidence of attending two or more years of higher education.

Figure 13: Heterogeneous Effects: Household Income



These results suggest that the underlying reasons why spending more time in LIHTC housing might be beneficial to children can be explained by differences at the household level. When families have access to rent subsidies they have better housing security and more disposable income, both of which appear to have positive effects on the educational outcomes of their children (and subsequently on their earnings as adults). Although there are still positive and statistically significant effects for families with higher earnings and fewer moves prior to entering into a LIHTC building, the high estimates that I see for those with lower earnings and housing security are likely driving up the overall estimated LIHTC effect.

7 Conclusion

In sum, I find that growing up in LIHTC housing has a large positive effect on both education and earnings, with an estimated 4.3 percent increase in the probability of attending four or more years of higher education, and a 5.7 percent increase in earnings for every additional year spent living in a LIHTC property. I find that the effect is somewhat heterogeneous in age, with a greater increase in the probability of enrolling in higher education for those who move in before age 13 (comparing individuals who remain in LIHTC through age 18). I also find that the primary mechanism through which LIHTC housing affects earnings is through the effect on higher education.

In general, I find that changes in location do not provide a good explanation for the positive estimated effect of spending an additional year in LIHTC housing. Although there is evidence in the data and in the previous literature to suggest that where people grow up has a large impact on their future outcomes, it is not clear whether location is a driving mechanism behind the LIHTC effect. The only statistically significant differences in the estimated LIHTC effect based on location are between individuals residing in neighborhoods with different racial composition, or in neighborhoods with different opportunity scores. However, there is reason to believe that these differences can be attributed to individual characteristics, such as race.

Moreover, the findings from my analysis of neighborhood effects are inconclusive because a majority of individuals in my data do not move far away from the neighborhood they already lived in prior to entering LIHTC housing, and the ones who do move are not relocating to "better" neighborhoods on average (places with lower poverty rates or higher opportunity scores). It may be that growing up in a more affluent neighborhood has a large effect on individuals' future outcomes, but the estimated LIHTC effect in this study cannot be attributed to changes in neighborhood since most of the families who move into LIHTC housing do not change locations.

On the other hand, there is strong evidence that the LIHTC effect is in large part a measure of the effect of housing stability and household income. The more times an individual changes addresses prior to moving into a LIHTC building, the more positive the effect of LIHTC housing is on their outcomes. Similarly, the lower the family's income, the greater the effect on education. Based on these findings, it seems that one of the main benefits of constructing subsidized housing is that it can provide low-income families with a more stable living situation, and with more disposable income to invest in their children.

Generally, I find that families who are in a worse financial or housing situation prior to entering into LIHTC housing are the ones whose children benefit the most. I see the largest effect of LIHTC housing on education − and subsequently earnings − for children whose families earn less and move around more. However, it is notable that nearly 40 percent of individuals in the birth cohort with the widest range of LIHTC Years (those born in 1994) only stay in LIHTC housing for one year. Thus even though the effect of moving into LIHTC housing may come from greater housing stability, a large section of the population still moves out of their building within one year.

These findings raise further questions about the effect of growing up in tax-subsidized housing. If positive outcomes are driven largely by individuals who moved around frequently prior to moving into a LIHTC building, then it is important to evaluate whether LIHTC housing really does provide greater stability than market-rate housing, or other forms of low-income housing like public housing or Section 8 housing. In the future, it would be useful to evaluate these programs using the same methods to compare the outcomes of residents, and to determine whether LIHTC housing does provide greater housing stability for families.

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Appendix A: Data Matching Procedure for Identifying Families in LIHTC Housing

In order to identify families living in LIHTC housing between 1999 and 2012, I match parents' addresses with the publicly available addresses of LIHTC buildings placed in service prior to 2012. I match addresses based on year, zip code, street number, and a unique word or phrase from the street name. For example, if the street address of a LIHTC building constructed in 2002 is "333 Garden Park Road", the algorithm pulls any W-2 form filed in 2002 or later with the same zip code, with the street number "333", and with a street name including the phrase "Garden Park". Common words like "Road" are ignored to ensure that the algorithm also matches street names with abbreviated words like "Garden Park Rd". Numerical street names like "13th Street" are matched using both the numerical form of the street address ("13th") and the alpha-numerical version ("thirteenth"). In order to ensure that these unique street name words or phrases result in accurate matches, I check each LIHTC address individually (38,722 in total), making sure to use phrases that are neither too broad (resulting in too many matches) nor too narrow. Using the same example, I make sure I match street names based on the phrase "Garden Park" rather than "Garden", as the phrase "Garden Park" would provide a better match that would not likely be abbreviated or altered on tax or information returns.

This algorithm is designed to match the addresses of existing LIHTC buildings (placed in service before the date I observe people living in that building) with the addresses of the *parents* of individuals in my sample. A "parent" is defined as any person who claims a child (a person under the age of 18) as a dependent on any tax return from 1999 to 2012. I later restrict this sample to include only families who have children born between 1982 and 1994. If a child is claimed by more than one filer I consider both people to be parents of that child. A very small percentage (less than 1 percent) of children in my sample are claimed as dependents by more than two people. In this case, I select the two people who claim the child as a dependent for the longest period of time and assign those people as the child's parents. I also compare the ages of the parents to that of the individuals they are claiming as dependents. If the difference between the ages of the parent and child is less than 13 or greater than 75, I drop the individual from my sample. This restricts my sample to children between the ages of 6 and 18 who are living with their parents or grandparents (or another relative such as an aunt).

Once I have identified parents living in LIHTC housing, I use their tax identification numbers (TINs) to extract data on their birth dates, addresses, earnings, marital status, and the TINs of children they list as a dependents from 1999 to 2012. This information comes primarily from the Social Security Administration (SSA) database, W-2 form, 1099-MISC form, and 1040 individual tax returns. Since not all units in LIHTC buildings are subsidized, using data from HUD I calculate the LIHTC income ceilings for each building in each year and keep only households that I observe with income limits below the threshold. If I observe two people claiming a child as a dependent at the same address in the same year, I use the sum of both parents' annual earnings as my measure of household income. I also drop anyone in my sample that I observe living in LIHTC housing in 1999 (the first year I am able to observe my data) because I cannot observe how many additional years they may have spent living in the same building prior to 1999. Thus, I limit my sample to families who moved into LIHTC housing in 2000 or later.

I use dependents' TINs to find their birth dates and gender (SSA database), earnings in 2018 (W-2, 1099-MISC, and F-1040 forms), and higher education attendance (1098-T form). I use information return 1098-T to determine how many years each dependent is enrolled in post-secondary education programs. 1098-T forms are tuition statements filed on behalf of students by eligible education institutions in the United States, including all accredited colleges, universities, and vocational schools. I count every year that I observe each dependent receiving a 1098-T tuition statement as a year they are enrolled in higher education, regardless of whether the statement has a positive tuition amount listed (there are circumstances under which a student would still receive a 1098-T tuition form even if they did not pay tuition that year). I then create indicator variables for dependents I observe with two or more years of higher education, and with four or more years of higher education.

All post-secondary education institutions who qualify for federal financial aid under Title IV of the Higher Education Act of 1965 are required to file the 1098-T tuition form, with a few exceptions. Institutions are not required to file for students who are "nonresident aliens", for students whose "qualified tuition and related expenses are entirely waived or paid entirely with scholarships", or for students whose "qualified tuition and related expenses are covered by a formal billing arrangement between an institution and the student's employer or a governmental entity" (The Internal Revenue Service, 2018). This does introduce some measurement error into my data, as there are likely individuals in my sample who receive a full scholarship every year they are in college or university. However, although institutions are not required to file 1098-T forms for students if their expenses are paid entirely with scholarships many schools do still issue these statements with zero tuition amounts for enrolled students (I see over a million 1098-T tuition statements in my data with zero or missing tuition amounts). Furthermore, data on the 1098-T form are not self-reported to the IRS by individuals, and do include students who receive partial scholarships, or a mix of scholarships and loans.

Appendix B: Regression Variable Details

4+ Years of Education. My first outcome variable is a binary indicator equal to 1 if individual i is enrolled in a higher education program for four or more years, and 0 otherwise. As explained above, I determine the number of years that an individual is enrolled in a higher education program by summing up the number of years that I observe them receiving a 1098-T tuition statement, including statements filed with zero tuition payments or missing tuition amount, since there are circumstances under which a school would file a tuition statement for as student who did not pay tuition that semester. For the youngest cohort, this is a measure of the number of years up to age 24 that the individual is enrolled in a higher education program. Although some individuals may take longer to complete a four year program, or delay entry into university to serve in the military, most individuals complete four year university degrees by this age. My sample does also include older cohorts − up to age 36 in 2018 − who are more likely to have completed a four year program, if they enrolled in one.

2+ Years of Education. This outcome variable is also a binary indicator, equal to 1 if individual i is enrolled in a higher education program for two or more years, and 0 otherwise. This measure of education would include individuals who completed a 2 year associate's degree, or partially completed a four-year college or university program. It is calculated in the same way I calculate the outcome variable for four years of education.

Log Earnings in 2018. My final outcome variable is the log of gross earnings that individual i earned in 2018. I use the larger amount of two possible calculations of earnings: either the sum of all pre-tax earnings listed on information returns (W-2 and 1099 forms), or the total gross income listed on the F1040 individual tax return. If an individual does not have any income reported on information or tax returns, I interpolate earnings using 2017 returns, adjusted for inflation. Some of the individuals in my sample (about 16 percent) are missing income information or have a reported income of zero in 2017 and 2018. Since they are at an age in 2018 when they could plausibly have zero earnings, I allow earnings to equal zero for these individuals.

Male. This control variable is a binary gender indicator. The variable is equal to 1 if individual i is male, and 0 otherwise. The determination of gender is made according to data from the Social Security Administration database.

Log Household Income. Household income is the most important variable that I control for, since it directly impacts whether families qualify for low-income housing, and can also affect children's outcomes later in life. I control for parental income by taking the average of the parents' combined gross earnings − or just a single parent's earnings if only one person claims the child as a dependent − over the full period of time that I observe the family between 1999 and 2012, and up until the year before the family enters into LIHTC housing. The reason I measure parental income prior to entry into LIHTC housing is that the LIHTC can be considered a type of in-kind transfer, which have been shown to have effects on income and labor supply (van Dijk, 2019; Jacob and Ludwig, 2012). In general, I avoid including any post-treatment control variables that could be considered endogenous.

Household income/earnings (I use the two terms interchangeably in this paper) are gross earnings that are reported either on Form 1040 individual tax returns, or on W-2 and 1099 information returns filed by employers. If two separate filers claim the same individual as a dependent then I use the sum of those two people's gross earnings as my measure of household income, whether or not the couple are identified as spouses. All earnings are converted to 2018 dollars to adjust for inflation. Since my data start in 1999 I only have a one or two years of data for some families. If there are missing data for parents in some years I impute the parents' earnings for those years using other income information I have for the parents when the child is between 6 and 18 years old (with different windows of time depending on the birth year of the child). After this imputation only 0.56 percent of dependents have parents with zero or missing household income, and I allow household income to simply remain at zero for these families.

Since household income is such an important variable I try two other specifications to ensure I am controlling for household income in the best way possible. First, I run a separate regression controlling for log household income for every observed year from 1999 to 2012. This ensures that I capture both average income effects and income fluctuation over time. It also controls for household income beyond age 18 for all but one of the dependent cohorts. Aside from the estimated coefficient on household income, changing this specification does not seem to have much of an effect on my results. I also seem to lose some predictive power from household income as there seems to be a much less significant effect on the control variable once children are older than 18. This causes the coefficient on household income in later years (2005 to 2012) to become smaller and close to zero. Thus, I do not use this specification in my final regression.

I also run my regressions with log mean household income (as before) as well as the standard deviation of household income, and the ratio between the maximum and minimum income observed for each family to control for volatility in parents' earnings from year to year. Again, my regression results remain the same, save for the predicted household income effect. So for the ease of interpretation I do not include the standard deviation and min/max ratio of household income in my final regression results.

Parent's Age at Time of Birth. I use parental age at time of birth to control for differences in children's outcomes as adults stemming from variation in the ages of their parents. I specifically use the mother's age at time of birth, if available. About 65 percent of the individuals in my sample do have a woman of an appropriate age who claims them as a dependent. This does not necessarily mean that the rest of the individuals live only with a father or grandfather. Instead, the reason for this is probably that men are more likely to be the primary tax filer, and mothers who do not work are not likely to report income. If an individual does not have a female parent claiming them as a dependent then I use the male parent's age at the time of birth instead.

Log Area Median Income. I include gross area median income (AMI) as a control variable since it directly affects LIHTC income limits and could also affect dependents' outcomes later in life. AMI is reported by the US Department of Housing and Urban Development annually at the county level. Since AMI changes from year to year, I use the following approach to calculate the control variable. First, I find the AMI for the county corresponding to the LIHTC building that each dependent lives in each year (converted into 2018 dollars to adjust for inflation). I then take the average AMI across all years I observe the dependent living in that building. For dependents who live in more than one LIHTC building, I use the average AMI across county and year (if the buildings are located in different counties). I then take the log of this average to estimate the effect of AMI on education and earnings in terms of percentage changes.

Family Size. Since the number of children a family has can affect the type of unit and building that the family moves into, I include family size (in terms of siblings) in my regression as well. Family size may also affect outcome variables like education and earnings since families with a greater number of children might have less income to spend on each individual child when they are growing up (less income to invest in education, for example). I measure family size by finding the number of unique tax identification numbers (TINs) up to age 18 claimed as dependents by each parent or set of parents.

Total Moves. This is the total number of times that a dependent moves to a different zip code before age 18. I do not include this variable in my main regressions but I do include it to check for estimate robustness in **Tables 5 through 7** in **Appendix C**. I include the variable in these regressions to control for variation coming from moves to a different area in a city, or to a different city or state. These moves could contribute both to the timing of when families move into a LIHTC building, and may also affect children's development and subsequent outcomes later in life. One concern with controlling for this variable is that housing stability is a reason why moving into LIHTC housing may lead to better outcomes later in life. Thus, including this control variable may take away some of the explanatory power of my estimate $\hat{\theta}$. However, I also do not want my estimated LIHTC effect to be solely a measure of housing stability, since this would not tell me anything about whether growing up in LIHTC housing specifically leads to better outcomes. If that is the case then I am simply measuring the effect of living in one place for a longer period of time. However, as shown in **Appendix C**, when I include total moves in my regression, the estimated $\hat{\theta}$ does not change significantly.

Log Units in Building. I use the reported number of units in each LIHTC building (provided by HUD) as a control for variation in outcomes that may arise from differences in the type of LIHTC housing that families move in to. There may be differences, for example, between moving into a duplex with two units and a large apartment complex with hundreds of units.

Filing Status. I include parents' filing status as a control variable as this can influence both the timing of when a family moves into LIHTC housing and dependents' outcomes later in life. I use dummy variables to indicate if parents file in one of six categories: Single, Married Filing Jointly, Married Filing Separately, Head of Household, Qualifying Widow(er) and Spouse not Filing (Other). This variable does not determine marital status exactly, as one can file as Head of Household whether single or married, but most filers fall into one of the first three categories, which provide a clearer marital status designation.

Birth Year. I used a birth year fixed effect to control for differences between individuals of different ages, who enroll in higher education and enter the workforce in different years. Including this fixed effect also helps control for the fact that I cannot observe where individuals are living prior to 1999, so I have data for earlier childhood years for younger cohorts, and less so for the older ones.

Zip Code. I use a zip code fixed effect to account for differences in outcomes due to the location of LIHTC housing. This helps control for differences in housing built in areas that are more rural versus urban, are located in different cities, or even located in parts of the same city that have very different characteristics.

Appendix C: LIHTC Effect Regression Results Controlling for Total Moves

Table 5: Regression Results Controlling for Total Moves: 4+ Years Higher Education

	4+ Years Higher Education (Odds Ratios)		
	All LIHTC	Stayers	New Building
LIHTC Years	0.038***	0.048***	0.036**
	(0.002)	(0.011)	(0.018)
Male	-0.541***	-0.543***	-0.540***
	(0.003)	(0.010)	(0.018)
Log Household Income	0.159***	0.241***	0.194***
	(0.005)	(0.022)	(0.035)
Parent's Age at Birth	0.006***	0.008***	0.006**
	(0.000)	(0.002)	(0.003)
Total Moves	-0.029***	-0.028***	-0.037***
	(0.001)	(0.004)	(0.009)
Log Area Median Income	1.646***	0.669**	0.010
	(0.171)	(0.269)	(0.325)
Family Size	-0.098***	-0.115***	-0.129***
	(0.004)	(0.011)	(0.020)
Log Units in Building	0.035**	0.040**	0.031
	(0.007)	(0.023)	(0.052)
Filing status fixed effects	✓	✓	✓
Birth year fixed effects	✓	✓	✓
Zip code fixed effects	✓	✓	✓
Observations	540,839	531,088	108,825
Baseline Enroll Rate	0.201	0.201	0.238
Note:			*p<0.10, **p<0.05, ***p<0.01

Table 6: Regression Results Controlling for Total Moves: 2+ Years Higher Education

	2+ Years Higher Education (Odds Ratios)		
	All LIHTC	Stayers	New Building
LIHTC Years	0.052***	0.055***	0.037**
	(0.002)	(0.009)	(0.015)
Male	-0.538***	-0.540***	-0.547***
	(0.003)	(0.008)	(0.015)
Log Household Income	0.129***	0.196***	0.164***
	(0.004)	(0.017)	(0.028)
Parent's Age at Birth	0.002***	0.003***	0.003
	(0.000)	(0.001)	(0.002)
Total Moves	-0.015***	-0.014***	-0.023***
	(0.001)	(0.004)	(0.007)
Log Area Median Income	1.974***	0.812***	0.345
	(0.162)	(0.245)	(0.394)
Family Size	-0.084***	-0.105***	-0.119***
	(0.003)	(0.009)	(0.017)
Log Units in Building	0.034***	0.036**	0.004
	(0.006)	(0.018)	(0.043)
Filing status fixed effects	✓	✓	✓
Birth year fixed effects	✓	✓	✓
Zip code fixed effects	✓	✓	✓
Observations	540,839	531,088	108,825
Baseline Enroll Rate	0.376	0.373	0.424

Note: *p<0.10, **p<0.05, ***p<0.01

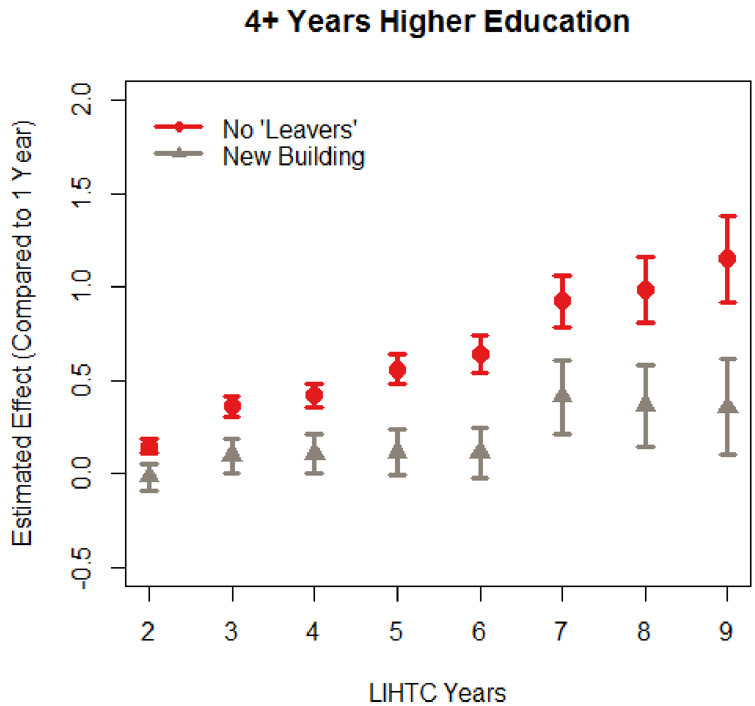
Table 7: Regression Results Controlling for Total Moves: Earnings in 2018

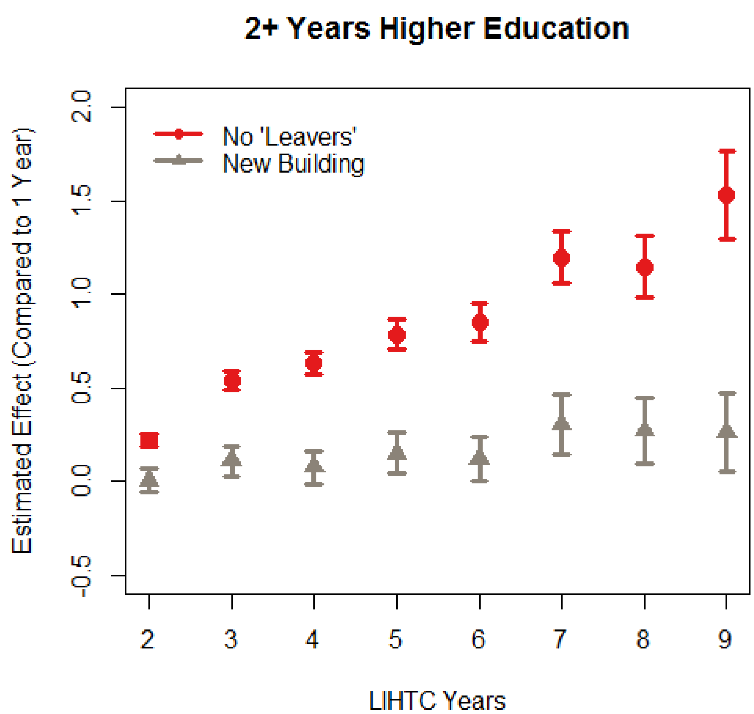
	Log Adult Earnings (in 2018)		
	All LIHTC	Stayers	New Building
LIHTC Years	0.046***	0.068***	0.061***
	(0.003)	(0.007)	(0.013)
Male	-0.430***	-0.447***	-0.524***
	(0.020)	(0.020)	(0.032)
Log Household Income	0.137***	0.160***	0.165***
	(0.006)	(0.011)	(0.019)
Age of Parent at Birth	-0.000	0.000	0.002
	(0.001)	(0.001)	(0.002)
Total Moves	-0.033***	0.036***	0.019***
	(0.004)	(0.004)	(0.007)
Log Area Median Income	0.694***	0.326	0.750*
	(0.113)	(0.213)	(0.402)
Family Size	-0.104***	-0.111***	-0.110***
	(0.007)	(0.010)	(0.018)
Log Units in Building	0.015	0.016	-0.058
	(0.013)	(0.017)	(0.041)
Filing status fixed effects	✓	✓	✓
Birth year fixed effects	✓	✓	✓
Zip code fixed effects	✓	✓	✓
Observations	540,839	531,088	102,476
Baseline Mean Wage	$23,007	$22,505	$24,127

Note: *p<0.10, **p<0.05, ***p<0.01

Appendix D: LIHTC Fixed Effect Results for Individuals who Remain in LIHTC Housing Through Age 18

Figure 14: LIHTC Fixed Effects Results for Stayers through Age 18 (Education)





Appendix E: Heterogeneous Neighborhood Effects Quantile Cutoffs

Table 8: Neighborhood Characteristics: Quantile Cutoff Points

Quantile	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Poverty Rate	5.5	8.4	11.3	14.5	17.9	22.2	27.1	32.3	39.7
Med HH Inc (1990)*	21.7	29.1	33.9	38.5	43.3	48.6	53.8	60.3	72.8
Med HH Inc (2012)*	21.6	26.1	30.1	34.2	37.6	42.1	47.7	54.7	66.8
Percent High School Grad	7.5	12.4	16.7	21.1	25.2	30.2	35.3	41.4	48.8
Percent White	11.3	28.3	43.5	53.1	62.0	70.6	79.0	85.6	92.2
Opportunity Measure	0.04	0.06	0.08	0.10	0.12	0.15	0.18	0.22	0.27

* In thousands of US dollars, adjusted for inflation