

# Is the Low-Income Housing Tax Credit an Effective Policy for Increasing Neighborhood Income Diversity?

Therese J. McGuire<sup>a</sup>, Nathan Seegert<sup>b</sup>

<sup>a</sup>*Kellogg School of Management, Northwestern University, 2211 Campus Drive, Evanston, IL 60208*

<sup>b</sup>*Eccles School of Business, University of Utah, 1655 Campus Center Drive, Salt Lake City, UT 84108*

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## Abstract

We investigate the impact of the federal Low-Income Housing Tax Credit on the diversity of income in neighborhoods. We collect data on LIHTC applications in Utah from 2000 to 2018 and compare neighborhoods in which developers' LIHTC applications were accepted to those that were declined. We document three facts. First, contrary to the policy's goals, we find that income diversity declined in neighborhoods with LIHTC developments. Second, this decrease was not caused by high-income households leaving the neighborhood but by the relative prevalence of the lowest-income households falling. Third, the number of households increased across the income distribution.

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*Email addresses:* therese-mcguire@northwestern.edu (Therese J. McGuire),  
nathan.seegert@eccles.utah.edu (Nathan Seegert)

## 1. Introduction

We study the impact of the federal government's Low-Income Housing Tax Credit (LIHTC). This program was passed as part of the Tax Reform Act of 1986 and has been the largest source of affordable housing in the United States since then. The total cost in tax expenditures is estimated to be around \$9 billion per year.<sup>1</sup>

The effectiveness of this program is hotly debated. Proponents highlight that the program has subsidized over 3 million housing units since 1986, it helps to overcome a market failure that leads to a lack of quality affordable housing, and it has positive spillovers that revitalize low-income neighborhoods (Diamond and McQuade, 2019). Detractors highlight the program's high cost (20% more per square foot than average industry estimates (Eriksen, 2009)) and often ambiguous effects on neighborhoods depending on whether the neighborhoods are growing or not (Green et al., 2002; Baum-Snow and Marion, 2009).

We document three novel facts on the effects of Low-Income Housing Tax Credits that contribute to our broader understanding of the effectiveness of this program. First, we document that income diversity decreases in neighborhoods with more Low-Income Housing Tax Credits. This fact is in direct contrast to one of the stated goals of the LIHTC program to increase income diversity. Specifically, the US Department of Housing and Urban Development in August 2000 stated, "Several recent housing policy initiatives have been aimed at reducing the spatial concentration of very poor households. ... Hence, the economic diversity of LIHTC properties and their contribution to economic diversity in the neighborhood are important policy issues." The decrease in income diversity may be particularly harmful as research continues to show the importance of economic connectedness for upward mobility (Chetty et al., 2022).

The second fact we document is that the *share* of households at the bottom of the income distribution (roughly incomes less than \$25,000) decreases. In interviews with developers and

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<sup>1</sup>Department of Housing and Urban Development, Office of Policy Development and Research, "Low-Income Housing Tax Credits," June 5, 2020, <https://www.huduser.gov/portal/datasets/lihtc.html>. A state may allocate an amount equal to \$2.15 per resident per year to subsidize affordable housing developments. <https://utahhousingcorp.org/pdf/2011%20LIHTC.pdf>.

city planners, we learned that new development, particularly from LIHTC developments, helped revitalize neighborhoods, leading low-rent buildings to be replaced by higher-rent buildings. Our finding contrasts the arguments often made by households near proposed LIHTC developments that these developments would lead to the flight of high-income households.<sup>2</sup>

How the LIHTC program defines low-income housing is also critical for understanding our findings. Specifically, low income is defined as no more than 60% of the Area Median Income (AMI), which for a place like Salt Lake City, Utah, in 2021 is \$55,200 ( $0.6 \times \$92,900$ ). Therefore, our finding that the share of households with less than \$25,000 decreases with more Low-Income Housing Tax Credits is consistent with the mechanism that LIHTC increases the share of households around 60% AMI at the expense (at least in shares) of lower-income households.

The third fact we document is that the number of households at every level of income increases with LIHTC, importantly including the number of households at the bottom of the income distribution. Anecdotally, developers and city planners told us that LIHTC developments spark additional market-rate housing developments in the area, increasing the number of households across the income distribution. Thus, our third fact provides important context for the previous two findings. While the previous two facts show that LIHTC leads to less income diversity and a smaller share of households in the lowest-income groups, LIHTC still increases the number of households in the lowest-income groups.

We demonstrate these three facts using detailed data from the Utah Housing Corporation, which tracks all project applications. Focusing on one state allows us to track both accepted developments and developments for which developers applied for the credit but their applications were declined. We provide consistent evidence using two different types of variation. First, we use the continuous measure of the number of credits awarded in a census block group. We show that census block groups that received above and below the median number of credits look similar across different characteristics. Second, we use an indicator variable equal to one for census-block groups that received any credits, zero for census-block groups that had applications for credits but did not

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<sup>2</sup><https://www.nytimes.com/2020/11/05/us/affordable-housing-suburbs.html>

receive them, and missing otherwise. Variation on whether a census block group had a development funded uses the random variation created by the application process---where a development's success depends on the other applications and the number of credits awarded. We again find that census-block groups with a development funded look similar to census-block groups with developments that were not funded across different characteristics.

We provide estimates with additional controls, placebo tests, and different variable choices to dampen concerns about spurious findings. First, we provide estimates with controls for development in the neighborhood using the number of credits awarded in future periods. Second, we provide placebo tests using definitions of credits from earlier periods. Third, we provide estimates using the number of units built and indicator variables defined in various ways using application designations of declined, nonconforming, and ineligible applications.

In the Appendix, we provide additional estimates of neighborhood change based on household age, demographics, and housing characteristics. We find that the share of younger households (18--29) increases with the number of LIHTCs and slightly decreases for older households. We also find that the share of Hispanic households declines with the number of LIHTCs. Finally, we find weak evidence that occupied and rental housing shares increase, and vacant and owner-occupied housing shares decrease. These additional estimates provide context for our three findings.

Focusing on one state provides many advantages, including access to detailed data not available nationally and the ability to interview developers and policymakers in the state. The weakness of focusing on one state is the uncertainty of whether these findings apply outside the state.

## **2. Background**

### *2.1. What we know about the Low-Income Housing Tax Credit*

The Low-Income Housing Tax Credit (LIHTC) is a federal government policy that subsidizes the provision of affordable housing. The policy provides financial incentives for the private sector to build low-income housing rather than have governments build it themselves. The program was established as part of the Tax Reform Act of 1986. The Low-Income Housing Tax Credit is

not granted mechanically, as with other tax credits, but is awarded by state government agencies. Private investors apply for a limited amount of tax credits given to state governments. In general, and in Utah specifically, the government receives many more requests than they have allotments causing many developments that qualify to be declined.

Previous studies have examined the effectiveness of the LIHTC program as measured by spurring development and changes in neighborhood median income, crime, and property values (Sinai and Waldfogel, 2002; Eriksen and Rosenthal, 2010; Baum-Snow and Marion, 2009; Freedman and Owens, 2011). Unsurprisingly, these studies often find mixed results---not all developments are created equal. Baum-Snow and Marion (2009) find substantial differences in the effect of the tax credit, depending on whether the neighborhood is gentrifying. For example, they find substantially more crowd-out of private construction in gentrifying neighborhoods, suggesting the credit is less effective in those areas. Eriksen and Rosenthal (2010) suggest that the effectiveness of the credit varies substantially by other characteristics of the neighborhood as well. Housing values have been shown to be positively affected in New York City (Schwartz et al., 2006) and negatively affected in Milwaukee (Green et al., 2002). These differences, and an interest in investigating heretofore unexplored impacts on communities, motivated us to focus in detail on one state.

## *2.2. What is the effect of the Low-Income Housing Tax Credit on the variance of income?*

One of the main goals of the LIHTC program is to alleviate problems of concentrated poverty oftentimes associated with other low-income housing programs. The credit is set up to compensate developers for producing units that they agree to let at below market rate, i.e., affordable rents. In theory, the credit allows developments that otherwise would not be profitable -- because the lower rents do not cover costs -- to become profitable and be built. In Utah, the formula for accepting developments gives extra points to developments in higher-income areas to further encourage building low-income housing units in otherwise higher-income areas. However, it does not seem that the credit is sufficient to encourage the creation of low-income units in the highest-income areas in Utah, possibly a reflection of NIMBYism.

Given that one goal of the program is to integrate neighborhoods by income, we investigate the

effect of the LIHTC program on measures of income inequality within a block group. If the program effectively achieves this goal, we should observe income inequality increasing as more low-income housing developments are built due to the program's credits. We note, however, that there is a debate about whether increasing income diversity within neighborhoods is desirable, something outside of the scope of this paper. On one side, the results in [Chetty et al. \(2016\)](#) would seem to support the goal of increased neighborhood income diversity because they find large benefits from moving children from high-poverty to low-poverty areas. In contrast, [Diamond and McQuade \(2019\)](#) find that LIHTC developments placed in low-income areas increase house values, while LIHTC developments placed in high-income areas decrease house values. They summarize their results thus: "moving LIHTC properties from higher-income to lower-income neighborhoods may therefore benefit both the residents of the higher- and lower-income neighborhoods" (pp. 1066-1067).

### **3. Data**

We combine data from the Utah Housing Corporation and the US Census. The Utah State Legislature created the Utah Housing Corporation in 1975 to promote affordable housing for low- and moderate-income persons. The main program provides mortgage money to qualifying first-time home buyers. After the introduction of the LIHTC in 1986, the Utah Housing Corporation gained responsibility for administering the credit for the State of Utah. In 1990, Congress mandated that the LIHTC program be administered through a competitive process.

#### *3.1. Utah Housing Corporation*

The Utah Housing Corporation developed a scoring system to implement its competitive process for Low-Income Housing Tax Credits. The scoring system includes features about project location, housing needs, and tenant populations. For example, one of the areas for which a project can receive points is if it is located in an area with a high Opportunity Index. The Opportunity Index provides an incentive to develop affordable housing in otherwise high-priced areas. This index

was developed by James Wood, a researcher at the University of Utah, and combines measures of school proficiency, job access, labor market engagement, poverty, and housing stability.

The data include the universe of Low-Income Housing Tax Credit applications in Utah. These include 455 accepted developments, including 211 since 2000, across 24 of the 29 counties in Utah. The credits have funded 23,459 low-income units with over \$90 million in credits. The data also include information about the 108 developments that were declined since 2000. The data consist of address, latitude and longitude, a series of variables about the characteristics of the project (such as the number of units with two bedrooms), the number of low-income units, the allocation amount applied for (and awarded), as well as the overall score on the Opportunity Index.

There are 1,554 block groups (2010 definitions) in the State of Utah. Numerous block groups span counties, creating two identifiable areas within one block group. For the block groups that overlap counties, we have two separate observations, one on either side of the county line. Including the block groups that overlap counties, we have 1,676 observations. Of these observations, 1,411 have not had an application for Low-Income Housing Tax Credits and are excluded from the analysis. Of the remaining, we designate 86 as accepted block groups and 179 as declined block groups.

### *3.2. US Census*

We collect 2000 and 2018 Census data at the block-group level ([Manson et al., 2020](#)). Census block groups are defined as having between 600 and 3,000 people. For our areas, which include subdivisions across counties, the median number of households is 487, with a mean of 567.

Table 1 compares census block groups in the full sample (Column 1), the declined block groups (the control group, Column 2), and the accepted block groups (the treatment group, Column 3) with p-values of the difference between the control and treatment block-groups reported in Column 4. Treatment block groups are defined as block groups that have more allocated amounts accepted than declined, and control block groups are defined as those with more allocated amounts declined than accepted. We provide estimates with different definitions of treatment and control and find the estimates are not sensitive to these definitions.

Simple comparisons across Columns 1, 2, and 3 provide insights into block groups receiving Low-Income Housing Tax Credits. All estimates are from 2000. As expected, treatment and control block groups have lower average and median incomes than the full sample. For example, the average income of areas with Low-Income Housing Tax Credit developments is \$42,940 compared to \$55,479 in the full sample. Treatment and control block groups look similar. For example, they have median incomes of \$36,389 and \$38,813, respectively, relative to the median income in the full sample of \$48,193. Treatment and control block groups are similar across measures of income diversity reported in the third to sixth rows: the standard deviation of income, coefficient of variation, the ratio of the 75th and 25th percentiles of income, and the ratio of the 60th and 40th percentiles of income. Across all of these measures, the difference in income diversity between the accepted and declined block groups is not statistically significant at the 10% level (Column 4).

#### **4. Empirical Model**

The main complication with studying the effectiveness of the LIHTC program is that the locations where the developments are built are endogenous to the developer's expectations of rents and potentially a political process because the state awards the credits. Previous studies have used a variety of ingenious sources of variation to overcome these complications. [Baum-Snow and Marion \(2009\)](#) use a threshold in the eligibility for higher tax credits to compare Census tracts just above and below the threshold, defined as 50 percent of households eligible to rent a LIHTC unit. The strength of this approach is that the variation is plausibly exogenous. The potential weaknesses are that the analysis is at a large geographic area (Census tract) and provides an estimate local to the threshold. [Diamond and McQuade \(2019\)](#) exploit the timing of when funding is granted and the exact geographic location. Because developers apply for Low-Income Housing Tax Credits, the timing and often the precise geographic location could be plausibly exogenous. The strength of this approach, and the other econometric advances in the paper, is that it exploits finer geographic details, including property prices at the property level. The potential weakness of looking at property values is that the study is limited to 129 of the 3,007 counties in the United States, excluding 35



states, including Utah.

We complement these previous studies by exploiting a different type of variation created from the application process. In particular, we collected data on all applications submitted to the state of Utah from 2000 to 2018. These data provide the exact address of each project, whether the project was accepted, declined, ineligible, or nonconforming, and a series of other variables, such as the amount of credit being asked for, number of units, and types of units, and how they rate on the Opportunity Index.<sup>3</sup> We, therefore, can compare block groups that received a preponderance of accepted developments to those with a preponderance of developments whose applications were declined. The advantage of this variation is two-fold. First, both sets of block groups were determined by developers to be suitable for a Low-Income Housing Tax Credit project. This alleviates some selection concerns due to the developers' expectations of future growth of areas. Second, we compare nearly similar areas by exploiting the score from the formula and noting that the threshold changes across years due to the supply and demand of the credits. In this way, our study is similar to [Baum-Snow and Marion \(2009\)](#) in that we exploit a threshold in the policy. The advantage of our threshold is that it does not limit us to developments in specific areas (like those in Census tracts close to the 50% threshold). Our estimates include all census blocks in which LIHTC developments were proposed.

#### *4.1. Estimation strategy*

We estimate how income diversity in block groups changes as they receive more Low-Income Housing Tax Credits. To do this, we compare changes from 2000 to 2018. Our dependent variable is the change in the standard deviation of income from 2000 to 2018 scaled by average income in 2000 for census block-group  $i$ ;  $(STD_{i,2018} - STD_{i,2000})/AVE_{i,2000}$ . Our focal independent variable is the number of Low-Income Housing Tax Credits a census block group received from 2000 to 2010 scaled by the average amount of credits across census block groups;  $Credits_i/\overline{Credits}$ . We use

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<sup>3</sup>Nonconforming project applications are those that are incomplete, lacking documentation, and ineligible project applications are projects outside the scope of LIHTC, for example, projects licensed for assisted living [https://utahhousingcorp.org/pdf/2024\\_Final\\_QAP-230614.pdf](https://utahhousingcorp.org/pdf/2024_Final_QAP-230614.pdf).

the number of credits from 2000 to 2010 (instead of 2018) to capture the impact of potential effects that may take several years to develop.

Our empirical design controls for differences across census block groups and years. To identify the effect of LIHTC on income diversity, we compare the change in income diversity in census block groups that received LIHTC to the change in census block groups that were denied credits. This comparison controls for time trends in income diversity. Level differences across census block groups are controlled for by taking the difference in the standard deviation of income between 2018 and 2010. Our empirical design captures both the direct effect of LIHTC on income diversity in the neighborhood and any spillover effects associated with having a LIHTC development.

The coefficient of interest is  $\beta_1$ , the coefficient on the number of Low-Income Housing Tax Credits a census block group received from 2000 to 2010 scaled by the average number of credits across census block groups. We use different control variables to account for different potential confounding factors across different specifications. These include average income in 2000 and credits/units awarded from 2011 to 2018. This gives the specification,

$$(STD_{i,2018} - STD_{i,2010})/AVE_{i,2000} = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + X\beta + \varepsilon_i. \quad (1)$$

In Section 5.2 and Appendix A, we provide additional estimates using different variation in the independent variable, different measures of income diversity for the dependent variable, and placebo tests. We also consider other neighborhood characteristics including demographics (e.g., age and race) and housing characteristics (e.g., owner-occupied and rental) in Appendix A.2

## 5. Results

### 5.1. Evidence on the impact of the Low-Income Housing Tax Credit on Neighborhood Income Diversity

We employ our empirical strategy to investigate the impact on income diversity at the block-group level of developments built with Low-Income Housing Tax Credits. The sign of the change

in income diversity due to LIHTC could be positive or negative. Intuitively, one might think that the LIHTC program would result in an increase in income dispersion because LIHTC units enable lower-income households to move into a neighborhood. Indeed, one of the stated goals of the LIHTC program is to create more integrated neighborhoods by providing better access to lower-income households to higher SES neighborhoods. On the other hand, one might think income dispersion would decrease because higher-income households would move out as the LIHTC enables low-income housing to be built in the neighborhood, a perhaps undesirable change in the neighborhood (NIMBYism). In fact, we find that income diversity decreased as a result of Low-Income Housing Tax Credits. As we will show, this result appears to be due to the LIHTC incentives being targeted at middle-income rather than low-income households.

Figure 1 depicts the policy impact of LIHTC. It displays the impact of LIHTC on census block groups with the average amount of LIHTCs from 2000 to 2010 compared to census block groups with unsuccessful applications for LIHTC during this period. We measure the Low-Income Housing Tax Credit in two ways, first as dollars awarded and second as units built. Our focal outcome variable is the change in the standard deviation of income from 2000 to 2018, scaled by average income in 2000. The figure depicts the estimates with 95% confidence intervals.

The baseline estimate reported in the top row suggests that the standard deviation of income decreased by 4.1% of average income in 2000. This estimate is statistically significant at the 1% level.<sup>4</sup> In the second row of Figure 1, we report that the standard deviation of income decreased by 3.6% of average income when we control for average income in 2000. The similarity between this estimate and the baseline estimate alleviates some concern about differences across areas captured by the income level in 2000. In the third row of Figure 1, we report that the standard deviation of income decreased by 4.0% of average income when we control for credits received between 2011 and 2018. This result alleviates some concerns about sample selection tied to successful applications between 2000 and 2010, the period over which we measure LIHTC received.

In the fourth row of Figure 1, we estimate the model for the subset of census block groups with

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<sup>4</sup>All estimates are reported in the appendix in Table A.1.

positive credits between 2000 and 2010. This estimate captures the intensive margin, in contrast to the previous estimates that capture the intensive and extensive margins. This estimate, while less precisely estimated than the previous estimates because it relies on fewer observations, is still statistically different from zero at the 1% level. The intensive margin suggests that the standard deviation of income decreased by 4.0% of average income in 2000. The similarity of this estimate and the previous estimates alleviates concerns of differences between census block groups that received credits and those that did not.

We report in the final four rows of Figure 1 estimates using a different measure of the extent of the LIHTC: the number of low-income housing units built in a census block group scaled by the average number of units. We report estimates without controls (Figure 1, fifth row), with average income in 2000 (sixth row), with units built with LIHTC between 2011 and 2018 (seventh row), and the intensive margin estimate (eighth row). These estimates are negative, statistically significant and similar to estimates using the number of credits as the independent variable.

We consistently find that income dispersion declines with the building of LIHTC projects in the neighborhood, but what is driving this result? Is it because higher-income households move out? Or is it because lower-income households do not move in? The evidence paints a more complicated picture.

To understand why income dispersion fell in neighborhoods with more LIHTCs, we explore in Figure 2 what happened, in various income bins, to (a) the share of households and (b) the number of households.<sup>5</sup> An examination of *shares* of households by income bin allows us to see whether the compression of the income distribution is occurring because of changes in the relative prevalence of households at the bottom or the top of the income distribution. An examination of the *number* of households by income bin allows us to see whether changes in shares of households by income bin are attributable to actual declines or increases in the number of households by income bin living in the neighborhood. The evidence on changes in the shares of households by income bin (Figure 2a) indicates that the share of the lowest-income households (less than \$15,000) decreases as the

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<sup>5</sup>We also consider changes in percentages in the appendix and arrive at similar conclusions.

amount of LIHTC increases. The share of households with income between \$15,000 and \$24,999 also decreases with LIHTC, but this estimate is not precisely estimated at the 95 percent confidence level. All other shares are positive and imprecisely estimated. These estimates suggest that income diversity decreased in neighborhoods with LIHTC developments because it dampened the relative prevalence of the lowest-income households and not because it decreased the share of high-income households.

We examine in Figure 2b changes in the number of households by income bin to dig deeper into the impact of LIHTC on neighborhoods. We find that the number of households in every income bin increased in neighborhoods with more LIHTC credits relative to neighborhoods where developers' LIHTC applications were declined. Specifically, we find that the number of households in the lowest income bin (income less than \$15,000) increased by 8.5 households in census blocks with the average number of credits relative to census blocks that did not receive credits, while the corresponding number for an increase in households in the top two income bins was 18.5 for households with income between \$60,000 and \$99,999 and 14.0 for households with income of \$100,000 or more. We find it remarkable that a program aimed at increasing the number of affordable housing units would increase the number of households at every level of income.

Taken together, the evidence in Figures 2a and 2b indicates that the decrease in income dispersion in neighborhoods with more LIHTC is due to the program being a draw for households of all incomes but disproportionately for middle- and higher-income households, resulting in the share of households in the lowest income bins falling. There are at least two explanations for this perhaps surprising finding. First, by design, the LIHTC program is targeted at providing housing for households with up to 60% AMI on average, and the average can include households with up to 80% AMI. In Salt Lake City, Utah, in 2021, 60% of AMI was \$55,200, and 80% of AMI was \$73,600. It is perhaps no surprise, then, that we find the largest increase in the number of households to be in the \$60,000-\$99,999 bin. It appears that the target of the LIHTC is being hit with a fair degree of accuracy.

Second, the LIHTC program may create positive spillovers to the neighborhood that make it

more attractive for all developers. The developers we spoke with consistently made this point. We find that the income bins with the greatest increase in the number of households are the richest two bins: \$60,000 to \$99,999 and \$100,000 and more. The result is that neighborhoods with more LIHTC appear to have become more attractive to higher-income households and developers of all housing types.

## 5.2. Sensitivity of estimates

In Figure 3, we provide estimates with different variation and identifying assumptions used to establish our three facts. The previous estimates relied on the continuous variation in the number of credits awarded to a census block group (or the continuous variation in the number of units awarded). Alternatively, we can use an indicator variable as our independent variable of interest to denote census block groups as either accepted or declined, i.e., as being treated by LIHTC or not. We define this indicator variable  $\mathbb{1}(\text{accepted})_i$  in different ways. Our baseline specification defines the indicator variable as one if the census block group has an accepted LIHTC development from 2000 to 2010. The indicator variable is zero if the census block group has an application for LIHTC but no developments and is excluded from the sample if there are no LIHTC applications in the census block group between 2000 and 2010. The coefficient of interest is  $\beta_1$  in the specification

$$(STD_{i,2018} - STD_{i,2010})/AVE_{i,2000} = \beta_0 + \beta_1 \mathbb{1}(\text{accepted})_i + X\beta + \varepsilon_i. \quad (2)$$

The identifying assumption in this specification with the indicator variable is slightly different than the previous estimates. In particular, it is more similar to a differences-in-differences model by comparing the difference in standard deviation across time (2000 to 2018) and across accepted or declined census block groups. Therefore, the identifying assumption is that the difference in standard deviation across time in the accepted census block groups would have been the difference across time in the declined census block groups in the absence of the LIHTC development. We cannot test for the parallel trend assumption because we do not have data on the denied projects in the pre-period. Instead, we rely on two placebo tests using whether an area received a LIHTC

development or not between 1987 and 1995 and the number of credits awarded between 1987 and 1995 to test for similar differences in time for areas that did or did not receive LIHTC credits.

In Figure 3a, we report estimates from specifications given in equation (2) using several different definitions of accepted.<sup>6</sup> The baseline estimate in the top row is -0.132, and it is statistically significant at the 1% level. This estimate suggests that the standard deviation of income decreased by 13% of income in 2000 more in neighborhoods with accepted LIHTC developments than neighborhoods with LIHTC applications but no applications accepted. This accepted definition compares census block groups with and without LIHTC developments, conditional on having a LIHTC application. We also compare census block groups with more LIHTC developments than declined developments, nonconforming developments, ineligible developments, or the sum of declined, nonconforming, and ineligible developments. Each of these comparisons relies on slightly different randomization due to the administrative process of allocating LIHTC developments. Across all of these definitions, the point estimates remain similar and statistically significant at the 5% level, reported in the second through fifth rows of Figure 3a. Finally, we compare census block groups above and below the median number of credits allocated, conditional on having a LIHTC application. This estimate, reported in the sixth row, suggests that the standard deviation of income decreased by 20% of income in 2000 more in neighborhoods with an above-median amount of LIHTCs than neighborhoods with below median LIHTC, conditional on having a LIHTC application. This estimate is consistent with the estimates in Figure 1 that the standard deviation of income decreases in a neighborhood more as the amount of LIHTC credits increases.

We provide estimates of two placebo tests in the last two rows of Figure 3a. The first placebo test uses an indicator variable that equals one if the census block group had an accepted LIHTC project from 1987 to 1995 (instead of 2000 to 2010 as in our baseline estimates). The second placebo test uses a continuous variable of the number of credits awarded in a census-block group, scaled by the average, from 1987 to 1995 (instead of 2000 to 2010 as in our baseline estimates). In both of these placebo tests, the point estimate is close to zero and is not statistically significant.

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<sup>6</sup>We report the estimates in this figure in the appendix and Table A.4.

In Figure 3b, we replicate the estimates in Figure 2a using the indicator for accepted developments instead of the number of credits as the independent variable.<sup>7</sup> These estimates, similar to those in Figure 3a, provide a test of sensitivity to the specific variation used for identification. The estimates are similar to those in Figure 2a, suggesting the estimates are not overly sensitive. Specifically, the change in the share of households is negative for the lowest-income households (less than \$15,000) and positive for households with income between \$60,000 and \$99,999, though the latter estimate is not statistically significant.

In Figure 3c, we replicate the estimates in Figure 2b using the indicator for accepted developments instead of the number of credits as the independent variable.<sup>8</sup> These specifications are consistent with our baseline estimate; however, they are less precisely estimated. Specifically, the largest increase in the number of households is in the \$60,000 to \$99,999 income bin, which is the same as in Figure 2b and is statistically significant. We also find that the point estimates for the change in households in the lowest-income bin, less than \$15,000, is positive, but this estimate is only statistically significant at the 10% level.

In Figure 3d, we replicate the estimates in Figure 2a, expanding the number of income bins from seven to 15.<sup>9</sup> This figure provides evidence consistent with our earlier finding, specifically that the share of the lowest-income households declined with the number of LIHTCs. The point estimates are negative for the lowest four income bins and statistically significant for the lowest income bin. The point estimates for the other income bins are close to zero or positive, and none are statistically significant.

## 6. Conclusion

The externalities associated with a neighborhood depend critically on its composition. For this reason, many policies aim to increase neighborhood diversity across various characteristics including income. A key aspect of increasing neighborhood income diversity is expanding the

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<sup>7</sup>We report the estimates in this figure in the appendix and Table A.5.

<sup>8</sup>We report the estimates in this figure in Table A.6 in the appendix.

<sup>9</sup>We report the estimates in this figure in Table A.7 in the appendix.



supply of affordable housing in sought-after areas. To this end, many cities and states use Low-Income Housing Tax Credits provided by the federal government to encourage affordable housing in areas that otherwise would not have any.

We explore the effect of LIHTC using detailed administrative data on all applications for the Low-Income Housing Tax Credit in Utah. These data allow us to compare neighborhoods with accepted LIHTC developments to neighborhoods whose LIHTC applications were declined. The advantage of these data is that we have the universe of applications in Utah and can provide estimates of the implementation of this program across all areas that received LIHTC. Our evidence complements the literature that has used estimates local to thresholds ([Baum-Snow and Marion, 2009](#)) or in select counties across the country ([Diamond and McQuade, 2019](#)).

We document three facts. First, the Low-Income Housing Tax Credit results in a decrease in neighborhood income diversity. Second, we find that the decrease in income diversity associated with the construction of LIHTC units is not caused by high-income households leaving but by the share of low-income households falling. Third, despite the share of low-income households declining, we find the number of low-income households increased---just not as fast as the number of households in other income groups.

An advantage of focusing on one state's implementation of the federal LIHTC program is that we were able to interview developers and policymakers in the state. These interviews provide support, context, and policy implications for our three findings. In interviews, we found that developers tailor their developments to increase the probability that their developments are awarded the credits, implying that the policy is salient and has an impact. While policymakers noted that developments in high-income neighborhoods receive more points in the application process, developers indicated other frictions (e.g., NIMBYism) limited them from putting low-income housing developments in those neighborhoods. Another key institutional detail for developers and policymakers is that housing targeted at 60% of the area median income qualifies for the Low-Income Housing Tax Credit. In practice, this means that in places like Salt Lake City, Utah, housing targeted at households making around \$60,000 qualifies. The result is that the program

appears to increase the housing supply for households in the targeted income range, but the target is too high to incentivize developers to provide housing for the lowest-income households.

Our findings have implications for the interpretation of past academic studies and the evaluation of policy effectiveness. Previous studies have shown an increase in housing values and a decline in median income in neighborhoods with LIHTC developments ([Baum-Snow and Marion, 2009](#)). We expand on these results by demonstrating changes throughout the income distribution within neighborhoods. We find that LIHTC leads to a) a decrease in neighborhood income diversity, b) an increase in the number of households with income at 60-80% of the area median income, and c) an increase in the number of households across the income distribution. One goal of greater provision of low-income housing developments is to increase neighborhood income diversity. Our results suggest that the LIHTC program has not succeeded at this goal. The program has seen some success in providing affordable housing for households with income at 60-80% of AMI, but it has been less successful at helping the neediest households; we find that the share of households in the lowest income brackets falls in neighborhoods with LIHTC developments.

Future research could consider whether affordable housing policies are increasing the concentration of the poorest households in poorer neighborhoods. The potential unintended consequences on neighborhoods that did not receive LIHTC have been relatively unexplored.

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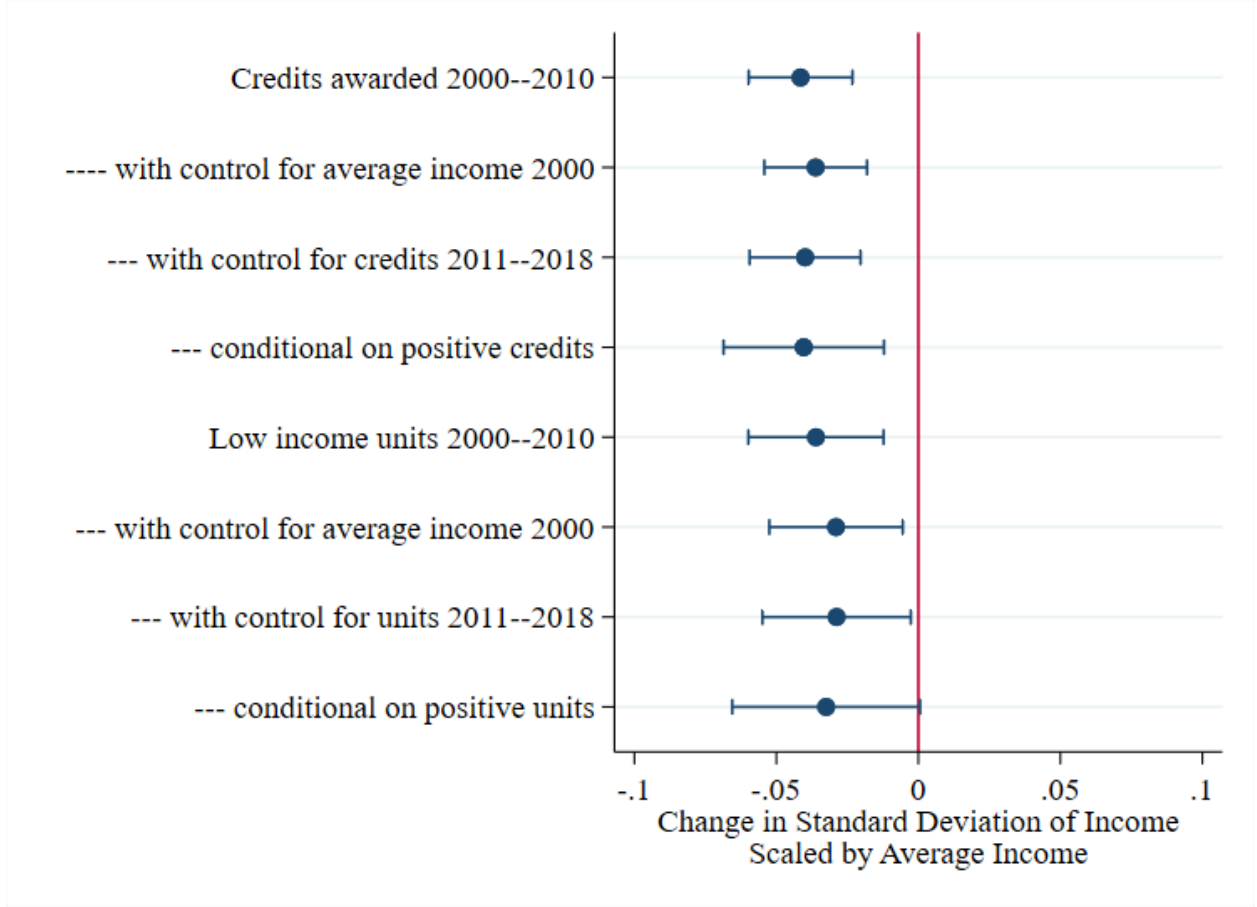
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Table 1: Comparisons Across Census Block Groups

Block-group characteristic	Full Sample (1)	Control (2)	Treatment (3)	P-values (4)
Average income	\$55,479.64	\$45,999.13	\$42,940.91	0.11
Median income	\$48,193.08	\$38,813.37	\$36,389.45	0.20
Std income	\$36,833.96	\$33,503.71	\$30,506.03	0.13
Coefficient variation	0.67	0.73	0.72	0.52
75/25 Income ratio	2.4	2.55	2.54	0.89
60/40 Income ratio	1.37	1.42	1.42	0.92
Observations	1,676	179	86	265

NOTE.— The full sample includes 1,676 census block groups in Utah based on 2010 definitions (characteristics given in column 1). Census block groups that had applications for Low Income Housing Tax Credits (LIHTC) between 2000 and 2010 but did not receive any are defined as control block groups (characteristics given in column 2). Census block groups that were awarded Low Income Housing Tax Credits (LIHTC) between 2000 and 2010 are defined as treatment block groups (characteristics given in column 3). Column 4 provides p-values of the T-test of difference in characteristics between control and treatment census block groups. The data for characterizing treatment and control census block groups come from the Utah Housing Corporation, the regulatory institution responsible for LIHTCs in Utah. The characteristics include average income, median income, the standard deviation of income, coefficient of variation of income, and the ratios of the 75th and 25th percentiles of income and the ratios of the 60th and 40th percentiles of income. These characteristics are reported for the year 2000 to investigate the balance between treatment and control census block groups. The data for characteristics come from the American Community Survey.

Figure 1: Changes in Income Dispersion 2000 to 2018



NOTE.— Figure 1 shows that income dispersion decreased between 2000 and 2018 for census blocks with more LIHTC credits and low income units built with LIHTC credits. The horizontal axis reports the coefficient  $\beta_1$  from the regressions,

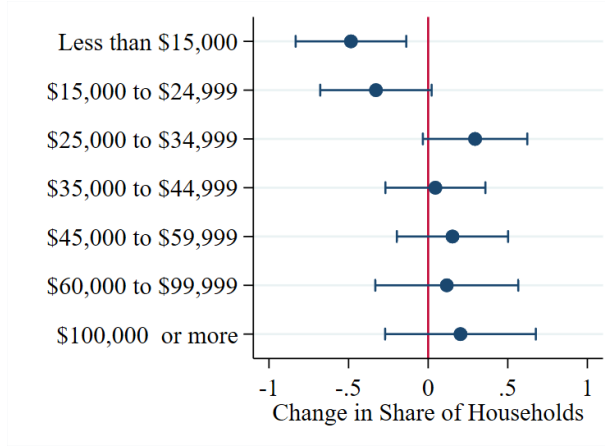
$$(STD_{i,2018} - STD_{i,2000})/AVE_{i,2000} = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + X\beta + \varepsilon_i,$$

$$(STD_{i,2018} - STD_{i,2000})/AVE_{i,2000} = \beta_0 + \beta_1 \text{Low-Income Units}_i / \overline{\text{Low-Income Units}} + X\beta + \varepsilon_i,$$

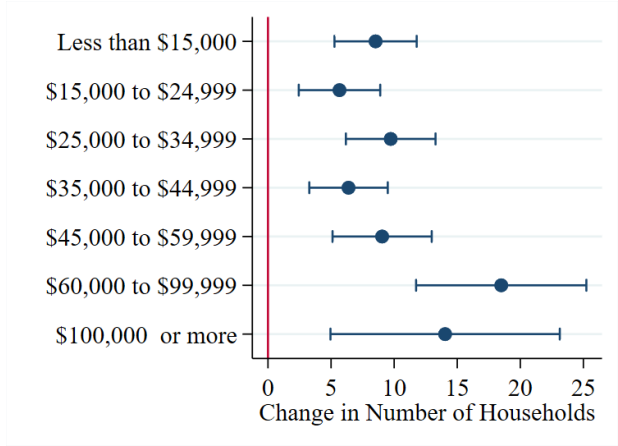
where the dependent variable is the change in standard deviations from 2000 to 2018 scaled by income in 2000. The independent variable of interest is either the number of credits awarded in a census block from 2000 to 2010 scaled by the average amount of credits awarded during this period (the top four estimates) or the number of low-income units built between 2000 and 2010 scaled by the average number of units built during this period (the bottom four estimates). Controls are at the census block group level and include average income in 2000 (rows 2 and 6), the number of credits awarded between 2011 to 2018 (row 3), and the number of low-income units built between 2011 to 2018 (row 7). The estimates reported in the fourth and eighth rows condition the regression on having positive credits or low-income units built from 2000 to 2010. The estimates in the fourth and eighth rows provide an intensive margin estimate. These estimates are also reported in Table A.1 in the appendix. This figure shows 95% confidence intervals.

Figure 2: Share of lowest income households decreased despite increasing in level

(a) Change in the share of households by income



(b) Change in the number of households by income



Notes: Figure 2a shows the change between 2000 and 2018 in the share of households by income as the amount of low income housing tax credits increase in a census block group. The share of households is calculated as the ratio of the number of households in an income range (e.g., \$15,000 to \$24,999) to the total number of households in a given census block group and year. The change in the share of households by income as the number of LIHTCs increases is given by  $\beta_1$  from the regression

$$(\text{Households}_{i,j,2018} / \text{Total Households}_{2018} - \text{Households}_{i,j,2000} / \text{Total Households}_{2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i.$$

This figure shows the coefficient  $\beta_1$  with 95% confidence intervals.

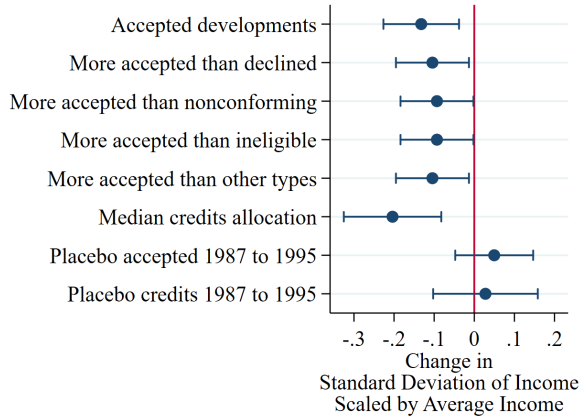
Figure 2b shows the change between 2000 and 2018 in the number of households by income as the amount of low income housing tax credits increases in a census block group. The change in the number of households by income as the number of LIHTCs increases is given by  $\beta_1$  from the regression

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i.$$

This figure shows the coefficient  $\beta_1$  with 95% confidence intervals. The estimates are also reported in the appendix in Tables A.2 and A.3.

Figure 3: Sensitivity of estimates

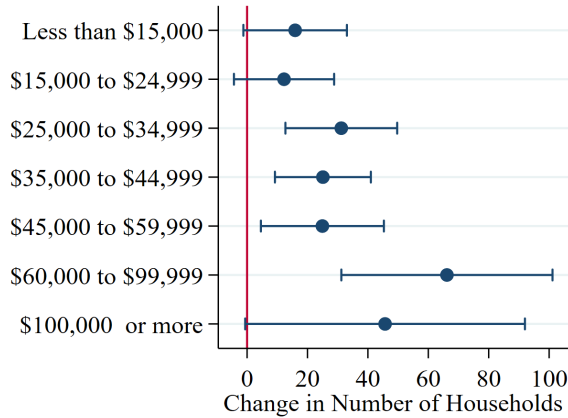
(a) Change in income dispersion using indicators



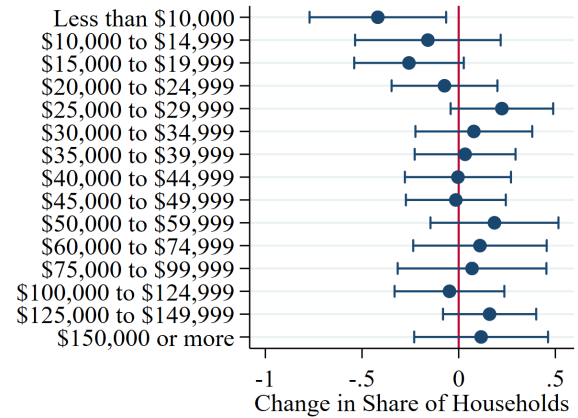
(b) Change in the share of households (indicator)



(c) Change in the number of households (indicator)



(d) Change in the share of households



Notes: Figures 3a, 3b, and 3c replicate the estimates in Figures 1 and 2 using an indicator variable to designate treatment and control census block-groups instead of using the continuous variables amount of credits or number of units. Figure 3a reports estimates using indicator variables that equal 1 if a census block group has an accepted development, more accepted developments than declined, more accepted than nonconforming, more accepted than ineligible, more accepted than other types, or above median credits allocated and 0 otherwise. Figure 3a also reports two placebo tests using accepted projects and credit amounts from 1987 to 1995. Figure 3d replicates estimates in Figure 2a using finer categories of income. This figure shows the coefficient  $\beta_1$  with 95% confidence intervals. We also report these estimates in Tables A.4-A.7 in the appendix.

## APPENDIX FOR ONLINE PUBLICATION

### Appendix A. Tables and Additional Specifications

This supplemental appendix reports the estimates in the paper in table format, instead of figures as in the paper, explores other neighborhood changes associated with LIHTC, and provides additional specifications.

#### *A.1. Table companions*

Table A.1 is the companion table to Figure 1, Tables A.2 and A.3 are companion tables to Figure 2, Tables A.4--A.7 are companion tables to Figure 3, and Tables A.8--A.10 are companion tables to Figure A.1.

#### *A.2. Other neighborhood changes associated with the Low-Income Housing Tax Credit*

In Figures 1 and 2, we document that LIHTC is associated with a decrease in neighborhood income diversity that is driven by declines in the shares of households in the lowest income bins. In Figures A.1a and A.1b, we explore whether these changes were concentrated in households whose household heads were young or old; in Black, white, or Hispanic households; and in households headed by a female. In Figure A.1a, we show that the share of young households, those whose household head is aged 18 to 29, increases with the number of LIHTCs in a census block group, and the share of older households, those whose household head is aged 70 to 79, decreases. Other age groups are not precisely estimated but follow a general trend. Households headed by people from younger age groups have positive point estimates, while households headed by people from older age groups have negative ones.

In Figure A.1b, we consider how the share of Black, white, and Hispanic households and the share of households headed by a female change with Low-Income Housing Tax Credits. We find that the share of Hispanic households decreases with LIHTC. We do not find statistically significant changes for Black, white, or female-headed households, but the point estimate for the latter is positive.

Finally, in Figure A.1c, we explore whether Low-Income Housing Tax Credits are associated with a change in the relative composition of housing types in a neighborhood. Specifically, we consider whether the shares of occupied, vacant, owner-occupied, and rental housing increase or decrease with LIHTCs. We find that the share of occupied and rental housing increased, and the share of vacant and owner-occupied housing decreased, but no coefficients are precisely estimated.

An important question for policymakers, and in the literature, is to what extent Low-Income Housing Tax Credits crowd-out other developments. Sinai and Waldfogel (2002) find that government-financed units increased the stock of housing but at a rate of less than one unit for every unit built. They also find substantial heterogeneity in the amount of crowd-out depending on market demand for subsidized housing.

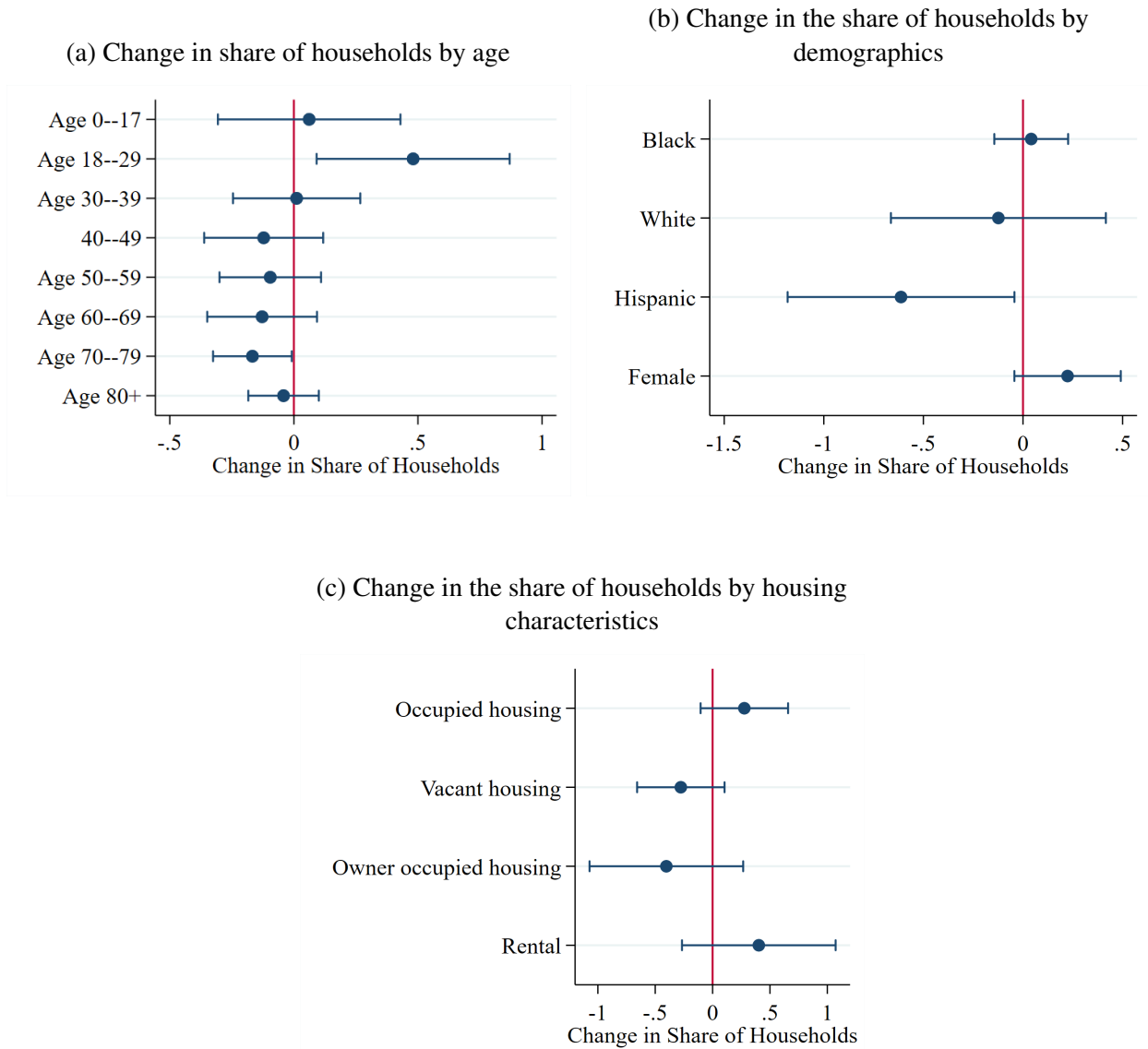
#### *A.3. Additional specifications*

We also provide estimates based on the change in the number of households by finer income groups with credits and an indicator variable in Tables A.11 and A.12. We provide estimates in the paper based on change in share and change in the number of households. Tables A.13--A.16



provide estimates based on percentages for income groups (7 and 15) and with credits and indicator variables for independent variables. Finally, we provide estimates of the change in the number of households by demographics, housing characteristics, and age in Tables [A.9](#), [A.10](#), and [A.17](#).

Figure A.1: Other neighborhood changes



Notes: Figures A.1a, A.1b, and A.1c provide estimates of additional changes in the census block groups as the amount of LIHTCs increase. Figure A.1a reports changes in the share of households by age categories. Figure A.1b reports changes in the share of households by demographic characteristics. Figure A.1b reports changes in the share of households by housing characteristics. All three graphs report the coefficient  $\beta_1$  with 95% confidence intervals from the regression

$$(\text{Households}_{i,2018}/\text{Total Households}_{2018} - \text{Households}_{i,2000}/\text{Total Households}_{2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i.$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., age 18--29, Black, or Rental). We also report these estimates in Tables A.8--A.10 in the appendix.

Table A.1: Changes in income diversity

This table provides estimates reported in Figure 1. These estimates show that income diversity decreased between 2000 and 2018 for census blocks with more LIHTC credits and low income units built with LIHTC credits. The coefficient of interest is  $\beta_1$  from the regressions,

$$(STD_{i,2018} - STD_{i,2010})/AVE_{i,2000} = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + X\beta + \varepsilon_i,$$

$$(STD_{i,2018} - STD_{i,2010})/AVE_{i,2000} = \beta_0 + \beta_1 \text{Low-Income Units}_i / \overline{\text{Low-Income Units}} + X\beta + \varepsilon_i,$$

where the dependent variable is the change in standard deviations from 2000 to 2018 scaled by average income in 2000. The independent variable of interest is either the amount of credits awarded in a census block from 2000 to 2010 scaled by the average amount of credits awarded during this period (the top four estimates) or the number of low-income units built between 2000 and 2010 scaled by the average number of units built during this period (the bottom four estimates). Controls are at the census block group level and include average income in 2000, the number of credits awarded between 2011 to 2018, and the number of low-income units built between 2011 to 2018. The fourth and eighth estimates condition the regression on having positive credits or low-income units built from 2000 to 2010. The estimates in the fourth and eighth columns provide an intensive margin estimate.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credits	-0.041*** (0.009)	-0.036*** (0.009)	-0.040*** (0.010)	-0.040*** (0.014)				
Units					-0.036*** (0.012)	-0.029** (0.012)	-0.029** (0.013)	-0.032* (0.017)
Constant	-0.337*** (0.024)	-0.668*** (0.094)	-0.334*** (0.025)	-0.344*** (0.065)	-0.342*** (0.026)	-0.696*** (0.096)	-0.338*** (0.026)	-0.358*** (0.052)
Control average income 2000		✓				✓		
Control credits 2011 to 2018			✓					
Conditional on positive credits				✓				
Control units 2011 to 2018							✓	
Conditional on positive units								✓
Adj. R-Square	0.067	0.109	0.064	0.077	0.029	0.077	0.032	0.022
Observations	265	265	265	86	265	265	265	125

Table A.2: **Change in share of households by income**

Table A.2 provides estimates of the change between 2000 and 2018 in the share of households by income as the number of LIHTCs increases in a census block group (replicating Figure 2a). The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,j,2018}/\text{Total Households}_{2018} - \text{Households}_{i,j,2000}/\text{Total Households}_{2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

where the share of households is calculated as the ratio of the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$15,000-\$24,999) to the total number of households in a given census block  $i$  in year  $t$ . Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	\$0-\$15,000 (1)	\$15,000-\$24,999 (2)	\$25,000-\$34,999 (3)	\$35,000-\$44,900 (4)	\$45,000-\$59,999 (5)	\$60,000-\$99,999 (6)	\$100,000-more (7)
LIHTCs	-0.485** (0.210)	-0.328 (0.212)	0.295 (0.199)	0.046 (0.190)	0.153 (0.212)	0.117 (0.272)	0.203 (0.287)
Constant	-3.850*** (0.550)	-5.574*** (0.554)	-5.130*** (0.519)	-3.795*** (0.497)	-2.398*** (0.553)	6.694*** (0.711)	14.054*** (0.749)
Adj. R-Square	0.016	0.005	0.005	-0.004	-0.002	-0.003	-0.002
Observations	265	265	265	265	265	265	265

Table A.3: **Change in number of households by income**

Table A.3 provides estimates of the change between 2000 and 2018 in the number of households by income as the number of LIHTCs increases in a census block group (replicating Figure 2b). The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$15,000-\$24,999). Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	\$0-\$15,000 (1)	\$15,000-\$24,999 (2)	\$25,000-\$34,999 (3)	\$35,000-\$44,900 (4)	\$45,000-\$59,999 (5)	\$60,000-\$99,999 (6)	\$100,000-more (7)
LIHTCs	8.530*** (1.655)	5.669*** (1.640)	9.728*** (1.804)	6.385*** (1.579)	9.049*** (1.996)	18.489*** (3.427)	14.042*** (4.616)
Constant	-14.289*** (4.323)	-24.585*** (4.283)	-20.057*** (4.713)	-11.419*** (4.125)	-1.813 (5.214)	58.078*** (8.951)	105.230*** (12.056)
Adj. R-Square	0.088	0.040	0.096	0.055	0.069	0.096	0.030
Observations	265	265	265	265	265	265	265

Table A.4: Changes in income diversity

This table provides estimates reported in Figure 3a. These estimates show that income diversity decreased between 2000 and 2018 for census blocks with more LIHTC credits and low-income units built with LIHTC credits. The coefficient of interest is  $\beta_1$  from the regressions,

$$(STD_{i,2018} - STD_{i,2010})/AVE_{i,2000} = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + \varepsilon_i,$$

where the dependent variable is the change in standard deviations from 2000 to 2018 scaled by average income in 2000. The independent variable of interest differs across specifications indicated above each column. Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	Accepted developments (1)	More accepted than declined (2)	More accepted than nonconforming (3)	More accepted than ineligible (4)	More accepted than other types (5)	Median credits allocation (6)	Placebo accepted 1987 to 1995 (7)	Placebo credits 1987 to 1995 (8)
Treatment	-0.132*** (0.048)	-0.104** (0.046)	-0.093** (0.046)	-0.093** (0.046)	-0.104** (0.046)	-0.204*** (0.062)	0.050 (0.049)	0.028 (0.066)
Constant	-0.331*** (0.029)	-0.331*** (0.031)	-0.334*** (0.032)	-0.334*** (0.032)	-0.331*** (0.031)	-0.345*** (0.025)	-0.394*** (0.028)	-0.382*** (0.025)
Adj. R-Square	0.025	0.015	0.011	0.011	0.015	0.036	0.000	-0.003
Observations	265	265	265	265	265	265	265	265

Table A.5: **Change in share of households by income indicator**

Table A.5 provides estimates of the change between 2000 and 2018 in the share of households by income for treated and control census blocks (replicating Figure 3b). The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,j,2018} / \text{Total Households}_{2018} - \text{Households}_{i,j,2000} / \text{Total Households}_{2000}) = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + \varepsilon_i,$$

where the share of households is calculated as the ratio of the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$15,000-\$24,999) to the total number of households in a given census block  $i$  in year  $t$ . The indicator variable designates treatment and control census blocks. This table defines treatment as a 1 if there is an accepted LIHTC development from 2000 to 2010 and 0 otherwise. Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	\$0-\$15,000 (1)	\$15,000-\$24,999 (2)	\$25,000-\$34,999 (3)	\$35,000-\$44,900 (4)	\$45,000-\$59,999 (5)	\$60,000-\$99,999 (6)	\$100,000-more (7)
LIHTCs	-1.918* (1.066)	-1.213 (1.072)	1.152 (1.004)	0.762 (0.958)	-0.383 (1.068)	1.667 (1.369)	-0.067 (1.448)
Constant	-3.655*** (0.635)	-5.472*** (0.638)	-5.244*** (0.598)	-4.020*** (0.571)	-2.109*** (0.636)	6.220*** (0.815)	14.281*** (0.862)
Adj. R-Square	0.008	0.001	0.001	0.001	0.003	0.002	0.004
Observations	265	265	265	265	265	265	265

Table A.6: **Change in number of households by income with indicator**

Table A.6 provides estimates of the change between 2000 and 2018 in the number of households by income for treated and control census blocks (replicating Figure 3c). The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000}) = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + \varepsilon_i,$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$15,000-\$24,999). Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	\$0-\$15,000 (1)	\$15,000-\$24,999 (2)	\$25,000-\$34,999 (3)	\$35,000-\$44,900 (4)	\$45,000-\$59,999 (5)	\$60,000-\$99,999 (6)	\$100,000-more (7)
LIHTCs	15.913* (8.703)	12.237 (8.423)	31.197*** (9.395)	25.108*** (8.063)	24.934** (10.341)	66.172*** (17.752)	45.687* (23.518)
Constant	-11.404** (5.183)	-23.256*** (5.016)	-21.395*** (5.596)	-13.941*** (4.802)	-1.608 (6.159)	53.094*** (10.573)	103.066*** (14.007)
Adj. R-Square	0.009	0.004	0.037	0.032	0.018	0.047	0.010
Observations	265	265	265	265	265	265	265



Table A.7: **Change in share of households by income finer income groups**

Table A.7 provides estimates of the change between 2000 and 2018 in the share of households as the number of LIHTCs increases in a census block group. (replicating Figure 3d). The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,j,2018} / \text{Total Households}_{2018} - \text{Households}_{i,j,2000} / \text{Total Households}_{2000}) = \beta_0 + \beta_1 \text{Credits}_i / \sqrt{\text{Credits}} + \varepsilon_i,$$

where the share of households is calculated as the ratio of the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$15,000-\$19,999) to the total number of households in a given census block  $i$  in year  $t$ . Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	\$0-\$10,000 (1)	\$10,000-\$14,999 (2)	\$15,000-\$19,999 (3)	\$20,000-\$24,999 (4)	\$25,000-\$29,999 (5)	\$30,000-\$34,999 (6)	\$35,000-\$39,999 (7)	\$40,000-\$44,999 (8)
LIHTCs	-0.418** (0.179)	-0.159 (0.191)	-0.257* (0.144)	-0.073 (0.139)	0.223* (0.135)	0.078 (0.153)	0.033 (0.132)	-0.004 (0.139)
Constant	-2.308*** (0.469)	-1.810*** (0.500)	-2.299*** (0.376)	-3.258*** (0.363)	-2.609*** (0.352)	-2.629*** (0.401)	-1.982*** (0.346)	-1.708*** (0.364)
Adj. R-Square	0.017	-0.001	0.008	-0.003	0.007	-0.003	-0.004	-0.004
Observations	265	265	265	265	265	265	265	265

	\$45,000-\$49,999 (9)	\$50,000-\$59,999 (10)	\$60,000-\$74,999 (11)	\$75,000-\$99,999 (12)	\$100,000-\$124,999 (13)	\$125,000-\$149,999 (14)	\$150,000-more (15)
LIHTCs	-0.015 (0.131)	0.185 (0.168)	0.110 (0.175)	0.069 (0.195)	-0.048 (0.144)	0.160 (0.122)	0.116 (0.176)
Constant	-1.223*** (0.343)	-1.001** (0.439)	1.405*** (0.458)	5.402*** (0.510)	5.303*** (0.377)	3.402*** (0.320)	5.314*** (0.459)
Adj. R-Square	-0.004	0.001	-0.002	-0.003	-0.003	0.003	-0.002
Observations	265	265	265	265	265	265	265

Table A.8: **Change in share of households by age**

Table A.8 provides estimates of the change between 2000 and 2018 in the share of households by age as the number of LIHTCs increases in a census block group (replicating Figure A.1a). The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,j,2018}/\text{Total Households}_{2018} - \text{Households}_{i,j,2000}/\text{Total Households}_{2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

where the share of households is calculated as the ratio of the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., age 18--29) to the total number of households in a given census block  $i$  in year  $t$ . Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	Age 0-17 (1)	Age 18-29 (2)	Age 30-39 (3)	Age 40-49 (4)	Age 50-59 (5)	Age 60-69 (6)	Age 70-79 (7)	Age 80+ (8)
LIHTCs	0.062 (0.187)	0.481** (0.197)	0.011 (0.130)	-0.122 (0.122)	-0.095 (0.104)	-0.128 (0.112)	-0.167** (0.081)	-0.042 (0.072)
Constant	-3.255*** (0.488)	-2.522*** (0.516)	1.439*** (0.340)	-0.988*** (0.318)	1.644*** (0.271)	3.061*** (0.293)	0.564*** (0.210)	0.056 (0.188)
Adj. R-Square	-0.003	0.018	-0.004	-0.000	-0.001	0.001	0.012	-0.003
Observations	265	265	265	265	265	265	265	265

Table A.9: **Change in the number and share of households by demographics**

Table A.9 provides estimates of the change between 2000 and 2018 in the number and share of households by demographics as the number of LIHTCs increases in a census block group (replicating Figure A.1b). The coefficient of interest is  $\beta_1$  from the specifications,

$$(\text{Households}_{i,j,2018} - \text{Households}_{i,j,2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

$$(\text{Households}_{i,j,2018} / \text{Total Households}_{2018} - \text{Households}_{i,j,2000} / \text{Total Households}_{2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

where the share of households is calculated as the ratio of the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., Black) to the total number of households in a given census block  $i$  in year  $t$ . Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	Number				Share			
	Black (1)	White (2)	Hispanic (3)	Female (4)	Black (5)	White (6)	Hispanic (7)	Female (8)
LIHTCs	5.370*** (1.879)	111.980*** (29.403)	16.984** (7.419)	62.864*** (16.485)	0.041 (0.094)	-0.124 (0.274)	-0.612** (0.289)	0.224 (0.136)
Constant	13.882*** (4.907)	117.176 (76.801)	129.580*** (19.379)	100.052** (43.060)	0.511** (0.246)	-10.227*** (0.716)	5.461*** (0.755)	-0.103 (0.354)
Adj. R-Square	0.026	0.049	0.016	0.049	-0.003	-0.003	0.013	0.006
Observations	265	265	265	265	265	265	265	265

Table A.10: **Change in the number and share of households by housing characteristics**

Table A.10 provides estimates of the change between 2000 and 2018 in the number and share of households by housing characteristics as the number of LIHTCs increases in a census block group (replicating Figure A.1c). The coefficient of interest is  $\beta_1$  from the specifications,

$$(\text{Households}_{i,j,2018} - \text{Households}_{i,j,2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

$$(\text{Households}_{i,j,2018} / \text{Total Households}_{2018} - \text{Households}_{i,j,2000} / \text{Total Households}_{2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

where the share of households is calculated as the ratio of the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., Rental) to the total number of households in a given census block  $i$  in year  $t$ . Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	Number				Share			
	Occupied housing (1)	Vacant housing (2)	Owner occupied housing (3)	Rental (4)	Occupied housing (5)	Vacant housing (6)	Owner occupied housing (7)	Rental (8)
LIHTCs	65.588*** (10.721)	8.079** (3.981)	17.922** (7.626)	47.666*** (5.177)	0.277 (0.194)	-0.277 (0.194)	-0.403 (0.340)	0.403 (0.340)
Constant	71.244** (28.005)	14.602 (10.398)	10.568 (19.919)	60.675*** (13.522)	-0.790 (0.506)	0.790 (0.506)	-6.618*** (0.888)	6.618*** (0.888)
Adj. R-Square	0.121	0.012	0.017	0.241	0.004	0.004	0.002	0.002
Observations	265	265	265	265	265	265	265	265

Table A.11: **Change in number of households by income with finer income groups**

Table A.11 provides estimates of the change between 2000 and 2018 in the number of households by income as the number of LIHTCs increases in a census block group. The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$15,000-\$19,999). Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	\$0-\$10,000 (1)	\$10,000-\$14,999 (2)	\$15,000-\$19,999 (3)	\$20,000-\$24,999 (4)	\$25,000-\$29,999 (5)	\$30,000-\$34,999 (6)	\$35,000-\$39,999 (7)	\$40,000-\$44,999 (8)
LIHTCs	4.178*** (1.117)	4.352*** (1.065)	2.391** (0.973)	3.279*** (1.007)	5.486*** (1.124)	4.242*** (1.039)	3.188*** (0.981)	3.197*** (0.992)
Constant	-8.378*** (2.917)	-5.911** (2.783)	-11.074*** (2.541)	-13.511*** (2.630)	-10.578*** (2.935)	-9.479*** (2.713)	-6.846*** (2.561)	-4.574* (2.592)
Adj. R-Square	0.047	0.056	0.019	0.035	0.080	0.056	0.035	0.034
Observations	265	265	265	265	265	265	265	265

	\$45,000-\$49,999 (9)	\$50,000-\$59,999 (10)	\$60,000-\$74,999 (11)	\$75,000-\$99,999 (12)	\$100,000-\$124,999 (13)	\$125,000-\$149,999 (14)	\$150,000-more (15)
LIHTCs	3.076*** (0.903)	5.973*** (1.453)	10.615*** (1.808)	7.873*** (2.064)	4.136** (2.018)	4.316*** (1.017)	5.590** (2.247)
Constant	-2.687 (2.360)	0.874 (3.795)	15.525*** (4.722)	42.554*** (5.392)	43.341*** (5.272)	22.247*** (2.656)	39.642*** (5.868)
Adj. R-Square	0.039	0.057	0.113	0.049	0.012	0.061	0.019
Observations	265	265	265	265	265	265	265

Table A.12: **Change in number of households by income with finer income groups and indicator**

Table A.12 provides estimates of the change between 2000 and 2018 in the number of households by income as the number of LIHTCs increases in a census block group. The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000}) = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + \varepsilon_i,$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$15,000-\$24,999). The indicator variable designates treatment and control census blocks. This table defines treatment as a 1 if there is an accepted LIHTC development from 2000 to 2010 and 0 otherwise. Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	-\$10,000 (1)	\$10,000-\$14,999 (2)	\$15,000-\$19,999 (3)	\$20,000-\$24,999 (4)	\$25,000-\$29,999 (5)	\$30,000-\$34,999 (6)	\$35,000-\$39,999 (7)	\$40,000-\$44,999 (8)
LIHTCs	7.146 (91.019)	8.768 (96.286)	3.980 (72.875)	8.257 (70.075)	13.545** (68.241)	17.652*** (77.162)	14.735*** (66.772)	10.373** (70.215)
Constant	-224.018*** (54.209)	-153.661*** (57.346)	-228.629*** (43.403)	-317.761*** (41.735)	-254.590*** (40.643)	-289.363*** (45.956)	-209.562*** (39.768)	-186.930*** (41.819)
Adj. R-Square	0.005	0.002	0.000	-0.002	-0.002	0.002	-0.002	-0.002
Observations	265	265	265	265	265	265	265	265

	\$45,000-\$49,999 (9)	\$50,000-\$59,999 (10)	\$60,000-\$74,999 (11)	\$75,000-\$99,999 (12)	\$100,000-\$124,999 (13)	\$125,000-\$149,999 (14)	\$150,000- (15)
LIHTCs	7.637 (66.146)	17.297** (84.990)	35.172*** (88.093)	31.000*** (98.489)	18.377* (72.742)	6.277 (61.931)	21.033* (88.697)
Constant	-109.915*** (39.395)	-82.480 (50.619)	103.572** (52.466)	529.778*** (58.658)	533.289*** (43.324)	362.780*** (36.885)	527.491*** (52.826)
Adj. R-Square	-0.002	-0.004	0.005	-0.003	-0.003	-0.003	-0.003
Observations	265	265	265	265	265	265	265

Table A.13: **Percent change in the number of households by income**

Table A.13 provides estimates of changes in the age distribution in the census block groups as the number of LIHTCs increases. The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000}) / \text{Households}_{i,2000} \times 100 = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$15,000-\$24,999). Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	\$0-\$15,000 (1)	\$15,000-\$24,999 (2)	\$25,000-\$34,999 (3)	\$35,000-\$44,900 (4)	\$45,000-\$59,999 (5)	\$60,000-\$99,999 (6)	\$100,000-more (7)
LIHTCs	2.948*** (0.644)	1.751*** (0.441)	4.528*** (1.361)	2.117*** (0.552)	3.159*** (0.701)	7.775*** (2.166)	6.401*** (1.901)
Constant	-0.956 (1.681)	-2.448** (1.153)	-1.288 (3.555)	-0.241 (1.441)	2.106 (1.831)	16.783*** (5.657)	24.196*** (4.965)
Adj. R-Square	0.070	0.053	0.037	0.049	0.068	0.043	0.038
Observations	265	265	265	265	265	265	265

Table A.14: **Percent Change in the number of households by income with finer income groups**

Table A.14 provides estimates of changes in the age distribution in the census block groups as the number of LIHTCs increases. The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000}) / \text{Households}_{i,2000} \times 100 = \beta_0 + \beta_1 \text{Credits}_i / \sqrt{\text{Credits}} + \varepsilon_i,$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$20,000-\$24,999). Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	-\$10,000 (1)	\$10,000-\$14,999 (2)	\$15,000-\$19,999 (3)	\$20,000-\$24,999 (4)	\$25,000-\$29,999 (5)	\$30,000-\$34,999 (6)	\$35,000-\$39,999 (7)	\$40,000-\$44,999 (8)
LIHTCs	1.548*** (0.361)	1.400*** (0.353)	0.864*** (0.263)	0.888*** (0.245)	2.912*** (1.013)	1.616*** (0.384)	1.203*** (0.389)	0.914*** (0.232)
Constant	-0.973 (0.943)	0.018 (0.921)	-0.840 (0.687)	-1.608** (0.640)	-0.435 (2.647)	-0.853 (1.004)	-0.271 (1.017)	0.030 (0.605)
Adj. R-Square	0.062	0.053	0.036	0.044	0.027	0.059	0.031	0.052
Observations	265	265	265	265	265	265	265	265

	\$45,000-\$49,999 (9)	\$50,000-\$59,999 (10)	\$60,000-\$74,999 (11)	\$75,000-\$99,999 (12)	\$100,000-\$124,999 (13)	\$125,000-\$149,999 (14)	\$150,000- (15)
LIHTCs	0.628*** (0.178)	2.531*** (0.631)	4.528*** (1.345)	3.248*** (0.878)	2.718** (1.097)	1.357*** (0.340)	2.326*** (0.595)
Constant	0.260 (0.464)	1.846 (1.648)	5.867* (3.514)	10.916*** (2.292)	9.929*** (2.866)	5.288*** (0.889)	8.979*** (1.554)
Adj. R-Square	0.042	0.054	0.038	0.046	0.019	0.053	0.051
Observations	265	265	265	265	265	265	265



Table A.15: **Percent change in the number of households by income with indicator**

Table A.15 provides estimates of changes in the age distribution in the census block groups as the number of LIHTCs increases. The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000})/\text{Households}_{i,2000} \times 100 = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + \varepsilon_i,$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$15,000-\$24,999). The indicator variable designates treatment and control census blocks. This table defines treatment as a 1 if there is an accepted LIHTC development from 2000 to 2010 and 0 otherwise. Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	\$0-\$15,000 (1)	\$15,000-\$24,999 (2)	\$25,000-\$34,999 (3)	\$35,000-\$44,900 (4)	\$45,000-\$59,999 (5)	\$60,000-\$99,999 (6)	\$100,000-more (7)
LITHCs	6.495* (3.349)	3.658 (2.281)	13.646* (6.957)	6.362** (2.832)	7.067* (3.644)	23.822** (11.090)	16.959* (9.735)
Constant	-0.311 (1.995)	-1.995 (1.359)	-1.600 (4.143)	-0.380 (1.687)	2.758 (2.170)	16.108** (6.605)	24.581*** (5.798)
Adj. R-Square	0.010	0.006	0.011	0.015	0.010	0.014	0.008
Observations	265	265	265	265	265	265	265

Table A.16: **Percent change in percent in the number of households by income with finer income groups and indicator**

Table A.16 provides estimates of changes in the age distribution in the census block groups as the number of LIHTCs increases. The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000})/\text{Households}_{i,2000} \times 100 = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + \varepsilon_i,$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., \$20,000-\$24,999). The indicator variable designates treatment and control census blocks. This table defines treatment as a 1 if there is an accepted LIHTC development from 2000 to 2010 and 0 otherwise. Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	-\$10,000 (1)	\$10,000-\$14,999 (2)	\$15,000-\$19,999 (3)	\$20,000-\$24,999 (4)	\$25,000-\$29,999 (5)	\$30,000-\$34,999 (6)	\$35,000-\$39,999 (7)	\$40,000-\$44,999 (8)
LIHTCs	3.676* (1.869)	2.819 (1.823)	1.388 (1.351)	2.270* (1.259)	8.545* (5.164)	5.101** (1.977)	4.001** (1.984)	2.361** (1.194)
Constant	-0.729 (1.113)	0.418 (1.086)	-0.469 (0.805)	-1.526** (0.750)	-0.554 (3.076)	-1.046 (1.178)	-0.487 (1.182)	0.107 (0.711)
Adj. R-Square	0.011	0.005	0.000	0.008	0.007	0.021	0.011	0.011
Observations	265	265	265	265	265	265	265	265

	\$45,000-\$49,999 (9)	\$50,000-\$59,999 (10)	\$60,000-\$74,999 (11)	\$75,000-\$99,999 (12)	\$100,000-\$124,999 (13)	\$125,000-\$149,999 (14)	\$150,000- (15)
LIHTCs	0.754 (0.916)	6.313* (3.255)	14.286** (6.874)	9.536** (4.502)	9.059 (5.570)	2.398 (1.761)	5.503* (3.068)
Constant	0.621 (0.545)	2.137 (1.939)	5.327 (4.094)	10.781*** (2.681)	9.435*** (3.317)	5.794*** (1.049)	9.353*** (1.827)
Adj. R-Square	-0.001	0.010	0.012	0.013	0.006	0.003	0.008
Observations	265	265	265	265	265	265	265

Table A.17: **Change in Number of Households by Age**

Table A.17 provides estimates of changes in the age distribution in the census block groups as the number of LIHTCs increases. The coefficient of interest is  $\beta_1$  from the specification,

$$(\text{Households}_{i,2018} - \text{Households}_{i,2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

where  $\text{Households}_{i,t}$  represents the number of households in census block group  $i$  in year  $t$  in the specific category (e.g., age 18--29). Standard errors are reported in parentheses. Statistical significance is denoted by \*:  $p < 0.10$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$ .

	Age 0-17 (1)	Age 18-29 (2)	Age 30-39 (3)	Age 40-49 (4)	Age 50-59 (5)	Age 60-69 (6)	Age 70-79 (7)	Age 80+ (8)
LIHTCs	29.383** (12.543)	45.274*** (7.335)	24.840*** (6.460)	15.688*** (4.947)	11.671*** (3.261)	5.792** (2.898)	0.614 (1.892)	0.878 (1.360)
Constant	19.706 (32.762)	-15.459 (19.160)	47.780*** (16.873)	2.114 (12.922)	40.908*** (8.518)	68.791*** (7.569)	22.657*** (4.943)	10.093*** (3.552)
Adj. R-Square	0.017	0.123	0.050	0.033	0.043	0.011	-0.003	-0.002
Observations	265	265	265	265	265	265	265	265