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

Therese J. McGuire[a], Nathan Seegert[b]

[a]*Kellogg School of Management, Northwestern University, 2211 Campus Drive, Evantson, IL 60208*
[b]*Eccles School of Business,University of Utah, 1655 Campus Center Drive, Salt Lake City, UT 84108*

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 neighborhoods where developers' applications were declined. We find that income diversity declined in neighborhoods with LIHTC developments. This decline is due to a reduction in the prevalence of the lowest-income households, not the highest-income households. We also find that the program increased the number of households across the income distribution, possibly indicating an increase in neighborhood desirability.

Keywords: Low-Income Housing Tax Credit, neighborhood income diversity
JEL MSC: H42; H77; R58

1. Introduction

We ask whether neighborhoods that obtain Low-Income Housing Tax Credit developments become more income-diverse. The Low-Income Housing Tax Credit (LIHTC), passed as part of the federal Tax Reform Act of 1986, was partly motivated to reduce the spatial concentration of poverty and increase the income diversity of neighborhoods.[1] As part of the LIHTC program, states are given an allotment of credits from Congress each year, which they can award to developers to incentivize them to build mixed-income housing in higher-income areas; the LIHTC buildings

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

[1]In a U.S. Department of Housing and Urban Development report, published in February 2000, the authors state: ‘‘The impetus for these policies is the consensus among policy makers and scholars that high concentrations of very low-income households in large developments and/or neighborhoods leads to negative social and behavioral outcomes.”

must include a percentage of units reserved for tenants with incomes below a certain threshold.[2] The Low-Income Housing Tax Credit replaced the public housing programs from the 1930s to the 1980s and has become the largest housing construction subsidy in the U.S. Twenty percent of all multifamily units built since 1987 have been funded through the Low-Income Housing Tax Credit.

Our focus on the effects of the LIHTC program on neighborhood income diversity is inspired by a growing body of research that points to improvements in long-run outcomes of children growing up in more income-diverse neighborhoods. Chetty et al. (2016), Chyn (2018), Chetty and Hendren (2018), and Chyn and Katz (2021) document the positive effects of growing up in more advantaged neighborhoods on labor market outcomes and on long-run educational outcomes. Reardon et al. (2022) find a strong link between racial school segregation and academic achievement gaps that they attribute to Black and Hispanic students attending schools in high-poverty neighborhoods. If the LIHTC program were to help neighborhoods become more income-diverse, the evidence suggests long-run outcomes for children from disadvantaged backgrounds would improve.

Our work complements and extends the existing literature on the effects of the LIHTC program by investigating its effect on neighborhood income diversity. Previous research on LIHTC analyzed whether the program increased the stock of affordable housing or crowded out other affordable housing that otherwise would exist (Cummings and DiPasquale, 1999; Eriksen, 2009; Malpezzi and Vandell, 2002; Sinai and Waldfogel, 2005). The literature tends to find considerable crowd out but acknowledges that LIHTC may affect where affordable housing units are built (Eriksen and Rosenthal, 2010). More recent research focuses on changes and spillovers in neighborhoods that receive LIHTC developments. Diamond and McQuade (2019) and Baum-Snow and Marion (2009) investigate the effects of LIHTC developments on property values, median incomes, and new construction in the surrounding neighborhood.

The effects of the LIHTC program on neighborhood income diversity are ambiguous *a priori*.

[2]For a project to be eligible for the Low-Income Housing Tax Credit, it must satisfy at least one of the following income tests: tenants with an income of 50 percent or less of area median income adjusted for family size (AMI) make up at least 20 percent of the projects units, tenants with an income of 60 percent or less of AMI make up at least 40 percent of units, or the average of tenants incomes is no more than 60 percent of AMI in 40 percent of units and no units have tenants with income greater than 80 percent of AMI.

On the one hand, the program is a large subsidy aimed at impacting the type of affordable housing and where it is built. The program provides explicit guidelines to encourage the development of mixed-income buildings. States also provide additional incentives to build mixed-income developments in areas where it may increase income diversity. On the other hand, people may move in response to LIHTC developments in a way that reduces neighborhood income diversity. If LIHTC developments are awarded to high-income neighborhoods, high-income households may move out of neighborhoods that receive LIHTC developments because of NIMBYism. If LIHTC developments are awarded to low-income neighborhoods, the lowest-income households may be crowded out if the neighborhood gentrifies. Ultimately, the effect of LIHTC on neighborhood income diversity is an empirical question.

We collected data tailored to identify the average treatment effect of LIHTC on neighborhood income diversity. The administrative data include the universe of proposed LIHTC projects in a single state (Utah) from 2000 to 2020. Our data allow us to compare neighborhoods where developers' applications to build LIHTC developments were approved to observationally similar neighborhoods where developers' LIHTC applications were denied. Our data on the universe of projects enables us to estimate average treatment effects, complementing previous studies that have identified local effects near thresholds. We also explore heterogeneous effects across different types of neighborhoods. Heterogeneous treatment effects are helpful to policymakers, who can use the estimates to project effects in different contexts.

We find that income diversity falls in neighborhoods with more Low-Income Housing Tax Credit developments. Specifically, we find that the standard deviation of income decreased by 7.8% between 2000 and 2018. Our baseline estimates consider the change in standard deviation from 2000 to 2018 scaled by average income in 2000. Here, we find that this measure of income diversity decreased by 4.1%. A host of additional tests supports this finding. We find the effect is similar when we use different measures of income diversity, refine neighborhood designations as treatment and control, and include different controls for neighborhood characteristics (e.g., income, urban, racial composition).

We explore why and how income diversity falls in neighborhoods with LIHTC developments by examining the change in the share of households by income bin and the change in the number of households by income bin. We find that income diversity fell because the share of households at the bottom of the income distribution (households with income below $25,000) fell. We also find that the number of households rose across the income distribution, with the largest absolute rise being in the number of households with income between $60,000 and $99,999. Our finding of an increase in the overall population of LIHTC neighborhoods compared to control neighborhoods is notable and possibly indicates that LIHTC developments have positive spillovers for the neighborhood.

To us, these facts together tell a story in which the LIHTC program appears to be working in the sense that more households across the income distribution are being housed. However, the program does not appear to be successful at increasing neighborhood income diversity because the program appears disproportionately to benefit middle- and upper-income households.

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; Baum-Snow and Marion, 2009; Eriksen, 2009; Eriksen and Rosenthal, 2010; 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 neighborhood characteristics 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 the problems of concentrated poverty, which is oftentimes associated with other low-income housing programs. The credit compensates 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 diversity within a block group. If the program effectively achieves this goal, we should observe income diversity 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). We focus on the positive question: how does the Low-Income Housing Tax Credit change neighborhood income diversity?

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, which includes 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 block groups as treatment (those with accepted projects) and 179 as control (those with declined projects). We discuss these designations and their characteristics more below.

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. We find similar findings when we use Census tract instead of block group, which limits the potential for spillovers or violations of the stable unit treatment value assumption (SUTVA), which we consider in more detail below.

Table 1 compares Census block groups in the full, control, and treatment samples. The control sample is defined as Census block groups that had applications for Low-Income Housing Tax Credits (LIHTC) between 2000 and 2010 but did not receive any (characteristics given in column 2). The treatment sample is defined as Census block groups that were awarded Low-Income Housing Tax Credits (LIHTC) between 2000 and 2010 (characteristics given in column 3). We provide the p-values of the difference between the control and treatment samples in Column 4. 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

Table 1: Comparisons Across Census Block Groups

Block-group characteristic	Full Sample (1)	Control (2)	Treatment (3)	P-values (4)
Average income	56,238.69	45,692.61	41,934.53	0.13
Median income	50,179.75	38,920.79	35,870.95	0.07
Std income	37,475.59	33,555.36	31,198.68	0.09
75/25 Income Ratio	2.43	2.61	2.70	0.29
60/40 Income Ratio	1.39	1.44	1.46	0.56
White	0.95	0.94	0.93	0.13
Hispanic	0.09	0.12	0.15	0.14
Male	0.50	0.50	0.51	0.12
Occupied Housing	0.93	0.90	0.89	0.33
Rental Housing	0.26	0.39	0.41	0.49
Age 0-17	0.32	0.30	0.31	0.54
Age 18-29	0.22	0.24	0.23	0.52
Age 30-39	0.13	0.14	0.14	0.71
Age 40-49	0.12	0.11	0.12	0.10
Age 50-59	0.08	0.08	0.08	0.16
Number Households Less than $15,000	52.53	87.19	88.26	0.90
Number Households $15,000 to $24,999	58.90	84.07	89.88	0.40
Number Households $25,000 to $34,999	68.32	88.61	86.67	0.79
Number Households $35,000 to $44,999	69.72	79.71	68.54	0.08
Number Households $45,000 to $59,999	89.20	90.11	76.05	0.07
Number Households $60,000 to $99,999	130.06	110.61	90.42	0.08
Number Households more than $100,000	62.57	45.19	27.20	0.06
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, 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.

block groups have lower average and median incomes than the full sample. For example, the average income in the control and treated samples are $45,692 and $41,934, respectively, compared to $56,238 in the full sample. In terms of median incomes, the control sample median is $38,920, the treatment sample median is $35,870, and the full sample median is $50,179.75. Treatment and control block groups are similar across measures of income diversity reported in the third to fifth rows: the standard deviation of income, 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 treatment and control block groups is not statistically significant at the 5% level (Column 4) and is not economically significant in terms of magnitudes.

We also find that the treated and control samples are similar in race and ethnicity, housing characteristics, and age. We report in Table 1, that the share white in the control sample is 94% compared to 93% in the treatment sample. The share of Hispanics is 12% in the control sample and 15% in the treatment sample. The share of housing that is occupied (not vacant) is 90% in the control sample and 89% in the treatment sample. The share of housing that is rental housing is 39% in the control sample and 41% in the treatment sample. These differences are not economically meaningful or statistically significant at the 10% level. The treatment and control samples are also more similar to each other than to the full sample. The share of different age groups is also similar, we report share of 0-17 year olds, 18-29, 30-39, 40-49, and 50-59. Finally, we also find that the distribution of income is similar across treated and control areas. We show the number of households in the income buckets less than $15,000, $15,000 to $24,499, $25,000 to $34,999, $35,000 to $44,999, $45,000 to $59,999, $60,000 to $99,999, and above $100,000 are all similar and more similar than the full sample. The similarity of the treatment and control samples across these dimensions provides additional confidence for our estimation strategy.

We find our results for Utah may be informative elsewhere in the country. First, we show that Census block groups that received LIHTCs in Utah are like those nationally. In Table B.1, we report census block characteristics for census block groups not in Utah and Utah in the first two columns and the p-values of the differences in the third column. The values within Utah and outside of Utah are very similar. The similarity of the census block groups that received LIHTCs in Utah and outside of Utah suggests our evidence may be informative for the broader discussion of the impact of the LIHTC. We discuss Table B.1 and its implications in more detail in Appendix B. Second, we provide heterogeneous treatment effects to provide external validity following Hsieh et al. (2023). Specifically, by showing estimates in different types of Census block groups, researchers and policymakers can adjust our estimates for their context. We discuss this further in Subsection 5.3.

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 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, how they rate on the Opportunity Index, and their combined final score.[3] We, therefore, can compare block groups that developers selected as good locations and either did or did not receive developments due to the limited number of credits available.

The advantage of the variation we use is two-fold. First, developers determined both sets of block groups 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. In addition, market forces push projects to be at the threshold, making acceptance more random. Specifically, the developers we talked to suggested two important market forces. The first is that the application process is costly, leading developers only to apply if their project had a reasonable chance of being over the threshold. The second is that it is costly to increase the project's score by including more amenities. These forces push developers to submit projects that they expect are just over the threshold. The threshold is also uncertain and changes from year to year. It depends on the number and quality of projects submitted and the dollar amount of credits awarded by the federal government. The state of Utah scores each project and funds the projects from the top of the list until the credits run out.

Second, we find corroborating evidence for our identifying assumption by using the continuous score. First, we follow work by Baum-Snow and Marion (2009) and consider projects with scores closer and closer to the threshold (inner 90%, 80%, and 60% of projects). Second, we use the score as an instrumental variable. The score predicts whether a project is accepted, but not perfectly because the threshold changes based on the supply and demand of the credits. The instrument, therefore, exploits the random nature of the changes in the threshold. This alleviates some concerns about our identifying assumptions' role in our baseline estimates.

[3] 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`.

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; $\text{Credits}_i/\overline{\text{Credits}}$. We use the dollar amount of credits from 2000 to 2010 (instead of 2018) to capture the impact of potential effects that may take several years to develop. This measure considers the combined intensive and extensive margin of LIHTC by using the continuous variables the dollar amount of credits and number of units. We also consider the extensive margin using an indicator variable for a treated census block group and consider the intensive margin separately by using the continuous variables conditional on having a dollar amount (or units) greater than zero. The extensive and intensive margins are discussed further in Appendix A.

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 2000. 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 β_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 dollar amount of credits across census block groups or the similarly scaled number of Low-Income Units. 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 specifications,

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

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

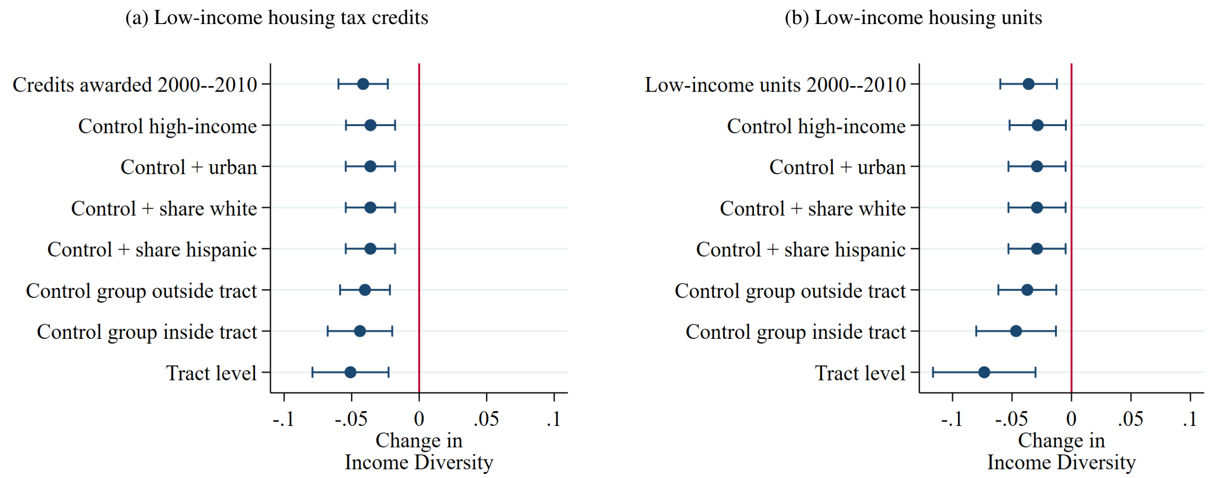
5. Results

5.1. Changes in income diversity as a result of the Low-Income Housing Tax Credit

We employ our empirical strategy to investigate how adding projects funded with Low-Income Housing Tax credits changes neighborhood income diversity. Income diversity could increase or decrease as a result of LIHTC developments. On the one hand, if LIHTC units enabled lower-income households to move into higher-income neighborhoods, then income diversity would increase. 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, if, in response to LIHTC projects, either lower-income households were less able to move into the neighborhood or displaced or if higher-income households left due to NIMBYism, then income diversity would decrease. We find that income diversity decreased due to Low-Income Housing Tax Credits. As we will show, this result appears to be partly due to the lowest-income households being less able to move into the neighborhood even as LIHTC enabled middle-income households, for which the program is targeted, to move in.

Figure 1 depicts the policy impact of LIHTCs on income diversity. We measure income diversity as the change in the standard deviation of income from 2000 to 2018, scaled by average income in 2000. As our dependent variable of interest, we use the dollar amount of credits awarded to measure the extent of the Low-Income Housing Tax Credit. This measure encapsulates the intensive and extensive margin, and we isolate these effects in Appendix A. The effects are all relative to our control sample of census block groups that had unsuccessful applications for LIHTC during this period. Figure 1 provides the estimates with 95% confidence intervals. Table 2 reports these estimates and shows that most of these estimates are statistically significant at the 1% level.

Figure 1: Changes in income diversity 2000 to 2018 as a result of LIHTC



NOTE.— Figure 1 shows that income dispersion decreased between 2000 and 2018 for census blocks with more LIHTC dollars awarded (1a) and low-income units built with LIHTC credits (1b). The horizontal axis reports the coefficient β_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 dollar amount of credits awarded in a census block from 2000 to 2010 scaled by the average amount of credits awarded during this period (Figure 1a) or the number of low-income units built between 2000 and 2010 scaled by the average number of units built during this period (Figure 1b). Controls are at the census block group level and include an indicator for above-median income (rows 2-5), urban (rows 3-5), above-median white share (rows 4-5), and above-median share Hispanic (row 5). The control group in row 6 consists of block groups outside of Census tracts with a LIHTC development. The control group in row 7 consists of block groups inside of Census tracts with a LIHTC development. In row 8, the variables are aggregated to the Census tract level, such that the unit of observation is a Census tract instead of a Census block group as in the previous estimates. These estimates are also reported in Table 2. This figure shows 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. In rows 2-5, we add controls being in neighborhoods that are above median income, urban, above-median white, and above-median Hispanic. The estimates in these rows indicate a decrease in the standard deviation of income of 3.6%, 3.6%, 3.6%, and 3.6%, all similar to the estimate in row 1 and all statistically significant at the 1% level. The inclusion of these controls should not dramatically change the estimates if the identification assumptions hold. These estimates, therefore, alleviate some concerns about differences across Census block groups, selection tied to successful applications, and other confounding factors, which could be threats to identification. Further, we implement selection on unobservable factors test following Oster (2019) and Altonji et al. (2005) and find a high level of selection is necessary for our estimates to be due to spurious correlation.[4]

We also consider potential spillovers and violations of the stable unit treatment value assumption (SUTVA). The interpretation of our results could differ if spillovers exist. On the one hand, LIHTC may result in positive spillovers for Census block groups neighboring Census block groups that receive LIHTCs. In this case, our estimates, while valid for the areas we study, may understate the changes in the broader neighborhood. On the other hand, LIHTCs may result in negative spillovers to neighboring areas due to developers choosing to place their developments in Census block groups that received LIHTC rather than in neighboring Census block groups that did not receive LIHTC. In this case, our estimates, again, while valid for the areas we study, may overstate the changes in the broader neighborhood. Another concern with spillover effects is that they could violate the stable unit treatment value assumption by affecting our control set of census block groups.

In the final three rows of Figure 1 and columns in Table 2, we test for spillovers and stable unit treatment value assumption (SUTVA) violations. In row 6, we report an estimate where we have excluded Census block groups from the control group if they are in a Census tract with a block group that received LIHTCs. This estimate minimizes the potential for spillovers to affect

[4]Specifically, we estimate a degree of selection on unobservables relative to observables (δ) of 2.19, which is well above the benchmark of 1 suggested by Oster (2019). This test relies on the assumption that the selection on unobservables is proportional to the selection on observables.

Table 2: Changes in income diversity 2000 to 2018 as a result of LIHTC

Table 2 shows that income diversity decreased between 2000 and 2018 for census blocks with more LIHTC dollars awarded (Panel A) and low-income units built with LIHTC credits (Panel B). The coefficient of interest β_1 captures the change in income dispersion (measured as the change in standard deviations from 2000 to 2018, scaled by income in 2000) due to LIHTC,

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

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

The independent variable of interest is either the dollar amount of credits awarded in a census block from 2000 to 2010 scaled by the average amount of credits awarded during this period (Panel A) or the number of low-income units built between 2000 and 2010 scaled by the average number of units built during this period (Panel B). Controls are at the census block group level and include an indicator for above-median income (rows 2-5), urban (rows 3-5), above-median white share (rows 4-5), and above-median share Hispanic (row 5). The control group in row 6 consists of block groups outside of Census tracts with a LIHTC development. The control group in row 7 consists of block groups inside Census tracts with a LIHTC development. In row 8, the variables are aggregated to the Census tract level, such that the unit of observation is a Census tract instead of a Census block group as in the previous estimates. This figure shows 95% confidence intervals. Standard errors are reported in parentheses. Statistical significance is denoted by *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Panel A dollar amount of credits awarded								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credits	-0.041***	-0.036***	-0.036***	-0.036***	-0.036***	-0.040***	-0.044***	-0.052***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.015)
Control high-income		✓	✓	✓	✓			
Control urban			✓	✓	✓			
Control share white				✓	✓			
Control share Hispanic					✓			
Control group outside tract						✓		
Control group inside tract							✓	
Unit observation	block group	block group	block group	block group	block group	block group	block group	tract
Adj. R-Square	0.067	0.104	0.100	0.100	0.100	0.072	0.089	0.092
Observations	265	265	265	265	265	226	125	105
Panel B low-income units								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Units	-0.036***	-0.028**	-0.029**	-0.029**	-0.029**	-0.037***	-0.047***	-0.068***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.017)	(0.021)
Control high-income		✓	✓	✓	✓			
Control urban			✓	✓	✓			
Control share white				✓	✓			
Control share Hispanic					✓			
Control group outside tract						✓		
Control group inside tract							✓	
Unit observation	block group	block group	block group	block group	block group	block group	block group	tract
Adj. R-Square	0.029	0.071	0.068	0.068	0.068	0.035	0.050	0.088
Observations	265	265	265	265	265	226	125	105

the control group. The estimate in this case is -4.0%, which is not statistically different from our baseline estimate of -4.1%. In row 7, we report an estimate where we have excluded Census block groups from the control group if they are outside a Census tract with a block group that received LIHTCs. This estimate allows us to capture and net out any unobservable neighborhood effects that could explain our result. The estimate in this case is -4.4%, which is not statistically different from our baseline estimate of -4.1%. Finally, in row 8, we report an estimate using a Census tract, a larger geographical area, instead of Census block group as our unit of analysis to capture spillover benefits/costs if they exist. The estimate in this case is -5.2%, which is not statistically different from our baseline estimate of -4.1%. In Section 7, we also provide estimates of a test using census tracts containing treated Census block groups as the unit of analysis but excluding the treated Census block groups from the Census tracts (see Figure 5 and Table 6). This test further examines whether treated block groups negatively or positively affect neighboring census block groups. We find little evidence of spillovers or SUTVA violations in all these tests.

We report estimates using a different measure of the extent of the LIHTC in Figure 1b. Specifically, we use the number of low-income housing units built in a Census block group scaled by the average number of units as the independent variable. We replicate the specifications in Figure 1a using this different measure of the extent of LIHTC. The estimates are negative, statistically significant, and similar to estimates using the dollar amount of credits as the independent variable. For the rest of the paper, we report estimates measuring the extent of LIHTC as the dollar amount of credits, and all estimates are qualitatively similar using the number of units.

5.2. Changes in income diversity with different measures

In this subsection, we investigate the sensitivity of our estimates to different measures of treatment and control group and income diversity. Our treatment and control groups are Census block groups where developers applied for credits and did or did not receive them, respectively. Despite consistent estimates with different control variables and spatial subsets, there could be concerns that census block groups with the best and worst proposed projects differ in unobserved ways. We test for this by refining the treatment and control groups using variation in the score.

In Figure 2 and Table 3 we report our first specifications that restrict the set of projects to those closest to the threshold. First, we consider the inner 90% of projects by excluding the 5% of projects with the highest and lowest scores. We report these estimates without controls in row 1 and with controls, which include above-median income, white share, Hispanic share, and urban in row 2. We find income diversity decreased by 3.9% and 3.4% in these specifications compared to our baseline estimate of 4.1% and 3.6%. Second, we consider the inner 80% and inner 60% by excluding the 10% and 20% of projects with the highest and lowest scores, respectively. These estimates suggest a decrease in income diversity of 4.0% and 3.4% when using the inner 80%, and 3.7% and 3.1% when using the inner 60%. These estimates are statistically significant at the 1% level, even though our observations decrease from 265 to 209. Note that we reduce the number of projects based on score, leading to a different number of Census block groups due to duplicate projects in a Census block group. The similarity between estimates with narrower windows around the threshold and our baseline estimates provides support for the comparability of our treatment and control groups.

Our second set of specifications use the evaluation score as an instrumental variable to predict the dependent variable $\text{Credits}_i/\overline{\text{Credits}}$. The IV specifications rely on the continuous nature of the evaluation score and the fact that a higher score increases the probability that a project is accepted, though not necessarily the dollar amount of credits. The second stage of the regression uses the predicted values,

$$\begin{aligned} \text{Credits}_i/\overline{\text{Credits}} &= \gamma_0 + \gamma_1 \text{score}_i + \nu_i \\ (STD_{i,2018} - STD_{i,2000})/AVE_{i,2000} &= \beta_0 + \beta_1 \widehat{\text{Credits}_i/\overline{\text{Credits}}} + \varepsilon_i, \end{aligned} \tag{2}$$

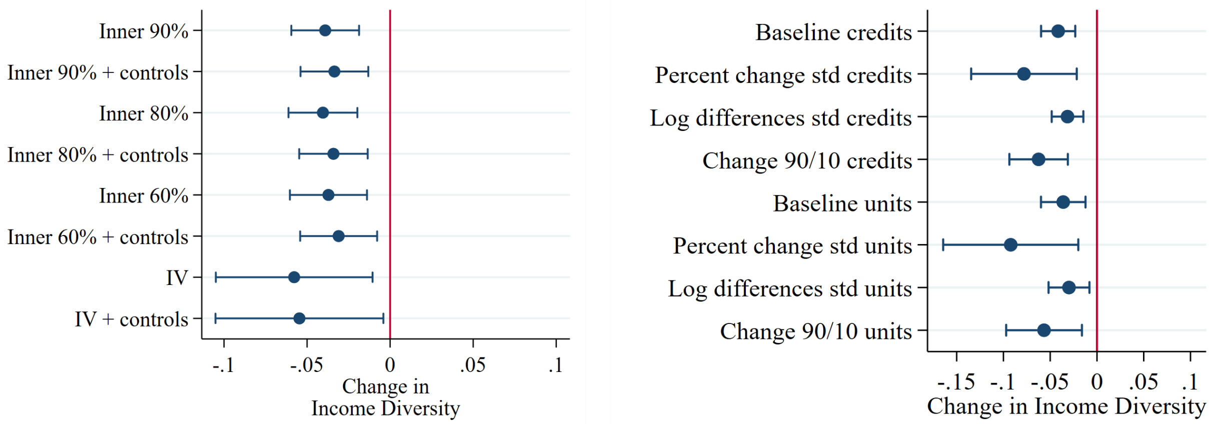
We report these two-stage least square estimates in the seventh and eighth rows of Figure 2 (columns 7 and 8 of Table 3). Using the instrumental variable specification, we find that the point estimate is larger in magnitude, -5.8% and -5.5%, with controls, and these estimates are statistically significant at the 5% level. Note, in the first-stage regression, the evaluation score strongly predicts our measure of LIHTC. The t-stat is 5.15, and the F-stat is 26.52.

The similarity in estimates using these different treatment and control groups alleviates some concerns that there could be unobserved differences between our treatment and control groups that are biasing our estimates.

Figure 2: Changes in income diversity 2000 to 2018 with different measures

(a) Different measures of treatment and control

(b) Different measures of income diversity



NOTE.— Figure 2a reports evidence using the inner 90%, 80%, and 60% of projects according to their evaluation score (rows 1-6) and instrumental variable specifications (rows 7 and 8).
The coefficient of interest β_1 captures the change in income dispersion (measured as the change in standard deviations from 2000 to 2018, scaled by income in 2000) due to LIHTC,

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

The instrumental variable specifications use the evaluation score as an instrument for the independent variables $\text{Credits}_i/\overline{\text{Credits}}$ The two-stage least square specifications are given by,

$$\text{Credits}_i/\overline{\text{Credits}} = \gamma_0 + \gamma_1 \text{score}_i + \nu_i$$

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

Figure 2b provides estimates with different measures of income dispersion, the dependent variable of interest in most of our analysis. The first four rows measure LIHTCs using the dollar amount of credits, and rows five through eight use the number of LIHTC units. The coefficient of interest is β_1 from the specifications

$$\text{Dependent Variable} = \beta_0 + \beta_1 \text{Credits}_i/\overline{\text{Credits}} + X\beta + \varepsilon_i,$$

$$\text{Dependent Variable} = \beta_0 + \beta_1 \text{Low-Income Units}_i/\overline{\text{Low-Income Units}} + X\beta + \varepsilon_i.$$

The baseline measure, shown in rows 1 and 5, is the change in standard deviation between 2018 and 2000 scaled by average income 2000 in a Census block group; $(STD_{i,2018} - STD_{i,2000})/AVE_{i,2000}$. This figure also considers the percent change in standard deviation between 2018 and 2000 (rows 2 and 6) $(STD_{i,2018} - STD_{i,2000})/STD_{i,2000}$, log differences in the standard deviation (rows 3 and 7) $log(STD_{i,2018}) - log(STD_{i,2000})$, and the change in the 90th and 10th percentiles (rows 4 and 8) $(STD_{i,90,2018}/STD_{i,10,2018}) - (STD_{i,90,2000}/STD_{i,10,2000})$. These estimates are also reported in Table 3. This figure shows 95% confidence intervals.

In Panel B of Figure 2 and Panel B of Table 2, we report estimates using different measures of income diversity. Our baseline measure of income diversity is the change in standard deviation from 2000 to 2018 of income scaled by average income in 2000. This measure captures the dispersion of income in each Census block group. We could also have measured the change in income diversity using the percent change in the standard deviation of income, the log differences in income, or changes in the difference between the 90th and 10th percentiles. All of these other measures capture income diversity in slightly different ways. Our baseline estimate scales the change in the standard deviation of income by average income in 2000 to account for differences in income across Census block groups. Alternatively, the percent change in the standard deviation of income scales the change by the standard deviation of income in 2000. Another common measure of change is the log difference, which does not scale the difference but down weights higher standard deviations to limit the effect of outliers. Finally, the difference between the 90th and 10th percentile is another way to measure dispersion while limiting outliers.

We find similar estimates with all of these different measures of income diversity. The first four estimates (rows in Figure 2b and columns in Panel B of Table 3) use credits as the independent variable. The last four estimates use units as the independent variable. The magnitudes differ across these measures because the measure is different, but the qualitative implication is the same: income diversity decreased due to LIHTCs.

We find an economically meaningful decrease in income diversity across all measures. The baseline estimate suggests that the standard deviation of income decreased by 4.1% of average income in 2000. In column 2, we report a negative 7.8% percent change in the standard deviation of income. In column 3, we report a negative 3.1% in log differences. In column 4, we report a negative 6.2% change in the 90th and 10th percentiles ratio. All of these estimates are statistically significant at the 1% level. We find similar estimates using units, instead of the dollar amount of credits, as the independent variable.

Table 3: Changes in income diversity 2000 to 2018 with different measures

Panel A of Table 3 reports evidence using the inner 90%, 80%, and 60% of projects according to their evaluation score (columns 1-6) and instrumental variable specifications (columns 7 and 8). The coefficient of interest β_1 captures the change in income dispersion (measured as the change in standard deviations from 2000 to 2018, scaled by income in 2000) due to LIHTC,

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

The instrumental variable specifications use the evaluation score as an instrument for the independent variables $\text{Credits}_i/\overline{\text{Credits}}$ The two-stage least square specifications are given by,

$$\text{Credits}_i/\overline{\text{Credits}} = \gamma_0 + \gamma_1 \text{score}_i + \nu_i$$
$$(STD_{i,2018} - STD_{i,2000})/AVE_{i,2000} = \beta_0 + \beta_1 \widehat{\text{Credits}_i/\overline{\text{Credits}}} + \varepsilon_i,$$

Panel B of Table 3 provides estimates with different measures of income dispersion, the dependent variable of interest in most of our analysis. The baseline measure, shown in columns 1 and 5, is the change in standard deviation between 2018 and 2000 scaled by average income 2000 in a Census block group. This figure also considers the percent change in standard deviation between 2018 and 2000 (columns 2 and 6), log differences in the standard deviation (columns 3 and 7), and the change in the 90th and 10th percentiles (columns 4 and 8). The first four columns measure LIHTCs using the dollar amount of credits, and columns five through eight use the number of LIHTC units. Standard errors are reported in parentheses. Statistical significance is denoted by *: p <0.10, **: p <0.05, ***:p <0.01.

Panel A: Different measures of treatment and control								
	Percent sample restrictions						Instrumental variable	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credits	-0.039***	-0.034***	-0.040***	-0.034***	-0.037***	-0.031***	-0.058**	-0.055**
	(0.010)	(0.010)	(0.011)	(0.010)	(0.012)	(0.012)	(0.024)	(0.026)
Control high-income		✓		✓		✓		✓
Control urban		✓		✓		✓		✓
Control share white		✓		✓		✓		✓
Control share Hispanic		✓		✓		✓		✓
Percent of projects used	Inner 90%	Inner 90%	Inner 80%	Inner 80%	Inner 60%	Inner 60%	100%	100%
IV estimates							✓	✓
Adj. R-Square	0.050	0.082	0.055	0.097	0.041	0.074	0.056	0.087
Observations	251	251	237	237	209	209	265	265

Panel B: Different measures of income diversity								
	Credits				Units			
	Baseline	% change STD	Log differences STD	Change 90/10	Baseline	% change STD	Log differences STD	Change 90/10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credits	-0.041***	-0.078***	-0.031***	-0.062***	-0.036***	-0.092**	-0.030***	-0.057***
	(0.009)	(0.029)	(0.009)	(0.016)	(0.012)	(0.037)	(0.011)	(0.021)
Adj. R-Square	0.067	0.024	0.045	0.052	0.029	0.020	0.023	0.024
Observations	265	265	265	265	265	265	265	265

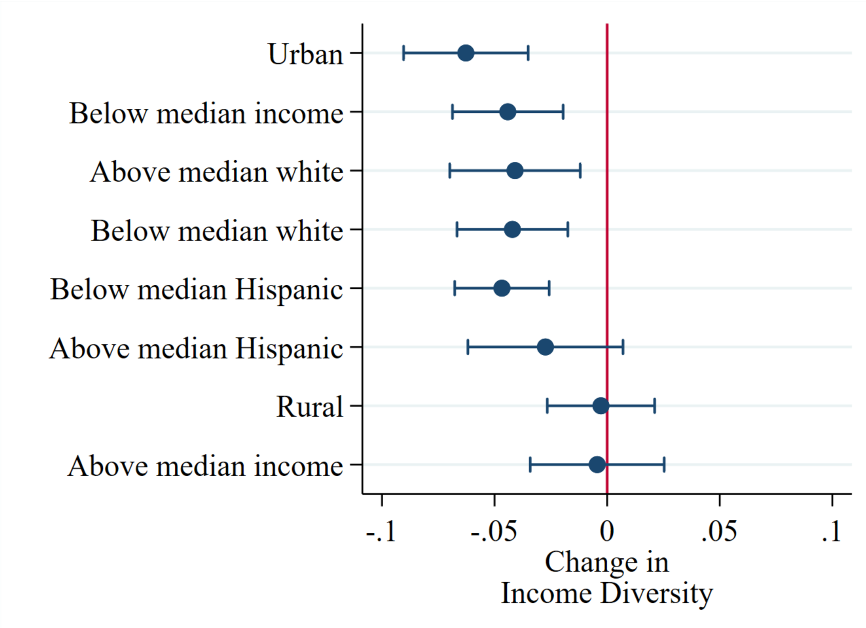
5.3. *Changes in income diversity in different neighborhoods*

In this subsection, we investigate whether the changes in income diversity we find are more or less pronounced in different types of neighborhoods. We suspect there might be different effects of the low-income housing tax credit across neighborhoods because of heterogeneous effects found in Diamond and McQuade (2019) across high- and low-income areas. Specifically, Diamond and McQuade (2019) found that house prices increased in low-income neighborhoods that received a low-income tax credit development, and house prices decreased in high-income neighborhoods with a new development. We build on that set of results to consider the income diversity within a neighborhood and consider effects in neighborhoods that are a) urban and rural, b) above and below median income, c) above and below median white, and d) above and below median Hispanic.

We find that low-income housing tax credits decrease income diversity in urban, below-median income, above- and below-median share white, and below-median Hispanic neighborhoods. We report estimates in these different neighborhoods in Figure 3 and Table 4. The top row reports that in urban Census block groups, the decrease in income dispersion is larger than in our baseline estimates (row 1 of Figure 1). Specifically, we find a decrease in the standard deviation of income from 2000 to 2018 of 6.3% of average income in urban census block groups, relative to our baseline estimate of 4.1%. In neighborhoods with below-median incomes (row 2), we find the decrease in income dispersion is slightly larger than in our baseline estimates: 4.4% relative to 4.1%. The effects with above- and below-median share white (rows 3 and 4) and below-median share Hispanic (row 5) are -4.1%, -4.2%, and -4.7%, respectively.

In contrast, we find small and statistically insignificant effects in neighborhoods with above-median share of Hispanics, rural residents, and above-median income. The effect in neighborhoods with above-median share of Hispanics (row 6) is -2.7% and is not statistically significant at the 10% level. The effect in rural and above-median income neighborhoods is -0.3% (row 7) and -0.04% (row 8), respectively, and are statistically insignificant.

Figure 3: Changes in income diversity in different neighborhoods



NOTE.— Figure 3 provides estimates replicating our baseline estimates in different subsamples of the data. The coefficient of interest β_1 captures the change in income dispersion (measured as the change in standard deviations from 2000 to 2018, scaled by income in 2000) due to LIHTC,

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

Urban neighborhoods (row 1) are defined as those in Metropolitan Statistical Areas and rural otherwise (row 7). Above- and below-median income (rows 2 and 8) are defined as relative to the median in our sample. Above- and below-median share of white (rows 3 and 4) are defined as relative to the median in our sample. Above- and below-median share of white (rows 5 and 6) are defined as relative to the median in our sample. This figure shows the 95% confidence interval. We also report these estimates in Tables 4 in the appendix.

Table 4: Changes in income diversity in different neighborhoods

Table 4 provides estimates replicating our baseline estimates in different subsamples of the data. The coefficient of interest β_1 captures the change in income dispersion (measured as the change in standard deviations from 2000 to 2018, scaled by income in 2000) due to LIHTC,

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

The first two columns restrict the sample to urban and rural Census block groups. The third and fourth columns restrict the sample to above- and below-median income Census block groups in our sample. The fifth and sixth columns restrict the sample to above- and below-median white share Census block groups in our sample. The seventh and eighth columns restrict the sample to above- and below-median Hispanic Census block groups in our sample. Standard errors are reported in parentheses. Statistical significance is denoted by *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

	Urban	Rural	Above-median income	Below-median income	Above-median white share	Below-median white share	Above-median Hispanic share	Below-median Hispanic share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credits	-0.063***	-0.003	-0.004	-0.044***	-0.041***	-0.042***	-0.027	-0.047***
	(0.014)	(0.012)	(0.015)	(0.012)	(0.015)	(0.012)	(0.017)	(0.011)
Adj. R-Square	0.142	-0.006	-0.007	0.081	0.049	0.073	0.011	0.123
Observations	117	148	132	133	132	133	132	133

We find that the effect of LIHTC developments on income diversity is more pronounced in some neighborhoods than in others. While we find that LIHTC developments result in a reduction in neighborhood income diversity regardless of the neighborhood's racial composition, both the neighborhood's median income level and the neighborhood's location in urban versus rural areas matter. If a neighborhood is in an urban area or if its average income is below the median income for the area, then LIHTC developments result in reductions in income diversity; there is no effect of LIHTC developments on income diversity if the neighborhood is in a rural area or if its average income is above the median income for the area. We speculate that LIHTC developments have a smaller impact on these neighborhoods because they are less dynamic.

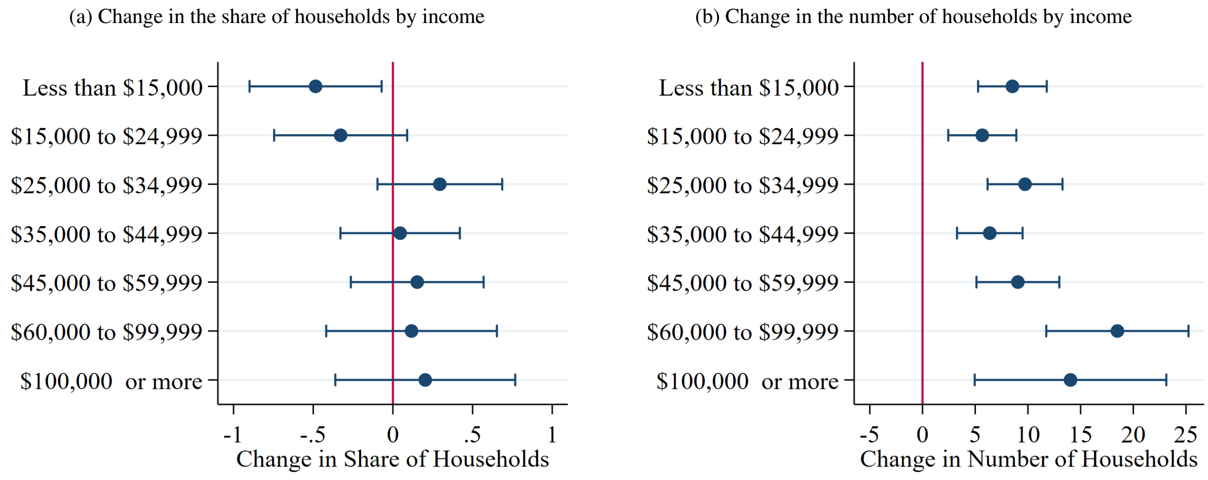
The implications of our results on heterogeneous neighborhood effects are twofold. First, when considering in which neighborhoods to approve LIHTC applications, policymakers might consider that the effect on neighborhood income diversity could differ depending on the underlying characteristics of the neighborhood. Second, following the methods in Hsieh et al. (2023), our results can be used by researchers studying neighborhoods outside Utah to gain insights into the effects of the LIHTC program in those settings.

6. Why did income diversity decrease

We investigate the forces behind the declining income diversity by considering how the share and number of households in different income bins change with more LIHTCs. We report these estimates in Figure 4 and Table 5. We find that income diversity declined in neighborhoods with LIHTCs because the prevalence of households with the lowest incomes decreased. Specifically, the share of households with income less than $15,000 had a statistically significant decrease (significant at the 5% level). We also find a decrease in the share of households with income between $15,000 and $24,999, but this is not statistically significant. All other shares of income increased but were also not statistically significant.[5]

[5] In Figure 4, we bin income into seven categories: less than $15,000, $15,000 to $24,999, $25,000 to $34,999, $35,000 to $44,999, $45,000 to $59,999, $60,000 to $99,999, and more than $100,000. The results are similar if we bin income in different ways. In Figure A.3 and Table A.5, we replicate the estimates in Figure 4a, expanding the number of income bins from seven to 15.

Figure 4: Change in share and number of households by income



Notes: Figure 4a shows the change between 2000 and 2018 in the share of households by income as the amount of low-income housing tax credits increased 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 β_1 from the regression

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

This figure shows the coefficient β_1 with 95% confidence intervals. Figure 4b 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 β_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 β_1 with 95% confidence intervals. The estimates are also reported in Table 5.

Table 5: Change in share and number of households by income

Panel A 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 4a). The coefficient of interest is β_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.
Panel B 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 4b). The coefficient of interest is β_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 *: $p<0.10$, **: $p<0.05$, ***: $p<0.01$.

Panel A Change in the share of households							
	$0-$15,000	$15,000-$24,999	$25,000-$34,999	$35,000-$44,900	$45,000-$59,999	$60,000-$99,999	$100,000-more
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LIHTCs	-0.485**	-0.328	0.295	0.046	0.153	0.117	0.203
	(0.210)	(0.212)	(0.199)	(0.190)	(0.212)	(0.272)	(0.287)
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
Panel B Change in the number of households							
	$0-$15,000	$15,000-$24,999	$25,000-$34,999	$35,000-$44,900	$45,000-$59,999	$60,000-$99,999	$100,000-more
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LIHTCs	8.530***	5.669***	9.728***	6.385***	9.049***	18.489***	14.042***
	(1.655)	(1.640)	(1.804)	(1.579)	(1.996)	(3.427)	(4.616)
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

There are three reasons why the prevalence of the lowest income households might fall: (1) the prevalence would decline if the number of such households fell, (2) if the number of such households fell faster than the number of households fell in the other income bins, or (3) if the number of such households grew more slowly than the number of households in the other income bins grew (all relative to their initial shares in the distribution). We sort through these alternatives in Figure 4b.

In Figure 4b, we examine the change in the number of households by income bin associated with greater numbers of LIHTCs. Remarkably, we find that the number of households in each income bin increased in census blocks with more LIHTCs. The largest absolute increase in numbers is in the top two income bins: households with income between $60,000 and $99,999 and households with income greater than $100,000. The fact that high-income households would register the largest increase in numbers in the LIHTC communities is a surprising finding, explained in part by the mechanics of the program, which targets affordable housing to households with up to 60% of the AMI, where the average can include households with up to 80% of the AMI ($55,200 and $73,600, respectively, in Salt Lake City in 2021). 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. The growth across the income distribution in the number of households in census blocks with LIHTC developments is consistent with a story we heard from local developers and policymakers: LIHTC developments appear to create positive externalities, making communities more attractive to households of all incomes, including higher-income households, and to developers of all housing types.

We conclude that income dispersion declined in census blocks with LIHTCs because the program spurred growth in the numbers of households across the income spectrum, and the growth in numbers of the lowest income households was small compared to the growth in numbers in higher income bins. The development of LIHTC projects appears to have reduced income diversity by reducing the share of the lowest-income households in the community. This shift occurred partly because of the relatively large growth in the number of households in the top two income bins (households with incomes greater than \$60,000). Is this a success story for the LIHTC program? Possibly because it means that the lowest-income households in the community are being exposed to a greater number of high-income households, thereby possibly reducing the spatial concentration of poor households, at least in the LITHC communities. But if the goal is to increase the income diversity of neighborhoods through increases in the shares of the lowest income households, then no, the program has not been successful.

7. Is the effect of LIHTC local, or are there spillovers?

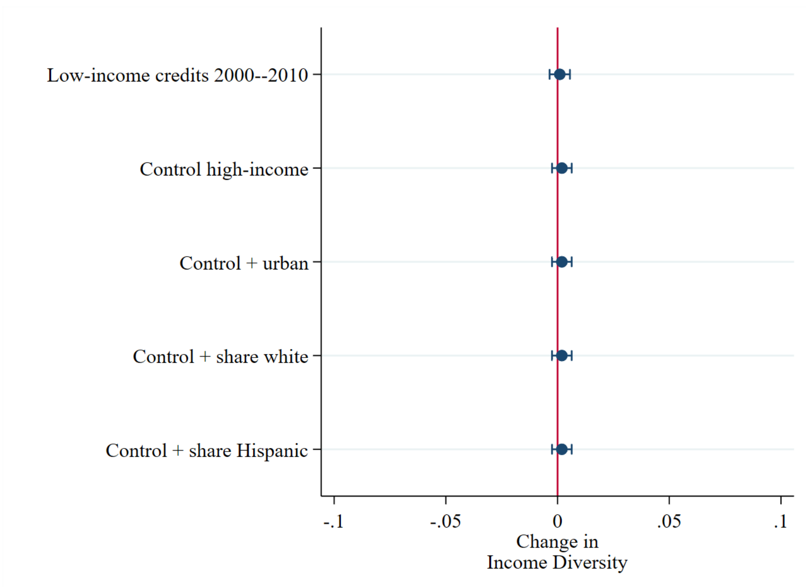
We provide one final set of tests to investigate how local the effects we find are. In particular, we are interested in whether the effects we find are local to the census block group that received the low-income housing tax credit or spill over to a greater geographic area, such as the census tract (the next largest census designation). To answer this question, we construct a new data set. First, we assign the dollar amount of LIHTCs in the Census tract to all Census block groups in the Census tract. Second, we exclude all Census block groups that received LIHTCs. Third, we use as a control group all census block groups that had applications for LIHTCs but did not receive any credits and that are in census tracts that did not receive any credits. We report these estimates in Figure 1 and Table 2.

We find the effects of LIHTCs on income diversity are very local and find no evidence of spillovers. If the effect is not local, we should expect to find similar treatment effects in the census tract as we did in the census block groups. Alternatively, if there are spillovers, we could find a positive or negative effect in the census blocks within the same census tract, depending on the nature of the spillover. In contrast, we find no effects in these census block groups. The point estimates are an order of magnitude smaller than our treatment effects (0.1% and 0.2%), positive (instead of negative in our baseline case), and statistically insignificant, with relatively small standard errors.

The implication that the effect of LIHTCs on income diversity is local is consistent with other papers (Diamond and McQuade, 2019; Eriksen and Yang, 2023) that find different local effects. This also suggests that policymakers (and other researchers) should look for the effects of LIHTCs and other similar policies in a local area.

These estimates also address concerns that other unobserved neighborhood effects could explain our estimates or that spillover effects could complicate the interpretation of our results. If this were the case, we should expect Census block groups adjacent to Census block groups that received LIHTCs but did not receive LIHTCs to have a similar treatment effect to those that did. We find no evidence of a treatment effect in those census block groups.

Figure 5: Is the effect of LIHTC local, or are there spillovers?



NOTE.— Figure 5 reports estimates of a test replicating the first five rows from Figure 1 with a different designation of treatment and control. In this test, we assign the number of credits awarded in the Census tract to each Census block group that did not receive any credits and exclude block groups that did. This increases the number of treated Census block groups such that the total observations increase from 265 in our baseline estimates (Figure 1) to 494. The independent variable of interest is the dollar amount of credits awarded in the census tract from 2000 to 2010 assigned to each census block group scaled by the average amount of credits awarded during this period. The horizontal axis reports the coefficient β_1 from the regressions,

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

where the dependent variable is the change in standard deviations from 2000 to 2018, scaled by income in 2000. Controls are at the census block group level and include an indicator for above-median income (rows 2-5), urban (rows 3-5), above-median white share (rows 4-5), and above-median share Hispanic (row 5). We also report these estimates in Table 6. This figure shows 95% confidence intervals.

Table 6: Is the effect of LIHTC local, or are there spillovers?

Table reports estimates of a test replicating the first five columns from Table 2 with a different designation of credits. In this test, we assign the number of credits awarded in the Census tract to each Census block group that did not receive any credits and exclude block groups that did. This increases the number of treated Census block groups such that the total observations increase from 265 in our baseline estimates (Table 2) to 494. The independent variable of interest is the dollar amount of credits awarded in the census tract from 2000 to 2010 assigned to each census block group scaled by the average amount of credits awarded during this period. The horizontal axis reports the coefficient β_1 from the regressions,

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

where the dependent variable is the change in standard deviations from 2000 to 2018, scaled by income in 2000. Controls are at the census block group level and include an indicator for above-median income (rows 2-5), urban (rows 3-5), above-median white share (rows 4-5), and above-median share Hispanic (row 5).
Standard errors are reported in parentheses. Statistical significance is denoted by *: $p<0.10$, **: $p<0.05$, ***:$p<0.01$.

	(1)	(2)	(3)	(4)	(5)
Credits	0.001	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Control high-income		✓	✓	✓	✓
Control urban			✓	✓	✓
Control share white				✓	✓
Control share Hispanic					✓
Adj. R-Square	-0.002	0.069	0.068	0.068	0.068
Observations	494	494	494	494	494

8. 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 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.

To understand more fully the implications for the lowest-income households, we need at least two pieces of evidence not provided by the current study: (1) how does LIHTC change the concentration of the lowest-income households in areas that do and do not receive LIHTC credits? (2) what are the spillover effects of LIHTC on the supply of affordable housing for the lowest-income households? In general, the potential unintended consequences on neighborhoods that did not receive LIHTC have been relatively unexplored.

References

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber, ''Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools,'' *Journal of Political Economy*, 2005, *113* (1), 151--184.

Baum-Snow, Nathaniel and Justin Marion, ''The Effects of Low Income Housing Tax Credit Developments on Neighborhoods,'' *Journal of Public Economics*, 2009, *93* (5-6), 654--666.

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

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

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

Chyn, Eric and Lawrence F. Katz, ''Neighborhoods Matter: Assessing the Evidence for Place Effects,'' *Journal of Economic Perspectives*, 2021, *35* (4), 197--222.

Cummings, Jean L. and Denise DiPasquale, ''The Low-Income Housing Tax Credit an Analysis of the First Ten Years,'' *Housing Policy Debate*, 1999, *10* (2), 251--307.

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

Eriksen, Michael and Guoyang Yang, ''Does Affordability Status Matter in Who Wants Multi-family Housing in Their Backyards,'' 2023. working paper.

Eriksen, Michael D., ''The Market Price of Low-Income Housing Tax Credits,'' *Journal of Urban Economics*, 2009, *66* (2), 141--149.

Eriksen, Michael D. and Stuart S. Rosenthal, ''Crowd Out Effects of Place-based Subsidized Rental Housing: New Evidence from the LIHTC Program,'' *Journal of Public Economics*, 2010, *94* (11-12), 953--966.

Freedman, Matthew and Emily G. Owens, ''Low-income Housing Development and Crime,'' *Journal of Urban Economics*, 2011, *70* (2-3), 115--131.

Green, Richard K., Stephen Malpezzi, and Kiat-Ying Seah, *Low Income Housing Tax Credit Housing Developments and Property Values*, Center for Urban Land Economics Research, the University of Wisconsin, 2002.

Hsieh, Meng Hsuan, Gerardo Sanz-Maldonado, and Joel Slemrod, ''External Validity in Empirical Public Finance,'' 2023.

Malpezzi, Stephen and Kerry Vandell, ''Does the Low-income Housing Tax Credit Increase the Supply of Housing?,'' *Journal of Housing Economics*, 2002, *11* (4), 360--380.

Manson, Steven, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles, ''IPUMS National Historical Geographic Information System: Version 15.0,'' *[dataset]. Minneapolis, MN: IPUMS.*, 2020, p. http://doi.org/10.18128/D050.V15.0.

Oster, Emily, ''Unobservable Selection and Coefficient Stability: Theory and Evidence,'' *Journal of Business & Economic Statistics*, 2019, *37* (2), 187--204.

Reardon, Sean F., Ericka S. Weathers, Erin M. Fahle, Heewon Jang, and Demetra Kalogrides, ''Is Separate Still Unequal? New Evidence on School Segregation and Racial Academic Achievement Gaps,'' *CEPA working paper* https://cepa.stanford.edu/content/separate-still-unequal-new-evidence-school-segregation-and-racial-academic-achievem 2022.

Schwartz, Amy Ellen, Ingrid Gould Ellen, Ioan Voicu, and Michael H. Schill, ''The External Effects of Place-based Subsidized Housing,'' *Regional Science and Urban Economics*, 2006, *36* (6), 679--707.

Sinai, Todd and Joel Waldfogel, ''Do Low-income Housing Subsidies Increase Housing Consumption?,'' Technical Report, National Bureau of Economic Research 2002.

Sinai, Todd and Joel Waldfogel, ''Do Low-Income Housing Subsidies Increase the Occupied Housing Stock?,'' *Journal of public Economics*, 2005, *89* (11-12), 2137--2164.

Online Appendix to "Is the Low-Income Housing Tax Credit an Effective Policy for Increasing Neighborhood Income Diversity?"

Therese McGuire Nathan Seegert[1]

Contents

List of Tables

List of Figures

[1]Contact information:
Therese McGuire Kellogg School of Management, Northwestern University, 2211 Campus Drive, Evanston, IL 60208. E-mail: therese-mcguire@northwestern.edu
Nathan Seegert Department of Finance, University of Utah, 1655 East Campus Center Drive, Salt Lake City, UT 84112, US. Office phone: +1 (801) 585-7131. E-mail: nathan.seegert@utah.edu
Disclosure:
The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Appendix A. Additional specifications

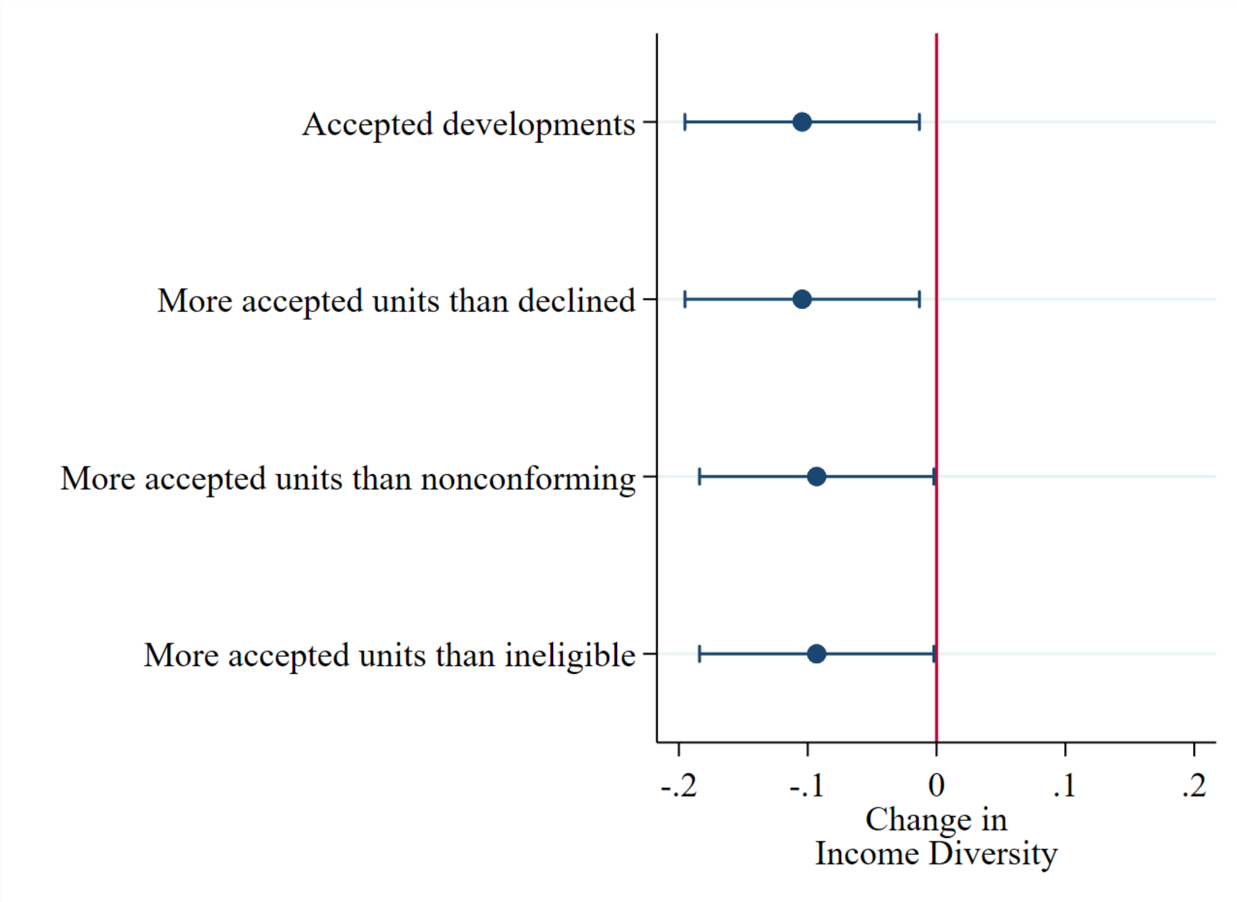
This appendix provides several additional specifications that bolster the estimates in the text and provide additional context. First, we provide estimates using different exposure to LIHTC. These estimates bolster our main results and show that our estimates are not sensitive to the choice of our independent measure. Second, we provide estimates of neighborhood demographic changes due to LIHTC. We consider whether there were meaningful changes in age distribution, the population share of black, white, Hispanic, and females, and shares of occupied, vacant, owner-occupied, and rental housing due to LIHTC. Third, we consider changes in the share of households by income groups that are finer than those reported in the text. We find similar estimates using 15 bins of income rather than the 7 in our baseline estimates. Fourth, we provide estimates separating the intensive and extensive margins. Finally, we consider dynamic effects by controlling for future LIHTC credits and running a placebo test using credits from an earlier period. Together, these estimates support the paper's main finding that LIHTC has not increased neighborhood income diversity.

Our baseline measure of exposure to LIHTC uses a continuous measure of the dollar amount of LIHTCs awarded in a Census block group. Alternatively, we could define exposure to LIHTC using an indicator variable. The coefficient of interest is β_1 from the specification

$$\text{Dependent Variable} = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + X\beta + \varepsilon_i,$$

where the indicator variable can be defined in different ways. Different definitions define different comparison groups. In the first row of Figure A.1, the specification compares Census block groups with accepted applications to those with denied applications. In the second row of Figure A.1, the specification compares Census block groups with *more* accepted applications than denied applications to those with more denied applications than accepted. In the third row of Figure A.1, the specification compares Census block groups with *more* accepted applications than nonconforming applications to those with more nonconforming applications than accepted. Finally, in the fourth row of Figure A.1, the specification compares Census block groups with *more* accepted applications than ineligible applications to those with more ineligible applications than accepted. We also report these estimates in Table A.1. The estimates are similar across all of these different definitions. The estimates are all statistically significant at the 5% level. The similarity in estimates suggests that our estimates are not particularly sensitive to any given definition.

Figure A.1: Different measures of LIHTC exposure



NOTE.— Figure A.1 provides estimates with different measures of LIHTC exposure, the independent variable of interest in most of our analysis. The first row reports estimates from a specification where treated is defined as an indicator equal to one if a Census block group has accepted applications for LIHTC and zero if a Census block has an unaccepted application and is missing for all others. The second row reports estimates from a specification where treated is defined as an indicator equal to one if a Census block group has more accepted applications for LIHTC than denied applications and zero if a Census block has more denied than accepted applications and is missing for all others. The third row reports estimates from a specification where treated is defined as an indicator equal to one if a Census block group has more accepted applications for LIHTC than nonconforming applications and zero if a Census block has more nonconforming than accepted applications and is missing for all others. The fourth row reports estimates from a specification where treated is defined as an indicator equal to one if a Census block group has more accepted applications for LIHTC than ineligible applications and zero if a Census block has more ineligible applications than accepted applications and is missing for all others. The coefficient of interest is β_1 from the specification

$$\text{Dependent Variable} = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + X\beta + \varepsilon_i,$$

This figure shows the 95% confidence interval. We also report these estimates in Tables A.1.

Table A.1: Different measures of LIHTC exposure

Table A.1 provides estimates with different measures of LIHTC exposure, the independent variable of interest in most of our analysis. The first row reports estimates from a specification where treated is defined as an indicator equal to one if a Census block group has accepted applications for LIHTC and zero if a Census block has an unaccepted application and is missing for all others. The second row reports estimates from a specification where treated is defined as an indicator equal to one if a Census block group has more accepted applications for LIHTC than denied applications and zero if a Census block has more denied than accepted applications and is missing for all others. The third row reports estimates from a specification where treated is defined as an indicator equal to one if a Census block group has more accepted applications for LIHTC than nonconforming applications and zero if a Census block has more nonconforming than accepted applications and is missing for all others. The fourth row reports estimates from a specification where treated is defined as an indicator equal to one if a Census block group has more accepted applications for LIHTC than ineligible applications and zero if a Census block has more ineligible applications than accepted applications and is missing for all others. The coefficient of interest is β_1 from the specification

$$\text{Dependent Variable} = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + X\beta + \varepsilon_i,$$

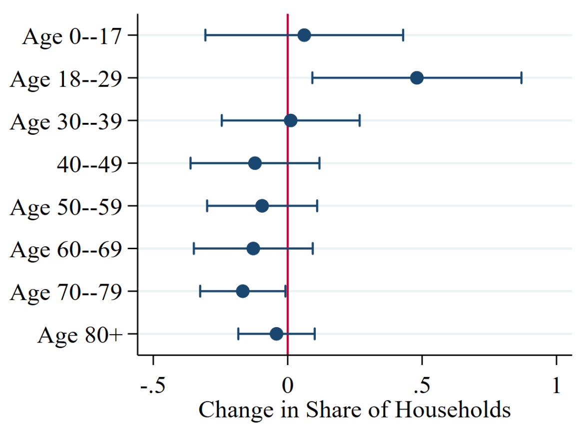
Standard errors are reported in parentheses. Statistical significance is denoted by *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

	Accepted	Accepted > Denied	Accepted > Nonconforming	Accepted > Ineligible
	(1)	(2)	(3)	(4)
$\mathbb{1}(\text{treated})_i$	-0.104**	-0.104**	-0.093**	-0.093**
	(0.046)	(0.046)	(0.046)	(0.046)
Adj. R-Square	0.015	0.015	0.011	0.011
Observations	265	265	265	265

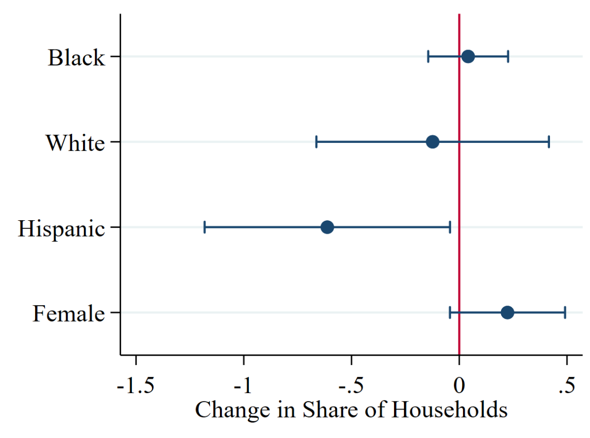
In Figure A.2 and Tables A.2, A.3, and A.4, we consider whether there are demographic changes in neighborhoods due to LIHTC projects. In Figure A.2a, we show that the share of young households, those whose household head is aged 18 to 29, increases with the number of LIHTCs in a census block group, and 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 older age groups have negative ones. In Figure A.2b, we find that the share of Hispanic households decreases with LIHTC, while the share of black, white and households headed by a female did not substantially change.

Figure A.2: Other neighborhood changes

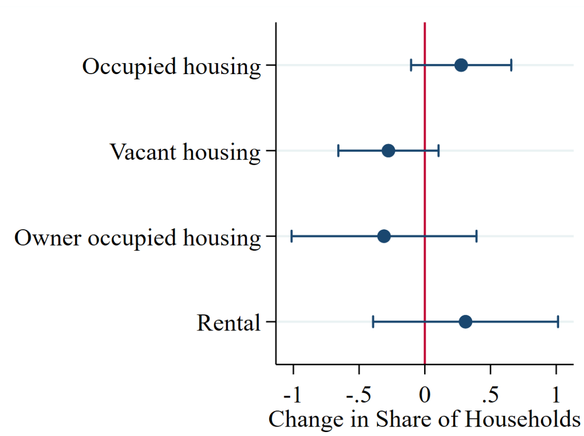
(a) Change in share of households by age



(b) Change in the share of households by demographics



(c) Change in the share of households by housing characteristics



Notes: Figures A.2a, A.2b, and A.2c provide estimates of additional changes in the census block groups as the amount of LIHTCs increase. Figure A.2a reports changes in the share of households by age categories. Figure A.2b reports changes in the share of households by demographic characteristics. Figure A.2b reports changes in the share of households by housing characteristics. All three graphs report the coefficient β_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.2--A.4 in the appendix.

In Figure A.2c, 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.

Table A.2: Change in the number and share of households by age

Table A.2 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.2a). The coefficient of interest is β_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 *: $p <0.10$, **: $p <0.05$, ***:$p <0.01$.

Panel A Number of households								
	Age 0-17	Age 18-29	Age 30-39	Age 40-49	Age 50-59	Age 60-69	Age 70-79	Age 80+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LIHTCs	29.383**	45.274***	24.840***	15.688***	11.671***	5.792**	0.614	0.878
	(12.543)	(7.335)	(6.460)	(4.947)	(3.261)	(2.898)	(1.892)	(1.360)
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
Panel B Share of households								
	Age 0-17	Age 18-29	Age 30-39	Age 40-49	Age 50-59	Age 60-69	Age 70-79	Age 80+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LIHTCs	0.062	0.481**	0.011	-0.122	-0.095	-0.128	-0.167**	-0.042
	(0.187)	(0.197)	(0.130)	(0.122)	(0.104)	(0.112)	(0.081)	(0.072)
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.3: Change in the number and share of households by demographics

Table A.3 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.2b). The coefficient of interest is β_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	White	Hispanic	Female	Black	White	Hispanic	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LIHTCs	5.370***	111.980***	16.984**	62.864***	0.041	-0.124	-0.612**	0.224
	(1.879)	(29.403)	(7.419)	(16.485)	(0.094)	(0.274)	(0.289)	(0.136)
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.4: Change in the number and share of households by housing characteristics

Table A.4 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.2c). The coefficient of interest is β_1 from the specifications,

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

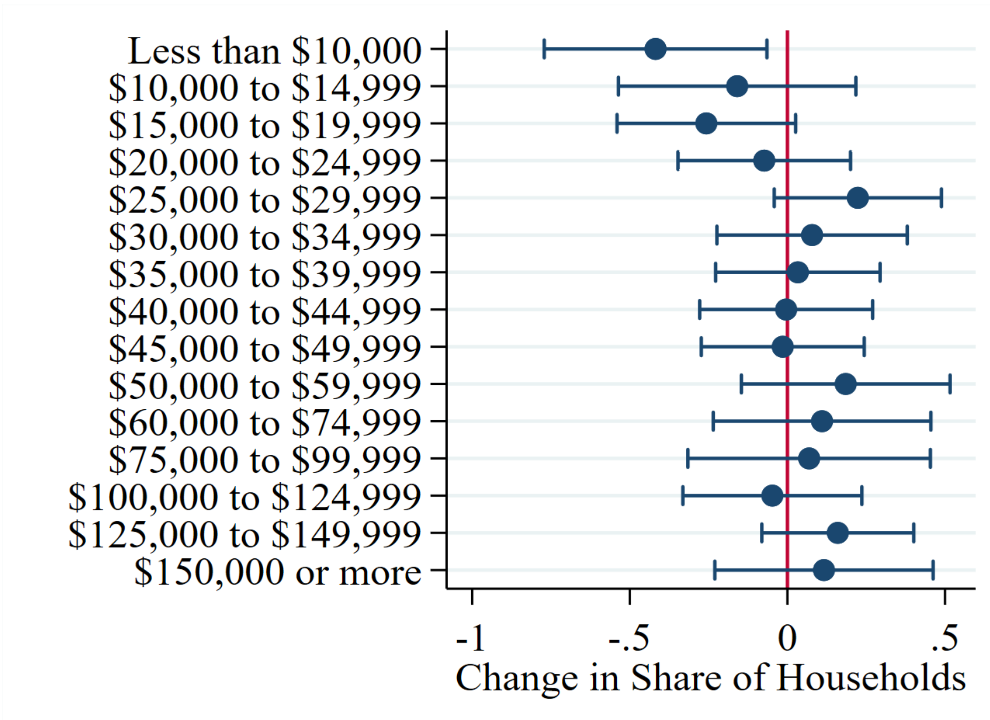
$$(\text{Households}_{i,j,2018}/\text{Total Households}_{2018} - \text{Households}_{i,j,2000}/\text{Total Households}_{2000}) = \beta_0 + \beta_1 \text{Credits}_i / \overline{\text{Credits}} + \varepsilon_i,$$

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	Vacant housing	Owner occupied housing	Rental	Occupied housing	Vacant housing	Owner occupied housing	Rental
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LIHTCs	65.588***	8.079**	17.922**	47.666***	0.277	-0.277	-0.403	0.403
	(10.721)	(3.981)	(7.626)	(5.177)	(0.194)	(0.194)	(0.340)	(0.340)
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

In Figure A.3 and Table A.5, we estimate changes in the share of households across 15 income bins rather than 7 in our baseline estimates. We find similar estimates. Specifically, the lowest income group saw a decrease in share while other groups did not experience a substantial change. These estimates bolster our results that the effects are concentrated in the lowest income bin.

Figure A.3: Change in share of households by income finer income groups



NOTE.— Figure A.3 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 4a with finer income groups. The coefficient of interest is β_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-$19,999) to the total number of households in a given census block i in year t. This figure shows the 95% confidence interval. We also report these estimates in Tables A.5 in the appendix.

Table A.5: Change in share of households by income finer income groups

Table A.5 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 4a with finer income groups. The coefficient of interest is β_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-\$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**	-0.159	-0.257*	-0.073	0.223*	0.078	0.033	-0.004
	(0.179)	(0.191)	(0.144)	(0.139)	(0.135)	(0.153)	(0.132)	(0.139)
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	0.185	0.110	0.069	-0.048	0.160	0.116
	(0.131)	(0.168)	(0.175)	(0.195)	(0.144)	(0.122)	(0.176)
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

We also separately estimate the effect of a Census block group receiving more credits (the intensive margin) and a Census block group receiving a LIHTC project (the extensive margin). We report these estimates in rows 1-4 in Figure A.4 and Table A.6. The even-numbered rows include controls for urban and above-median income, share white, and share Hispanic, indicated with a $+$.

We estimate the intensive margin by estimating the model for the subset of Census block groups with positive credits between 2000 and 2010. The first row of Figure A.4 indicates that as the number of credits awarded to a census block group increased from the average amount to double the average, the standard deviation of income decreased by 4.0% of average income in 2000. This estimate is statistically significant at the 1% level despite relying on fewer observations than our baseline estimates. We find similar estimates with controls. These estimates have several implications. First, these estimates suggest that the dollar amount of credits in a Census block group matters. Said differently, there is an important intensive margin effect. Second, the similarity of these estimates with our baseline estimate alleviates some concerns about differences between Census block groups that received credits and those that did not because these estimates did not use Census block groups that did not receive credits.

We estimate the extensive margin by estimating the model with an indicator variable as our independent variable of interest to denote Census block groups as either treated by LIHTC or not. The indicator variable $\mathbb{1}(\text{treated})_i$ is one for Census block groups that have 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.[2] The coefficient of interest is β_1 in the specification

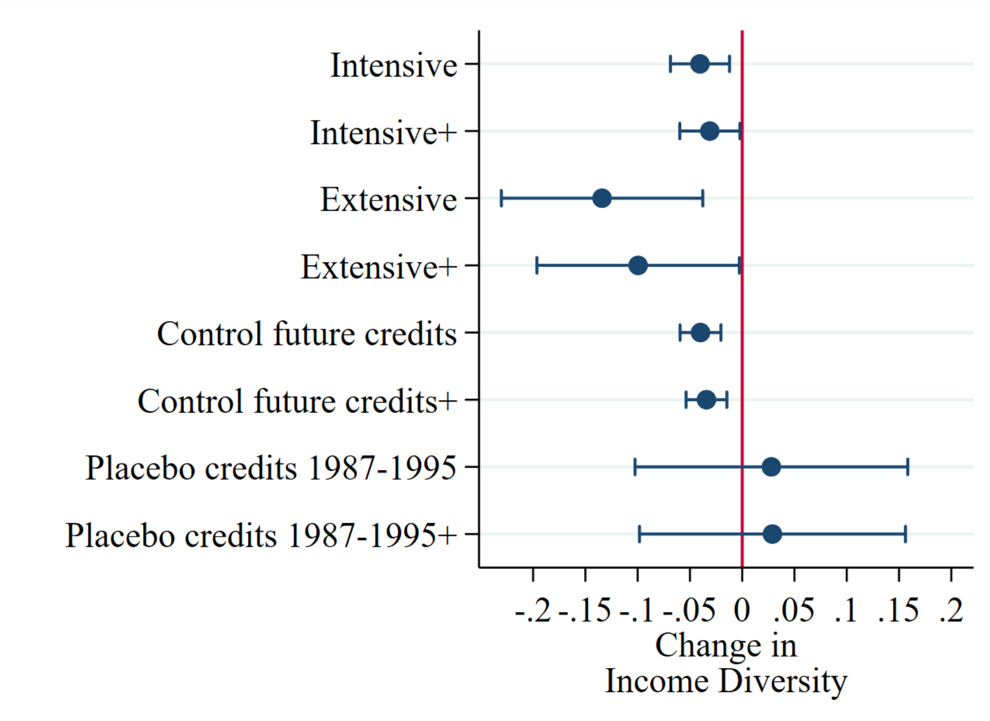
$$(STD_{i,2018} - STD_{i,2010})/AVE_{i,2000} = \beta_0 + \beta_1 \mathbb{1}(\text{treated})_i + X\beta + \varepsilon_i. \quad (.1)$$

The third row of Figure A.4 indicates that the standard deviation of income decreased by 13.4% of average income in 2000 in census block groups with an accepted LIHTC project relative to those that had declined LIHTC projects. This estimate is statistically significant at the 1% level. We find a similar effect when we control for urban and above-median income, share white, and share Hispanic. These estimates have several implications. First, these estimates suggest that the inclusion of LIHTCs in a neighborhood matters. Said differently, there is an important extensive margin effect. Second, these estimates provide corroborating evidence that relies on different identifying assumptions. The identifying assumptions with the indicator variable are 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

[2]Our estimates are similar if we define the indicator variable in different ways. In particular, in Figure A.1 and Table A.1 in the Appendix, we report estimates defining the indicator variable as one for Census block groups with more accepted LIHTCs than rejected LIHTCs or other categories. Specifically, some projects are designated as nonconforming or ineligible, and we can also use these projects. We define the indicator variable $\mathbb{1}(\text{treated})_i$ as one if the census block group has more accepted projects than declined, nonconforming, or ineligible projects and zero if the block group has more declined, nonconforming, or ineligible projects than accepted projects. Each comparison relies on slightly different randomization due to the administrative process of allocating LIHTC developments.

absence of the LIHTC development. We cannot test for the parallel trend assumption because we do not have data on the declined projects in the pre-period. Instead, we rely on placebo tests, which we report in rows 7 and 8 of Figure A.4. We find a small, positive, and statistically insignificant effect in the placebo tests, supporting the identifying assumption in this specification. These estimates provide further evidence that our findings are unlikely to be due to confounding factors or specific identifying assumptions.

Figure A.4: Intensive/extensive margin and dynamic effects



NOTE.— Figure A.4 provides estimates of the intensive margin (rows 1 and 2), extensive margin (rows 3 and 4), controls for future credits (rows 5 and 6), and two placebo tests (rows 7 and 8). The intensive margin estimates replicate row 1 in Figure 1 with the sample restriction that all census block groups have positive LIHTCs. This specification is given by

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

The extensive margin estimates replace the continuous independent variable with an indicator variable $\mathbb{1}(\text{treated})_i$.

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

The placebo estimates replace the independent variable with one using credits from 1987 to 1995,

$$(STD_{i,2018} - STD_{i,2000})/AVE_{i,2000} = \beta_0 + \beta_1 \text{Credits}_{i,1987-1995}/\overline{\text{Credits}} + X\beta + \varepsilon_i.$$

The even-numbered columns include controls for above-median income, urban, above-median share white, and above-median share Hispanic, indicated by a +. This figure shows the 95% confidence interval. We also report these estimates in Tables A.6.

Table A.6: Intensive/extensive margin and dynamic effects

Table A.6 provides estimates of the intensive margin (columns 1 and 2), extensive margin (columns 3 and 4), controls for future credits (columns 5 and 6), and two placebo tests (columns 7 and 8). The intensive margin estimates replicate row 1 in Figure 1 with the sample restriction that all Census block groups have positive LIHTCs. This specification is given by

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

The extensive margin estimates replace the continuous independent variable with an indicator variable $\mathbb{1}(\text{treated})_i$.

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

The placebo estimates replace the independent variable with one using credits from 1987 to 1995,

$$(STD_{i,2018} - STD_{i,2000})/AVE_{i,2000} = \beta_0 + \beta_1 \text{Credits}_{i,1987-1995}/\overline{\text{Credits}} + X\beta + \varepsilon_i.$$

The even-numbered columns include controls for above-median income, urban, above-median share white, and above-median share Hispanic. Standard errors are reported in parentheses. Statistical significance is denoted by *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

	Intensive		Extensive		Future credits		Placebo	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credits	-0.040***	-0.031**	-0.134***	-0.100**	-0.040***	-0.034***	0.028	0.029
	(0.014)	(0.014)	(0.049)	(0.049)	(0.010)	(0.010)	(0.066)	(0.065)
Control high-income		✓		✓		✓		✓
Control urban		✓		✓		✓		✓
Control share white		✓		✓		✓		✓
Control share Hispanic		✓		✓		✓		✓
Control future credits					✓	✓		
Adj. R-Square	0.077	0.124	0.024	0.063	0.064	0.097	-0.003	0.049
Observations	86	86	265	265	265	265	265	265

We also consider credits in different time periods to help rule out dynamic effects and different types of omitted variables. In our baseline estimates, we focus on credits awarded between 2000 and 2010 to allow for their effects to occur, but have data on credits after 2010. One concern could be that our estimates include both the effect of LIHTCs during this time period and the increased likelihood the Census block group receives additional LIHTCs in later years or other dynamic effects. To address this concern, we control for credits awarded after 2010. We find the estimates with this control are similar to our baseline estimates (-4% compared to -4.1%), suggesting that dynamic omitted variables are unlikely to explain our results.

Second, another concern could be that there are omitted variables about Census block groups that are awarded LIHTcs. To address this concern, we perform a placebo test using credits awarded since the beginning of the LIHTC program from 1987 to 1995 as our independent variable instead of credits from 2000 to 2010 in our baseline estimates. This placebo test captures the potential confounding factors of Census block groups that have accepted LIHTC projects but did not necessarily have any LIHTC projects in the relevant time period. With and without controls, we find small, positive, and statistically insignificant estimates in these placebo tests.

Appendix B. External validity

Our estimates rely on detailed administrative data from Utah. We conjecture, however, that these findings are informative about the LIHTC program more generally. We note, that while our study is local to Utah, we have the universe of LIHTCs in the state. How general our findings are, then depends on how similar the estimates from Utah are compared to other states. In comparison, other studies on the low-income housing tax credit also produce local estimates. For example, studies that use regression discontinuity around a specific threshold of type of area produce estimates local to that threshold. Similarly, studies using housing prices use select areas where that data is populated. In particular, these studies exclude all of Utah because Utah is a nondisclosure state and does not produce reliable data to third parties on housing sales. It is an open question which of these local estimates is more informative of the average treatment effect nationally as this depends on which sample is more likely to have heterogeneous treatment effects.

A benefit of using all of the low-income housing tax credits in Utah is that we can compare those areas to all other areas in the country that have received low-income housing tax credits. In Table B.1, we compare block-group characteristics of block-groups that received LIHTCs in states other than Utah consisting of 10,110 census block-groups (column 1) and Utah consisting of 86 census block-groups (column 2). In column 3, we report the p-values of the t-test of equality.

First, we compare a series of measures of income including average income, and median income, the standard deviation of income, the 75/25 income ratio, and the 60/40 income ratio. In each of these, the areas in Utah and outside Utah look similar. For example, the median income is $33,918.6 for areas that received LIHTC outside Utah and $35,870.95 for those areas in Utah. Areas outside of Utah look slightly more diverse, e.g., the 75/25 income ratio is 2.98 outside Utah and 2.70 in Utah, and this difference is not statistically significant.

Next, we compare demographic characteristics including percent white, Hispanic, and male. While Utah is not the average state demographically (it is considerably more white, for example), the areas that received LIHTCs look similar. The percent Hispanic is 15% in both non-Utah and Utah census block groups that received LIHTCs. THe percentage male is 48% in non-Utah and 51% in Utah census block groups that received LIHTCs. The percentage of white, unsurprisingly, is higher in Utah than in non-Utah areas.

Next, we compare the percentage of the census block group that is occupied (as opposed to vacant) and the percentage that is rental housing (as opposed to owner-occupied). Across both of these, the areas look similar and are not statistically significantly different. Specifically, 91% of the census block groups that received LIHTC are occupied outside of Utah compared to 89% in Utah. Similarly, 51% of the census block groups that received LIHTC outside of Utah are rental properties while 41% are in Utah.

We next compare the percentages of different age groups across areas that received LIHTC outside Utah and in Utah. Overall, Utah is a younger state than the nation, but again, conditional on receiving LIHTCs, the areas look more similar. Across these groups, the distribution is similar. The percentage of 18 to 29-year-olds is slightly lower in areas outside of Utah than in Utah (18% compared to 23% and this difference is not statistically different at the 10% level). Overall, however, the differences are quantitatively similar and generally not statistically different.

Finally, we consider the distribution of households by income. Here, we again find broad similarities. For example, the number of households with income between $35,000 and $44,999 is 70 outside of Utah and 69 in Utah. Utah does have fewer households below $15,000 and above $100,000, and these differences are statistically significant, meaning that the income distribution

Table B.1: Comparisons Across Census Block Groups Nationally

Conditional on ever having LIHTC Block-group characteristic	Non-Utah (1)	Utah (2)	P-values (3)
Average income	$41,225.25	$41,934.53	0.69
Median income	$33,918.96	$35,870.95	0.27
Std income	$34,098.80	$31,198.68	0.12
75/25 Income Ratio	2.98	2.70	0.17
60/40 Income Ratio	1.54	1.46	0.19
White	0.68	0.93	0.00
Hispanic	0.15	0.15	0.91
Male	0.48	0.51	0.22
Occupied Housing	0.91	0.89	0.12
Rental Housing	0.51	0.41	0.11
Age 0-17	0.27	0.31	0.12
Age 18-29	0.18	0.23	0.21
Age 30-39	0.15	0.14	0.15
Age 40-49	0.14	0.12	0.11
Age 50-59	0.10	0.08	0.13
Number Households Less than $15,000	143.42	88.26	0.00
Number Households $15,000 to $24,999	93.42	89.88	0.62
Number Households $25,000 to $34,999	83.86	86.67	0.69
Number Households $35,000 to $44,999	70.21	68.54	0.79
Number Households $45,000 to $59,999	78.82	76.05	0.72
Number Households $60,000 to $99,999	105.21	90.42	0.27
Number Households more than $100,000	49.86	27.20	0.02
Observations	10,110	86	10,196

NOTE.— This table compares census block groups that had a low-income housing tax credit awarded in Utah and the rest of the United States from 2000 to 2010. There are 215,472 census block groups in the United States; 10,196 had LIHTCs in this period, and 86 are in Utah. The data for characteristics come from the American Community Survey.

in areas in Utah with LIHTCs is a little less spread out than outside of Utah. Overall, the income distribution looks similar.

The similarity in the areas where LIHTC are awarded suggests that the estimates in our study may be informative for areas outside of Utah as well.