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Exploring Spatial Clustering Over Time and Spillover Effects of the Low-Income Housing Tax Credit on Neighborhood-Level Income Segregation

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Abstract
This study investigates the longitudinal and spatial patterns and spillover effects of Low-Income Housing Tax Credit (LIHTC) developments on neighborhood-level income segregation. Focusing on all MSAs in the U.S., the results show that LIHTC units have been spatially clustered in socioeconomically disadvantaged neighborhoods over time. This research also explores the spillover effects of LIHTC units on neighborhood economic status by utilizing propensity scores and weighted linear regression to address a self-selection bias of developers' decisions regarding the location of LIHTC projects. The results suggest that LIHTC developments, in general, are expected to increase the concentration of households that have lower income than the average household income of the MSA. However, in high-poverty neighborhoods, LIHTC developments yield positive spillover effects on neighborhood economic status. Moreover, providing LIHTC units in high-poverty neighborhoods where LIHTC units were built previously in the focal or any adjacent neighborhood also improves neighborhood economic status.

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Introduction

The desire to live in a safe and decent area is common across all societies. This desire often results in an avoidance of areas with highly concentrated poverty, which is associated with an array of social problems. The adverse effects of the concentration of poverty in a given geographical area are well-documented in many social science studies and include high crime rates, poor local services, lack of role models, and other social ills (Briggs 2005; Ellen and Turner 1997). Hence, concerns over such impoverished areas continue to spur a call for policies aimed at deconcentrating poverty. Nevertheless, the intensification of income segregation since the 1970s has led to a decrease in the number of mixed-income neighborhoods and a simultaneous increase in the number of both poor neighborhoods and affluent neighborhoods (Bischoff and Reardon 2014).

To address the goal of deconcentrating poverty, various housing policies have been implemented since the Housing Act of 1949 with its stated goal: "a decent home and a suitable living environment for every American family." Often, these housing policies include explicitly stated goals, but sometimes, implicit goals are sought during implementation. One of the housing programs that promote a set of goals for the production of low-income housing is the Low-Income Housing Tax Credit (LIHTC). Established as part of the Tax Reform Act of 1986, the LIHTC is the current primary tool for federal housing policy aimed at increasing the supply of affordable rental housing. The LIHTC program provides developers and investors with tax credits to reduce the costs of constructing housing units for low-income households. The LIHTC is one of the most influential programs for providing affordable rental housing in the U.S., and it also aims to revitalize communities with low incomes and a high poverty rate by constructing LIHTC units (Ellen et al. 2009). Therefore, the locational pattern and influence of LIHTC projects on the surrounding neighborhoods are important topics of inquiry.

Previous studies on LIHTC units have investigated the factors that influence LIHTC developers' decisions regarding building locations, the characteristics of the neighborhoods in which LIHTC developments are located, the clustering patterns of LIHTC units, and the impacts of the LIHTC programs on neighborhood outcomes (e.g., housing prices, poverty rates, or median income). In general, a consistent finding is that LIHTC units are disproportionately located in high-poverty and minority-concentrated neighborhoods. As a result, there is a rising concern that the concentration of LIHTC developments in disadvantaged neighborhoods may aggravate the initial concentrated poverty or residential segregation (Ellen et al. 2009; Horn and O'Regan 2011).

The primary goal of this research is to develop knowledge related to the siting patterns of LIHTC units and the impacts of LIHTC developments on income segregation. The specific research questions are: (1) What is the spatial distribution of LIHTC developments across neighborhoods over time? (2) What is the impact of LIHTC developments on neighborhood-level income segregation? (3) How do the effects vary by the initial poverty rates and the clustering pattern of LIHTC units over time in a neighborhood?

First, this study descriptively explores whether LIHTC units have been clustered in a neighborhood over time by considering LIHTC developments within the focal neighborhood and those in adjacent neighborhoods in previous periods. While extensive work has been done on the siting patterns of LIHTC developments, the temporal dimension of LIHTC developments has received less attention. Moreover, this study also descriptively explores whether LIHTC units were located in a neighborhood which had at least one adjacent neighborhood that also received LIHTC units during the same period.

Second, this study utilizes a propensity score method and weighted linear regression with the inverse probability of treatment weights to consider the self-selection process of developers' decision for choosing a certain neighborhood for their LIHTC developments. Thereby, this study examines the spillover effects of LIHTC units on neighborhood economic outcomes, and how the effects vary by the initial poverty rate and clustering pattern of LIHTC units of a neighborhood. Many scholars have mostly focused on the heterogeneous effects of LIHTC developments based on neighborhood attributes, such as poverty rates, racial composition, and median income (e.g., Diamond and McQuade 2019; Woo et al. 2016). Therefore, exploring the heterogeneous effects of LIHTC units based not only on the poverty rate but also on the clustering pattern of LIHTC units would contribute to the literature.

The remainder of this paper is organized as follows. The next section presents the background on the LIHTC program followed by a review of the literature on this program with a particular focus on its siting patterns and the spillover effects. Then, the data and analytical strategies have also been described. Thereafter, the results of the empirical analyses, comprising descriptive and multivariate analyses, have been elucidated upon. In the final section, the major findings of this study and the related policy implications are discussed.

About LIHTC

The LIHTC program is currently the primary tool for providing affordable rental housing in the United States. According to the U.S. Department of Housing and Urban Development (HUD) data, the program has contributed to the provision of about three million affordable housing units between 1987 and 2016. As established by the Tax Reform Act of 1986, this program grants federal tax credits to developers via state housing finance agencies to provide equity for developing or rehabilitating affordable rental housing.

The Internal Revenue Service (IRS) allocates a certain amount of federal tax credits to states based on their population size. In general, states designate state-level housing finance agencies that have the discretion to choose the individual awardees of the credits. The state-level agencies are also responsible for issuing yearly qualified allocation plans (QAP), which specify any priorities on proposed LIHTC projects. Each year, the agencies select the projects that conform to the QAP and have the potential to benefit the community (Lang 2012). QAPs typically include threshold requirements, credit set-aside for specific targets, scoring incentives, and other considerations. Because states can set additional criteria to pursue their housing policy goals (Ellen and Horn 2018), a great deal of variations exists between states' QAPs. Moreover, even within a state, QAPs vary over time. In Texas, extended affordability was used as a tie-breaker factor for final rankings in 2001 and earlier. During other periods, additional points were given to a project beyond 30 years of affordability. For example, projects with 40 years and above of affordability received additional 12 points in 2002 and 2003, 6 points in 2004, and 4 points from 2005 to 2012 (Loney and Way 2018).

Developers who win the tax credit competition typically sell the credits to investors to acquire capital for developing their LIHTC projects. There are two types of tax credits in the LIHTC program. A 9 percent credit is generally offered for new construction and significantly sized rehabilitation developments; it provides equity for approximately 70 percent of the present value of the qualified basis of a project. On the other hand, a 4 percent credit is offered for all other developments that are usually rehabilitation projects; it provides equity for approximately 30 percent of the qualified basis of a project. For 30 years, developers have to comply with one of two requirements: 20 percent of the units within projects should be only eligible for households whose income is less than 50 percent of the area median gross income (AMI) or 40 percent of the units within projects should only be eligible for households whose income is less than 60 percent of the AMI. However, most LIHTC developments assign the majority of their units as affordable to maximize their annual tax credits (Ellen et al. 2009, 2016). To incentivize the location of LIHTC units in high-poverty and minority-concentrated neighborhoods, developers can also increase credits by locating their projects in a “difficult to develop area (DDA)” or a “qualified census tract (QCT).”[1] After completing the 30-year requirements, it is up to the owner to decide whether the LIHTC units can be converted to market-rate rental units.

The mechanism of providing affordable housing through the LIHTC program is different from other place-based assisted housing programs initiated by the federal government which have been criticized for intensifying the concentration of poverty. While incorporating federal requirements, the LIHTC program also includes flexibility for states through the QAP as well as some flexibility for developers. That is, the credits from the LIHTC program are issued by the IRS, administrated by state and local housing agencies, and offered to profit or non-profit developers. Within the constraints of the program and local conditions, developers have discretion on the location and the characteristics of LIHTC developments. Therefore, the influence of LIHTC units on individual and neighborhood outcomes has been of major interest to both housing researchers and policymakers.

Literature Review

Siting Patterns of LIHTC Development

Many studies on the LIHTC program have attempted to answer the question of whether LIHTC units exacerbate concentrated poverty by investigating the sociodemographic attributes of neighborhoods in which LIHTC developments are constructed (Ellen et al. 2016; Horn and O’Regan 2011). The literature, in general, till date shows that LIHTC units are disproportionately located in high-poverty and minority-concentrated neighborhoods. Cummings and DiPasquale (1999) found that most LIHTC units in Los Angeles were concentrated in low-income neighborhoods with a median household income at or below 40 percent of the area median income. Other researchers found that the location patterns of LIHTC projects within the Dallas Metroplex area were associated with higher levels of poverty and minority populations as well as lower household levels of income, safety, and education (Van Zandt and Mhatre 2009). Diamond and McQuade (2019) reported that the shares of African Americans and Hispanics within the census block groups that receive LIHTC are higher than the national average. They also show a higher level of renter share and a lower level of median income in the census block groups with LIHTC developments. Other findings include the following: LIHTC developments tend to be located in dense and central areas that have more vacant units, higher poverty rates, and higher levels of minorities (Dawkins

2013) and in neighborhoods with lower median incomes and higher levels of minorities, female-headed families, and concentrated crime (Woo et al. 2016). Scholars also found that LIHTC units are more likely to be located in a QCT (Baum-Snow and Marion 2009; Dawkins 2013; Oakley 2008). Lang (2012), however, asserts that a QCT alone does not significantly affect the construction of LIHTC units because the roles of QCT and rent incentives overlap. In other words, without the QCT incentive, LIHTC units are more likely to be located in low-rent areas.

While research has identified some worrisome locational concerns with LIHTC units, other studies have found that the LIHTC program performed better than other project-based federally assisted housing programs. The LIHTC program placed a larger share of units in the suburbs and neighborhoods with less poverty than other project-based assisted housing initiatives (Freeman 2003, 2004). In his comparison of the spatial patterns of LIHTC units with those of other housing programs, such as the Housing Choice Voucher Program (HCVP), McClure (2006) found that the LIHTC program provides a greater share of housing in suburban low-poverty tracts than the HCVP. Due to the program structure, a greater variation in tenant income is also expected across LIHTC developments as compared to other housing programs. The LIHTC program not only targets extremely low-income households, but is also designed to serve a wide range of low-income households whose incomes are below 60 percent of the area median family income (AMFI). Moreover, because not all units within a LIHTC development are subsidized, many tenants of the developments come from other income strata (Ellen et al. 2016).

Another strand of studies has found that LIHTC developments are spatially clustered. Dawkins (2013) found that between 1995 and 2006, LIHTC developments were more clustered than general residential developments within the 10 largest U.S. metropolitan areas. Furthermore, when considering four metropolitan areas, one researcher found that LIHTC projects were spatially clustered at the census-tract level (Oakley 2008).

Thus, the literature, in general, suggests that LIHTC developments are likely to be located in socioeconomically disadvantaged neighborhoods and spatially clustered. Consequently, there is a growing concern that such patterns of LIHTC developments may further residential segregation (Ellen et al. 2009). In this respect, scholars have focused on whether revising a QAP can reshape the location patterns of LIHTC developments. Walter et al. (2017) found that the revision of QAP can change the spatial distribution of LIHTC developments. After the opportunity provision was included in the 2009 Texas QAP, LIHTC projects were increasingly located in neighborhoods with lower levels of poverty and higher levels of racial diversity. By focusing on 20 states, Ellen and Horn (2018) suggest that prioritizing high opportunity neighborhoods which have lower poverty rates, higher economic status, and lower minority population through QAP is associated with locating more LIHTC units in low poverty neighborhoods as well as fewer LIHTC units in predominantly minority neighborhoods. However, the authors made a cautious conclusion that it is not clear that the change of LIHTC developments' siting patterns is due to the change of developers' behavior or states' decisions.

Spillover Effects of LIHTC Units

Focusing only on the siting pattern limits the analysis to the direct effects of LIHTC units without considering the indirect or spillover effects on neighborhoods. The studies of LIHTC units' spatial patterns often assume that the concentration of the poor became worse and that the LIHTC residents have limited access to resources because the units were usually located in high-poverty neighborhoods (Van Zandt and Mhatre 2009). However, despite putting LIHTC units in disadvantaged neighborhoods can concentrate poverty in the short term as a direct effect due to the influx of low-income tenants, affordable housing units can also revitalize distressed neighborhoods by providing newly built housing in the long term (Baum-Snow and Marion 2009).

The first strand of the evidence of neighborhood-level spillovers due to LIHTC developments focused on the local housing market near LIHTC developments. Deng (2011) and Ellen et al. (2009) found a positive spillover effect of LIHTC developments on the sale prices of homes. Baum-Snow and Marion (2009) also found that new LIHTC units led to an increase in housing values in declining and stable neighborhoods. Eriksen and Rosenthal (2010) revealed the positive effect of LIHTC developments on home values of low-income areas, while a negative effect was found in high-income areas. They also found the crowd-out effects of LIHTC developments on the construction of private rental units. Woo et al. (2016) found mixed results: negative effects of LIHTC developments on sales prices of homes in Charlotte and positive effects on those in Cleveland. Diamond and McQuade (2019) found that the impact of LIHTC developments on local house prices was heterogeneous. That is, whereas LIHTC developments in low income neighborhoods increase house prices within 0.1 miles of the LIHTC developments, the opposite happens in high-income areas with lower shares of minority population.

The next strand of studies investigated the spillover effects of LIHTC developments on neighborhood economic status—such as poverty rates or median income. Researchers have found that LIHTC units are associated with decreasing poverty rates in high-poverty neighborhoods (Ellen et al.

2016). However, if LIHTC units were located in low-poverty neighborhoods (below 10% poverty rate), they were likely to increase the poverty rate in such areas. Similarly, Baum-Snow and Marion (2009) found that additional LIHTC units decrease median neighborhood income in moderately poor neighborhoods. Nevertheless, some of the research shows no evidence that building LIHTC units in high-poverty neighborhoods exacerbates poverty concentration (Ellen et al. 2009; Horn and O'Regan 2011), while others found that neighborhoods that received new LIHTC developments experienced an increase in poverty rates (Freedman and McGavock 2015). However, based on their research, Freedman and McGavock (2015) concluded that poverty increases are mainly due to the influx of LIHTC tenants rather than the spillover effects of LIHTC developments. One limitation of this study is that they did not examine whether the influences of LIHTC units are heterogeneous by poverty rates at the initial point of a period.

Some studies have explored the effect of LIHTC developments on residential segregation. Horn and O'Regan (2011) examined the relationship between LIHTC developments and racial segregation. They found that neighborhoods with a high share of minorities experienced a decrease in minority concentration after the construction of LIHTC units. Diamond and McQuade (2019) also found that LIHTC developments in an area with a high share of minorities increased the share of non-minority among new home buyers. Further, Owens (2015) examined the influence of assisted housing policies on income segregation in U.S. metropolitan areas from 1980 through the 2000s. Her results showed that a low degree of income integration at the metropolitan level is achieved through the assisted housing initiatives, including public housing, housing vouchers, Section 8 projects, LIHTC, and other smaller programs.

Research Questions

Although the practical and theoretical insights discussed above suggest spatial clustering and spillover effects of LIHTC units in neighborhoods, there are several limitations that should be addressed. Regarding the siting patterns of LIHTC units, previous studies mostly focused on LIHTC units built in specific periods, neglecting LIHTC units built before the study periods. Considering LIHTC units built in previous periods could be crucial since when housing units are once built, they usually last for at least several decades. Moreover, LIHTC units built in the adjacent neighborhoods of the focal neighborhood also have received marginal attention. In terms of the spillover effects of LIHTC units on the economic status of neighborhoods, previous studies have mostly focused on neighborhood summary measures, such as poverty rates or median income, which only consider within-tract economic attributes (Ellen et al. 2016). LIHTC units may reshape not only the receiving neighborhoods' economic attributes but also those of surrounding neighborhoods, influencing the spatial distribution of lower-income residents across neighborhoods. This research, therefore, seeks to contribute by examining the following research questions: (1) What is the spatial distribution of LIHTC developments across neighborhoods over time? (2) What are the spillover effects of LIHTC developments on neighborhood-level income segregation? (3) How do the effects vary by the initial poverty rates and clustering pattern of LIHTC units over time in a neighborhood?

The first research question addresses the limitation of existing studies that have explored the siting patterns of LIHTC developments. Specifically, this paper explores the clustering patterns of LIHTC units over the long term at the census tract level. For the long-term clustering of LIHTC units, a queen contiguity spatial weigh matrix was used to explore whether LIHTC units were constructed in a neighborhood in which LIHTC developments were already provided in the focal neighborhood or in any adjacent neighborhoods in previous periods. This study terms such neighborhoods as long-term clustered LIHTC neighborhoods (LLN). Figure 1 provides the concept of LLN. Moreover, for the contemporary concentration of LIHTC units, LIHTC units within a neighborhood as well as those constructed in any adjacent neighborhoods during the same period were also examined in the descriptive analysis.

Answering the second and third research questions expands the previous findings on the spillover effects of LIHTC developments on neighborhood-level economic outcomes. This study specifically focuses on two neighborhood economic variables, which capture the unequal distribution of income groups across neighborhoods within a Metropolitan Statistical Area (MSA). These measures can capture the spillover effects of LIHTC development on the process of residential redistribution between neighborhoods within metropolitan areas. This research also extends the analysis by considering possible heterogeneous effects of LIHTC units varied by the initial poverty rate and the long-term clustering pattern of LIHTC units in a neighborhood. To isolate the effect of LIHTC units on neighborhood economic outcomes, this study employs a propensity score method and weighted linear regression with inverse probability of treatment weights (IPTWs). This process addresses an issue that developers' decisions to choose a neighborhood for their LIHTC developmenhts are not exogenous to observed neighborhood contexts.

Data and Methodology

This research utilizes three different data sources. First, the LIHTC Database, distributed by HUD, provides location information such as census tract,

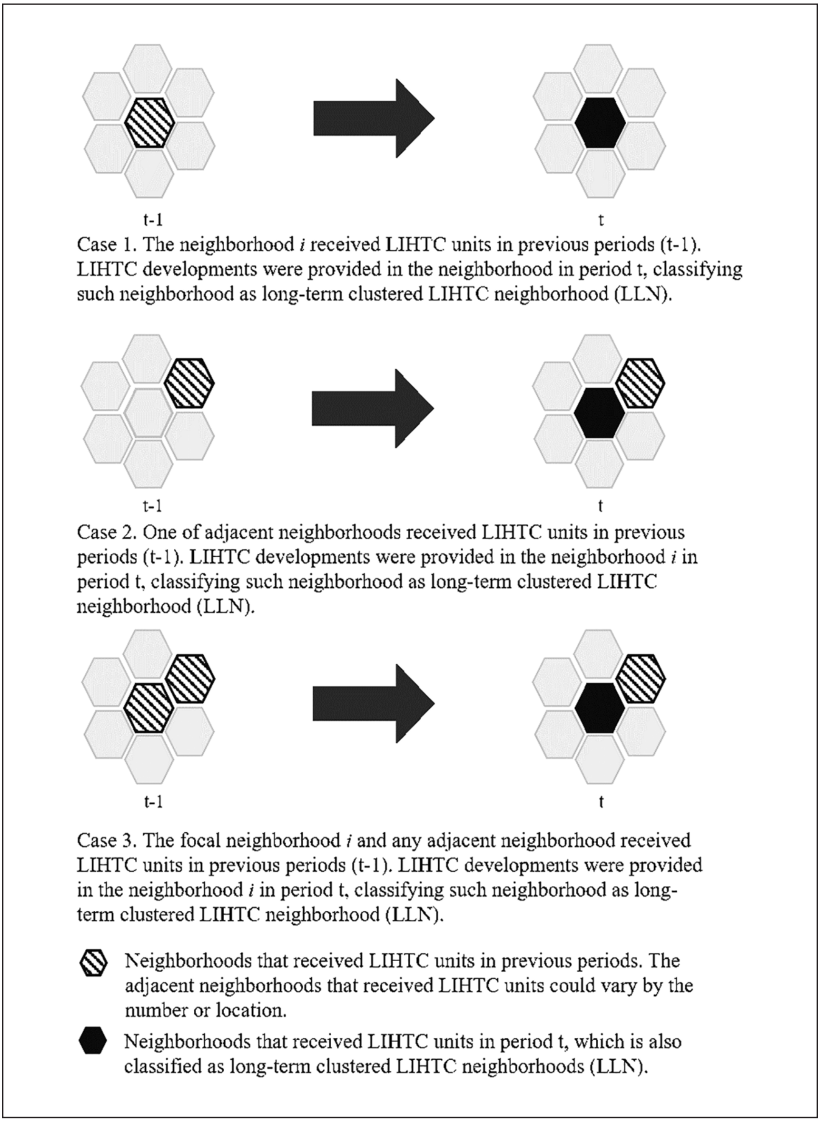

Figure 1. The concept of long-term clustered LIHTC neighborhoods (LLN).

place, county, and state code, and the number of LIHTC units and developments across the nation since 1987. For this study, the data for LIHTC units placed into service from 1987 to 2016 are used. The number of LIHTC units is aggregated to the census tract level according to the 2010 census tract boundary. In this study, census tracts—the unit of analysis—are defined as neighborhoods, and both terms are used interchangeably throughout the study. This study includes all metropolitan statistical areas (MSAs) in the analysis, which comprises of the 366 MSAs, based on the 2010 definition.

Neighborhood-level information is extracted from the Neighborhood Change Database (NCDB) from GeoLytics. NCDB contains economic and demographic data for census tracts in the U.S. for 1970, 1980, 1990, 2000, and 2010, which allows comparison of change over time since all the census tract boundaries are normalized to the 2010 tract boundaries. The normalized boundary allows the researcher to investigate the clustering patterns of LIHTC units over time in a neighborhood and their relationship to socioeconomic and racial contexts of neighborhoods. This study utilizes NCDB's census tract data from 1980, 1990, 2000, and 2010, which includes socioeconomic, demographic, and housing market information for each census tract. The census tract data of 1980, 1990, and 2000 are from the Decennial Census, while that of 2010 is from the American Community Survey five-year estimates for 2006 to 2010. The spatial boundary data from the TIGER/Lines dataset—available from the U.S. Census Bureau—is also used to create queen contiguity spatial matrices to define adjacent neighborhoods for each neighborhood.

Measuring Neighborhood-level Income Segregation

This study utilizes two measures of neighborhood economic status which consider the MSA-level contexts. Comparing the relative concentration of household income of a neighborhood to that of other neighborhoods in an MSA, the measures of this study measure neighborhood-level income segregation. The first economic measure is the local-level delta score (LDS), a decomposed component of the Delta Index (DI), one of the regional segregation indices that measure the concentration dimension of segregation.[2] Usually, concentration measures how the physical area of space in a region is unequally distributed to the population of each neighborhood (Massey and Denton 1988). By applying income data instead of physical area information, Bailey et al. (2017) used the decomposed element of DI to measure how the total income in an MSA is concentrated in neighborhoods with considering the neighborhood's population size. By definition, LDS, in this study, calculates the difference between the share of the total household income of a neighborhood to that of the MSA and the share of the household number of a neighborhood to that of the MSA. The formula for LDS is as follows:

$$LDS_{mi} = \frac{k_{mi}}{K_m} - \frac{h_{mi}}{H_m} \tag{1}$$

In the formula, k_{mi} refers to the aggregate household income of neighborhood i within MSA m, K_m refers to the aggregate household income of MSA m, h_{mi} represents the number of households in neighborhood i within MSA m, and H_m denotes the number of households in MSA m. Each LDS_{mi} implies the income segregation level of a neighborhood in an MSA. A positive value of LDS indicates that the average household income of a neighborhood is higher than the MSA-level average household income, and vice versa for a negative value of LDS. The value of LDS close to zero indicates that the neighborhood is not concentrated either by higher- or lower-income groups, on average. An increase in LDS_{mi}, which refers to neighborhood ascent, implies that a neighborhood experienced an influx of higher-income residents, whose income is higher than the MSA-level average household income or an out-migration of lower-income residents, whose income is lower than MSA-level average household income, and vice versa for a decrease in LDS_{mi}.

The second measure of neighborhood-level income segregation is the location quotient (LQ) of neighborhood household income. LQ is often used to explore the industrial specialization of a local area (i.e., county) by considering a broader geographical unit (i.e., state). In this study, LQ is defined as the share of neighborhood's aggregate household income divided by the share of neighborhood's household number in an MSA. LQ indicates the relative concentration of household income in a neighborhood compared to other neighborhoods within an MSA. The formula for LQ of a neighborhood i within an MSA m is as follows:

$$LQ_{mi} = \frac{\frac{k_{mi}}{K_m}}{\frac{h_{mi}}{H_m}} = \frac{\frac{k_{mi}}{h_{mi}}}{\frac{K_m}{H_m}} \tag{2}$$

The value of LQ with higher than one indicates a relative concentration of household income in neighborhood i compared to other neighborhoods within an MSA. If LQ equals to one, the neighborhood has the equal share of household income compared to other neighborhoods within the MSA, on average. The value of LQ with lower than one indicates that household income in neighborhood i is less concentrated compared to other neighborhoods within the MSA. LQ_{mi} increases when there is an in-movement of a household whose relative income to the MSA average income is higher than the relative neighborhood average income to the MSA average income or an out-migration of a household whose relative income to the MSA average income is lower than the relative neighborhood average income to the MSA average income, and vice versa for a decrease in LQ.

While LDS and LQ seem very similar to each other, the change of LDS and LQ is generated by different mechanisms. To be specific, LDS changes when a household has income different from MSA-level average income. On the other hand, LQ changes when a household has income different from a neighborhood's relative income. Therefore, while the change of LDS suggests a more general trend, the change of LQ is related to specific neighborhood-level contexts. Therefore, this difference would capture the nuanced impact of LIHTC developments on neighborhood-level income segregation.

Propensity Score Method

One methodological challenge of studying the spillover effects of LIHTC units on neighborhoods is controlling the self-selection of developers to build the units in specific areas. It is possible that developers choose a certain place for their projects because the particular neighborhood had specific socioeconomic attributes, such as a decrease in poverty rate or minority population. This indicates that the decision on the location of LIHTC developments by a developer is not random (Diamond and McQuade 2019; Ellen et al. 2009, 2016; Freedman and McGavock 2015). If the decision of developers to construct LIHTC units in a certain neighborhood is related to observed baseline covariates that also impact neighborhood-level income segregation, the effect of LIHTC units on the neighborhood economic status would be biased. Therefore, utilizing ordinary least squares (OLS) regressions cannot address the endogeneity issue that the location of LIHTC developments is associated with observed baseline socioeconomic contexts of a neighborhood (Freedman and McGavock 2015). Many studies have attempted to address this self-selection issue by employing advanced regression analyses or by utilizing a fine-grained data set (e.g., Baum-Snow and Marion 2009; Diamond and McQuade 2019; Ellen et al. 2009, 2016; Freedman and McGavock 2015; Owens 2016).

This paper employs weighted linear regression models by utilizing the inverse probability of treatment weights (IPTWs) created by a propensity score method to address the selection bias of developers. A propensity score model is often used in observational studies to create control (or untreated) groups that have similar observed characteristics to the treated groups, which makes the sample of a study similar to that in randomized studies. The propensity score refers to the conditional probability of a subject receiving the treatment given on the observed baseline covariates ($e = \mathrm{P}(Z = 1|\mathbf{X})$, where *e* denotes the propensity score, Z is a binary variable indicating whether an observation is assigned to the treatment group, and **X** is a vector of measured covariates) (Rosenbaum and Rubin 1983). Since observational studies cannot randomly assign the treatment (constructing LIHTC units in a neighborhood in this study), weighting the sample by the inverse probability of treatment, first introduced by Rosenbaum (1987), would generate a modified sample (pseudo-randomized sample) in which the systemic difference of observed baseline covariates between treatment and control groups is addressed (Austin 2011).[3] Theoretically, there will be no relationship between observed neighborhoods' attributes and the treatment assignment (receiving LIHTC units in this study) in the pseudo-randomized sample.

In this study, creating IPTWs based on propensity scores involves two steps. First, a propensity score for each subject is calculated. To be specific, the conditional probability of receiving LIHTC developments based on the observed baseline covariates for each neighborhood is estimated by utilizing a logistic regression, which is one of the most widely used methods to estimate a propensity score (Austin 2011). This study utilizes variables that have been empirically demonstrated by other scholars for predicting the location of LIHTC developments. This study also assumes that developers' decisions on the location of their LIHTC developments in a certain period are influenced not only by neighborhood socioeconomic conditions at the initial point of a decade but also by the tendencies of neighborhood socioeconomic conditions during the previous decade (see equation (3)).

$$D_{LIHTC(t+1d)-(t)} = \alpha + \beta X_t + \gamma Tendency_{(t)-(t-1d)} + Pre_{LIHTC(t)-(t-1)} + \mu I_i + \varepsilon \tag{3}$$

where t represents a single year and d indicates one decade, $D\_LIHTC_{(t+1d)-(t)}$ refers to a dummy variable which represents whether LIHTC developments occurred in a neighborhood within a decade (from *t* to *t+1*), X_t indicates a vector of neighborhood-level sociodemographic and housing market variables at t which is the initial year of a decade. Sociodemographic variables include population in the natural log, the percentages of African American, Hispanic, people who earned bachelor degree or above (highly educated population), and a composite index of the socioeconomically disadvantaged variables—which comprises of poverty rates, unemployment rates, high school dropout rates, the percentages of female-headed families with children, and the population who receive assistance—that are highly correlated to each other. The index is calculated by the sum of standardized score, calculated for each MSA, of each variable. Higher scores of the index indicate more socioeconomically disadvantaged contexts of a neighborhood. Housing market variables include homeownership rates, vacancy rates, and the percentage of middle-aged housing (21–30 years). $Tendency_{(t)-(t-1d)}$ refers to the change of X_t during the previous decade (from *t–1* to *t*), and $Pre\_LIHTC_{(t)-(t-1d)}$ includes two dummy variables of whether LIHTC developments occurred in neighborhood *i* or any adjacent neighborhoods of neighborhood *i* in the previous decade (from *t–1* to *t*). MSA-level fixed effects (I_i) are also considered.

Second, after estimating propensity scores for each neighborhood (e = P(Z = 1|**X**)), a weight for each observation is calculated by inversing the estimated probability of treatment. IPTW for a subject *i* is defined as $w_i = \frac{Z_i}{e_i} - \frac{(1-Z_i)}{1-e_i}$, where Z_i refers to a binary variable indicating whether the subject *i* received the treatment and e_i is the subject *i*'s propensity score (Austin 2011). In other words, the weight for each neighborhood is the inverse of the probability of whether the neighborhood *i* actually received LIHTC developments or not. Therefore, neighborhoods with $D\_LIHTC_{(t+1d)-(t)}$ = 1 (treated subjects, Z=1) receive weight $1/e_i$ and neighborhoods with $D\_LIHTC_{(t+1d)-(t)}$ = 0 (untreated subjects, Z=0) receive weight $1/(1–e_i)$. One potential issue of using IPTW is a very large weight created by treated observation's very low propensity score or untreated observation's propensity score close to one. An alternative approach is stabilizing the weights (Cole and Hernán 2008; Robins et al. 2000). Instead of simply inversing, the stabilized weights are derived by dividing the baseline probability of treatment by the conditional probability of treatment given the observed covariates. Therefore, the stabilized weights of treated observations are P(Z = 1)/P(Z = 1|**X**) and P(Z = 1)/(1–P(Z = 1|**X**)) for control observations.[4]

To present how the mean differences of the observed covariates between treated group and control group have been addressed by applying IPTWs, this study compares the standardized differences between treated and control groups in unweighted and weighted samples, respectively.[5] Figure 2 shows that the mean differences of observed baseline covariates between treated and control groups have been significantly reduced in the weighted samples (which used unstabilized weights and stabilized weights). After comparing the absolute standardized differences, this study decides to use unstabilized weights for regression analysis.[6]

Multivariate Analysis

To investigate the influence of LIHTC units on neighborhood-level income segregation, weighted linear regression models, which utilize the weights created from the propensity score method, are analyzed for the periods of 1990 to 2000 and 2000 to 2010, separately. As found in the descriptive

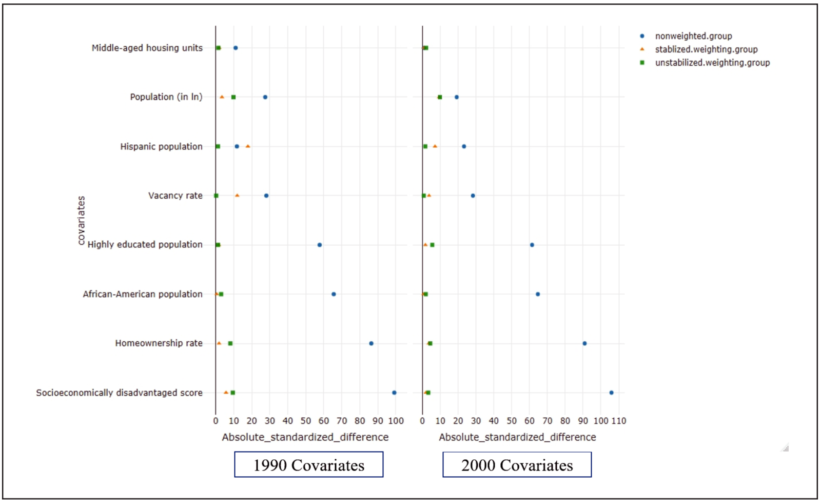

Figure 2. Absolute standardized differences in unweighted and weighted samples.
Note. The unit of the absolute standardized difference is percentage (%).

analysis, which will be discussed in the following section, the longitudinal clustering pattern of LIHTC units has significantly increased in the 2000s from the 1990s, indicating potential heterogeneous effects of LIHTC units on neighborhood-level income segregation between the two decades. For example, during the 1990s when LIHTC units were not familiar to non-poor residents, it was possible that a negative stigma on assisted housing resulted in neighborhood economic decline. However, in the 2000s when a huge amount of LIHTC units was provided during the 1990s, the stigma may have been reduced for residents, and LIHTC units may act as a redevelopment tool.

The change of LDS and the change of LQ for each decade are used for the dependent variable to estimate how LIHTC units influence neighborhood economic change. Periods of 1987 to 1990 and 2010 to 2016 were not included because three and six years may not be sufficient to study the long-term effects of LIHTC units on neighborhoods. The data sets of LIHTC units built from 1990 to 1999 and from 2000 to 2009 are linked to the change of LDS and of LQ between 1990 to 2000 and 2000 to 2010, respectively.

The LIHTC variables include a dummy variable which indicates whether a neighborhood *i* received a LIHTC development during a decade and the numbers of LIHTC units, measured in 100 units, in adjacent neighborhoods of neighborhood *i*.[7] Several control variables, which are also used in the propensity model, based on the literature that explores neighborhood economic change are also included (Ellen and O'Regan 2008). The first group of control variables includes housing market variables such as vacancy rates, homeownership rates, and the percentage of middle-aged housing. The second group of control variables comprises sociodemographic variables, such as population size (in natural log), socioeconomically disadvantaged score, the percentages of Hispanic, African American, and the population who earned bachelor's degrees or above. The empirical model of this analysis is specified as follows:

$$\Delta NECON_{(t+1d)-(t),i} = \alpha + \beta LIHTC_i + \gamma C_{t,i} + NECON_{t,i} + \Delta NECON_{(t)-(t-1d),i} + \mu I_i + \varepsilon \tag{4}$$

where $\Delta NECON_{(t+1d)-t}$ is the decadal change of the two neighborhood-level income segregation measures (LDS and LQ) of neighborhood i, $LIHTC_i$ refers to the two LIHTC variables in neighborhood i, C_{it} is a vector of control variables including the housing market variables and sociodemographic variables in neighborhood i at t. The level of the LDS and LQ in the initial year of a decade ($NECON_{t,i}$) and the change of those in the previous decade ($\Delta NECON_{(t)-(t-1d),i}$) were included to consider the mean reversion and serial correlation, respectively. MSA-level fixed effects (I_i) are also considered. Since this study analyses a weighted sample, the robust standard error is used (Joffe et al. 2004).

This research also performs regression analysis for several subsamples. First, to understand the general effects of LIHTC units on neighborhood-level income segregation, all neighborhoods within MSAs are analyzed in one model. Second, to update the findings from previous literature which focused on poverty rate (e.g., Ellen et al. 2009, 2016; Freedman and McGavock 2015), the research divides the whole sample into non-poor and poor neighborhoods, following the 30 percent poverty rate standard from previous literature (Ellen et al. 2016). Third, this research also extracts a subsample of poor neighborhoods (poverty rates over 30%) in which LIHTC units were already provided in the focal neighborhood or any adjacent neighborhoods in previous periods. One of the results of the descriptive analysis, presented in the following section (see Table 3 later), suggests that the longitudinal clustering pattern of LIHTC units was likely to occur in socioeconomically disadvantaged neighborhoods compared to non-LIHTC neighborhoods and all LIHTC neighborhoods. Therefore, this research analyzes this subsample to examine whether providing LIHTC units in a poor neighborhood in which LIHTC units have been provided in the focal neighborhood or in any adjacent neighborhoods may further poor concentration. Table 1 presents the descriptive statistics of variables used in the descriptive and multivariate analyses.

Table 1. Descriptive Statistics of Variables.

	All neighborhoods		Non-poor neighborhoods		Poor neighborhoods		Poor neighborhoods (which received LIHTC units in the focal or any adjacent neighborhoods previously)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Dependent variable								
Change of LDS between (t+1d)-t (× 100)	0.0001	0.17	−0.002	0.18	0.02	0.15	0.02	0.13
Change of LQ between (t+1d)-t	−0.018	0.19	−0.02	0.19	0.01	0.16	−0.002	0.15
LIHTC variables								
The presence of LIHTC development (Yes =1, No =0) between (t+1d)-t	0.12	0.32	0.10	0.30	0.31	0.46	0.39	0.49
Total LIHTC units built in adjacent neighborhoods between (t+1d)-t (100 units)	0.92	1.89	0.83	1.72	1.89	2.98	2.53	3.48
Control variables								
Change of LDS between t-(t-1d) (× 100)	0.0011	0.28	0.0002	0.29	0.01	0.22	0.02	0.17
LDS at t (× 100)	0.0007	0.31	0.02	0.31	−0.21	0.34	−0.19	0.31
Change of LQ between t-(t-1d)	−0.011	0.25	−0.01	0.27	−0.05	0.16	−0.03	0.14
LQ at t	1.00	0.42	1.05	0.41	0.52	0.16	0.51	0.15
Ln (population)	8.05	0.67	8.06	0.67	8.00	0.65	8.02	0.53
% African American	13.30	23.34	10.28	19.06	43.69	36.80	49.01	36.65
% Hispanic	11.60	18.95	10.12	16.44	26.50	31.80	23.55	30.25
Socioeconomically disadvantaged score[1]	−0.003	4.11	−0.82	3.01	8.22	4.61	8.65	4.17
Homeownership rates	63.89	23.87	66.98	21.82	32.90	21.37	30.91	19.66
% bachelors or above degree	23.81	16.71	25.05	16.44	11.36	14.25	11.01	12.86
Vacancy rate	7.57	7.412	7.10	7.12	12.35	8.55	12.60	7.53
% of middle-age housing (20–30 years old in 1990)	16.77	12.326	17.02	12.40	14.40	11.29	13.42	10.23

Note. [1]The Cronbach's Alpha of this variable for 1990 and 2000 were 0.87 and 0.89, respectively.

Descriptive Results on the Siting Patterns of LIHTC Units

Table 2 presents the longitudinal and spatial distribution of LIHTC units constructed in neighborhoods within 366 MSAs between 1987 and 1989, the 1990s, the 2000s, and between 2010 and 2016. About 87 percent of all LIHTC units were constructed in 366 U.S. MSAs from 1987 to 2016. To explore a more detailed picture of the pattern of LIHTC units, this study divides the 366 MSAs into three groups based on their 2010 population sizes: Large-sized MSAs in which population exceeds 1,000,000, Middle-sized MSAs in which population ranges from 250,000 to equal or below 1,000,000, and small-sized MSAs in which population is below 250,000 in 2010, following the approach from Wang et al. (2012).

The results indicate that LIHTC developments are geographically concentrated in specific areas, especially for larger MSAs. First, LIHTC units were likely to locate in a small portion of neighborhoods within each MSA. In general, LIHTC units were located in less than 20 percent of neighborhoods within each MSA. Table 2 also shows that the percentage of neighborhoods that received LIHTC units are higher in small-sized MSAs than middle- and large-sized MSAs during all periods, probably due to the small number of total neighborhoods in the small-sized MSAs.

Second, more than 50 percent of the LIHTC neighborhoods in an MSA with new LIHTC units built in a certain period had at least one adjacent neighborhood that also held LIHTC construction during the 1990s and 2000s, on average. More than 60 percent of LIHTC neighborhoods in the large-sized MSAs, on average, had at least one immediately adjacent neighborhood that also received LIHTC development during the 1990s and 2000s, while the percentages for middle- and small-sized MSAs were about 50 percent. Interestingly, Table 2 also reveals that while having continuously increased until the 2000s, the contemporary spatial pattern of LIHTC construction has decreased after 2010 in most MSAs.

Third, the descriptive results also show that LIHTC units have been increasingly located in neighborhoods in which, or in any adjacent neighborhoods, LIHTC units had already existed. While the longitudinally clustered pattern was relatively marginal during the 1990s, possibly due to the small amount of LIHTC units provided between 1987 and 1989, such clustering pattern rapidly increased during the 2000s and 2010s (2010–2016). For example, about 70 percent and 90 percent of LIHTC units built in an MSA, on average, were classified as LLN during the 2000s and 2010s, respectively. The three findings suggest that LIHTC units were likely to cluster in particular areas over time. The result of this study also reveals that considering the clustering patterns of LIHTC units presents variations of the siting patterns between decades.

Table 2. LIHTC Units' Distribution by the Size of Metropolitan Areas.

	All metropolitan areas (366)				Large-sized MSAs (51)			
	1987–1989	1990–1999	2000–2009	2010–2016	1987–1989	1990–1999	2000–2009	2010–2016
Total LIHTC units	74,127	623,343	1,093,542	540,317	45,564	415,941	762,343	387,570
Mean % of tracts that have LIHTC units	5.41%	13.22%	15.17%	9.52%	3.81%	11.03%	13.57%	7.61%
Within tracts that have LIHTC units (LIHTC neighborhoods)								
Mean % of tracts which receive LIHTC units and in its adjacent tracts during the decade – (1)	30.72%	52.02%	59.27%	41.54%	41.12%	61.45%	69.10%	46.64%
Mean % of LIHTC units constructed in the (1) LIHTC neighborhoods	27.94%	52.74%	61.54%	43.36%	33.72%	60.36%	70.81%	49.29%
Mean % of tracts which had LIHTC units previously or in any adjacent neighborhoods (LLN)		23.25%	69.22%	88.05%		28.66%	70.61%	87.53%
Mean % of LIHTC units constructed in the LLN		21.63%	70.52%	89.18%		25.33%	71.11%	88.64%
	Middle-sized MSAs (133)				Small-sized MSAs (178)			
	1987–1989	1990–1999	2000–2009	2010–2016	1987–1989	1990–1999	2000–2009	2010–2016
Total LIHTC units	21,223	146,260	228,754	106,763	7,340	61,142	102,445	45,984
Mean % of tracts that have LIHTC units	4.86%	11.78%	13.77%	8.75%	6.74%	14.74%	16.63%	10.67%
Within tracts that have LIHTC units (LIHTC neighborhoods)								
Mean % of tracts which receive LIHTC units and in its adjacent tracts during the decade – (1)	31.25%	52.21%	58.53%	41.77%	24.95%	48.49%	56.79%	38.99%
Mean % of LIHTC units constructed in the (1) LIHTC neighborhoods	28.79%	52.93%	60.49%	43.29%	24.07%	49.88%	59.45%	40.52%
Mean % of tracts which had LIHTC units previously or in any adjacent neighborhoods (LLN)		25.57%	67.53%	86.15%		19.56%	70.38%	90.89%
Mean % of LIHTC units constructed in the LLN		24.68%	68.88%	87.84%		17.94%	71.82%	91.63%

Table 3. Weighted Mean of Socioeconomic and Housing Attributes by Neighborhood Types.

	Census tracts without LIHTC units	All census tracts with LIHTC units	Lont-term clustered LIHTC neighborhoods (LLN)
2000–2010 (variables in 2000)			
% non-Hispanic White	70.65%	47.12%	43.48%
% African American	11.66%	29.18%	32.89%
% Hispanic	11.85%	17.57%	17.96%
% female-headed households	22.77%	36.86%	39.97%
% households with public assistance	6.95%	13.77%	15.38%
High school dropout rate	9.12%	14.26%	15.31%
Unemployment rate	5.48%	9.51%	10.55%
Poverty rate	10.81%	20.87%	23.31%
Socioeconomically disadvantaged score	−0.59	3.50	4.43
% bachelors or above degree	27.29%	19.34%	18.25%
Homeownership rate	66.02%	46.95%	42.92%
N	51,964	7,814	5,504
1990–2000 (variables in 1990)			
% non-Hispanic White	76.15%	61.01%	53.65%
% African American	10.77%	23.57%	32.16%
% Hispanic	8.79%	11.42%	9.89%
% female-headed households	21.69%	32.08%	38.89%
% households with public assistance	6.75%	11.21%	15.97%
High school dropout rate	10.99%	15.44%	17.04%
Unemployment rate	6.19%	8.59%	11.08%
Poverty rate	11.30%	19.10%	25.51%
Socioeconomically disadvantaged score	−0.32	2.62	4.93
% bachelors or above degree	22.74%	18.76%	15.97%
Homeownership rate	63.23%	47.40%	40.48%
N	53,187	6,368	1,921

In Table 3, the baseline neighborhood characteristics (1990 for 1990–1999 and 2000 for 2000–2009) of three types of neighborhoods are compared: neighborhoods without LIHTC units, neighborhoods with LIHTC units (LIHTC neighborhoods), and LLN.[8] Interestingly enough, the results show that the disadvantaged contexts were generally higher in the following order: LLN, all LIHTC neighborhoods, and neighborhoods without LIHTC units.

To be specific, the percentage of African American, female-headed households with children, and populations who received assistance as well as high school dropout rates, poverty rates, unemployment rates, and socioeconomically disadvantaged score were higher in the following order: LLN, all LIHTC neighborhoods, and neighborhoods without LIHTC units.

The proportion of the non-Hispanic White, of those who had the equivalent of or above a bachelor's degree, and homeownership rate, which are characteristics typically associated with the affluent, are higher in the following order: neighborhoods without LIHTC units, all LIHTC neighborhoods, and LLN. These results, in general, indicate that the spatial concentration of LIHTC units has occurred in the socioeconomically disadvantaged neighborhoods. Therefore, investigating the spillover effects of LIHTC units on neighborhood outcomes while considering the siting patterns of LIHTC units would be crucial for policy development.

The Spillover Effects of LIHTC Units on Neighborhood-Level Income Segregation

Tables 4 and 5 show the findings of the weighted regression analyses of neighborhood-level income segregation for the periods of 1990 to 2000 and 2000 to 2010, respectively. The results, in general, show that the spillover effects of LIHTC units exist. First, most of the LDS models of the 1990s and 2000s (seven of eight models) in this study show statistically significant, negative coefficients of the presence of LIHTC developments in the focal neighborhood. The results indicate that neighborhoods which received LIHTC developments experienced an influx of lower-income households, whose income is lower than MSA-level average income, and/or an outflow of higher-income households, whose income is higher than MSA-level average income for both 1990s and 2000s. For the non-poor neighborhoods, the negative signs of the LIHTC dummy variable in the LDS and LQ models for both periods suggest that the income of households moving to LIHTC neighborhoods is less than the average income of both MSA and the relative income of the focal neighborhood to MSA.[9]

The LQ models in the 1990s and 2000s, however, show a different story in poor neighborhoods in terms of the presence of LIHTC developments, as shown in Tables 4 and 5. In the 1990s model, the coefficient of the LIHTC dummy variable is not statistically significant, while presenting a positive sign. This result suggests that the LIHTC developments do not induce poorer households than the existing households in the poor neighborhoods. It is also possible that the incomes of households who moved out were not higher than the average income of the neighborhood. In the 2000s model, the LIHTC dummy variable shows a positive and statistically significant coefficient. This result suggests positive spillover effects that the presence of LIHTC units in a neighborhood leads to an influx of households whose income is higher than the average household income of the neighborhood. It is also possible that the original households who have a lower income than the average household income of the neighborhood had to leave the neighborhood, possibly because of the increased housing price in poor neighborhoods due to the LIHTC developments, as suggested by the literature. To explain the phenomena in detail, let's rewrite the formula of LDS and LQ, equations (1) and (2) as follows.

$$LDS_{mi} = \left[\frac{k_{mi}}{K_m} - \frac{h_{mi}}{H_m} \right] = \frac{1}{K_m} \left[k_{mi} - \frac{K_m}{H_m} h_{mi} \right] \tag{5}$$

$$LQ_{mi} = \frac{\dfrac{k_{mi}}{K_m}}{\dfrac{h_{mi}}{H_m}} = \frac{H_m}{K_m} * \frac{k_{mi}}{h_{mi}} \tag{6}$$

In order to focus on the movements within an MSA, let us assume the total household income, *Km*, and the number of households, *Hm*, of an MSA are constant. The change of LDS, then, will be negative if the income of households that move into the neighborhood *i* is less than the average income of the MSA, $\frac{H_m}{K_m}$. The change of LQ, however, could be positive if the income of moving-in households is greater than that of the average income of the focal neighborhood, $\frac{k_{mi}}{h_{mi}}$, even though the household income is lower than the MSA-level average income.

Second, LIHTC developments in poor neighborhoods which already received LIHTC developments in the focal (poor) neighborhoods or any adjacent neighborhoods in the previous periods, seem to have different effects on neighborhood economic status between the two periods. To be specific, in the 1990 to 2000 period, the coefficients of the LIHTC dummy variable are not statistically significant, while presenting a negative sign for both LDS and LQ models. During the 2000 to 2010 period, however, the effect of the LIHTC developments, shown in the LQ model, presents a positive and statistically significant coefficient. To be specific, receiving LIHTC developments in the neighborhood induced an inflow (outflow) of households whose income is higher (lower) than the average household

Table 4. 1990 to 2000 Models.

	All neighborhoods		Non-poor neighborhoods		Poor neighborhoods		Poor neighborhoods (which received LIHTC units in the focal or any adjacent neighborhoods previously)	
	LDS model	LQ model	LDS model	LQ model	LDS model	LQ model	LDS model	LQ model
LIHTC variables								
The presence of LIHTC development in the 1990s (Yes = 1, No = 0)	−0.0157*** (0.0021)	−0.0276*** (0.0043)	−0.0156*** (0.0021)	−0.0305*** (0.0046)	−0.0093** (0.0035)	0.0037 (0.0047)	−0.0050 (0.0037)	−0.0017 (0.0057)
LIHTC units built in the 1990s within adjacent tracts (100 units)	0.0008 (0.0005)	−3.10E-05 (0.0013)	0.0008 (0.0006)	−0.0007 (0.0015)	0.0003 (0.0004)	0.0050* (0.0022)	−0.0007 (0.0004)	−0.0010 (0.0014)
Control variables								
LDS (LQ) in 1990	−0.1739*** (0.0123)	−0.2232*** (0.0257)	−0.1636*** (0.0138)	−0.2078*** (0.0253)	−0.3129*** (0.0272)	−0.6827*** (0.1590)	−0.3271*** (0.0703)	−0.3901*** (0.0497)
LDS (LQ) change between 1980–1990	0.0288*** (0.0068)	0.0064 (0.0107)	0.0261*** (0.0066)	0.0077 (0.0110)	0.0569** (0.0219)	0.0344 (0.0275)	0.0420 (0.0351)	0.0538 (0.0376)
Ln (population)	−0.0140*** (0.0022)	−0.0245*** (0.0055)	−0.0163*** (0.0024)	−0.0220*** (0.0057)	−0.0043 (0.0030)	−0.0145 (0.0079)	−0.0062 (0.0083)	−0.0284* (0.0117)
% African American	0.0002*** (4.36E-05)	−0.0009*** (0.0001)	8.58E-05 (5.01E-05)	−0.0011*** (0.0001)	5.29E-05 (5.83E-05)	−0.0006*** (0.0002)	6.81E-05 (7.11E-05)	−0.0003 (0.0002)
% Hispanic	0.0001 (7.35E-05)	−0.0002 (0.0001)	0.0003*** (7.04E-05)	−0.0004** (0.0002)	−2.19E-05 (7.54E-05)	0.0005* (0.0002)	0.0001 (0.0001)	7.98E-05 (0.0002)
Socioeconomically disadvantaged score	0.0002 (0.0005)	0.0069*** (0.0011)	−0.0015* (0.0007)	0.0044*** (0.0013)	0.0007* (0.0003)	0.0009 (0.0018)	0.0022*** (0.0005)	0.0032 (0.0017)
Homeownership rates	0.0006*** (6.42E-05)	0.0019*** (0.0002)	0.0007*** (5.49E-05)	0.0016*** (0.0002)	0.0001 (9.17E-05)	0.0030*** (0.0006)	0.0005* (0.0002)	0.0020*** (0.0005)
% bachelors or above degree	2.60E-05 (0.0001)	0.0034*** (0.0004)	3.55E-05 (0.0001)	0.0029*** (0.0004)	−0.0003 (0.0002)	0.0037*** (0.0006)	0.0002 (0.0004)	0.0020** (0.0007)
Vacancy rate	0.0004* (0.0002)	0.0011*** (0.0003)	0.0008*** (0.0002)	−0.0007* (0.0003)	0.0001 (0.0002)	−0.0019* (0.0009)	0.0004 (0.0003)	−0.0017** (0.0006)
% of middle-age housing (20–30 years old in 1990)	−0.0008*** (8.63E-05)	−0.0010*** (0.0002)	−0.0008*** (7.28E-05)	−0.0012*** (0.0002)	7.66E-05 (0.0001)	−0.0005 (0.0003)	−0.0001 (0.0002)	−0.0009** (0.0003)
Intercept	0.0936*** (0.0193)	0.2952*** (0.0417)	0.1017*** (0.0221)	0.3727*** (0.0414)	0.0282 (0.0253)	0.5463*** (0.1091)	0.0170 (0.0636)	0.5515*** (0.0925)
MSA-fixed effects	Yes							
N	56,390		51,113		5,274		1,721	

Note. Robust standard errors in parentheses.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 5. 2000 to 2010 Models.

	All neighborhoods		Non-poor neighborhoods		Poor neighborhoods		Poor neighborhoods (which received LIHTC units in the focal or any adjacent neighborhoods previously)	
	LDS model	LQ model	LDS model	LQ model	LDS model	LQ model	LDS model	LQ model
LIHTC variables								
The presence of LIHTC development in the 2000s (Yes = 1, No = 0)	−0.0198*** (0.0027)	−0.0359*** (0.0035)	−0.0201*** (0.0029)	−0.0407*** (0.0039)	−0.0102** (0.0035)	0.0161*** (0.0045)	−0.0069* (0.0033)	0.0155*** (0.0047)
LIHTC units built in the 2000s within adjacent tracts (100 units)	0.0007* (0.0003)	0.0039*** (0.0007)	0.0006 (0.0004)	0.0037*** (0.0009)	0.0003 (0.0002)	0.0018* (0.0007)	0.0002 (0.0002)	0.0009 (0.0008)
Control variables								
LDS (LQ) in 2000	−0.0394** (0.0149)	−0.1866*** (0.0205)	−0.0369* (0.0165)	−0.1750*** (0.0219)	−0.2704*** (0.0358)	−0.4198*** (0.0449)	−0.2582*** (0.0440)	−0.3988*** (0.0433)
LDS (LQ) change during between 1990–2000	−0.0222 (0.0212)	−0.0969*** (0.0164)	−0.0113 (0.0225)	−0.0883*** (0.0175)	−0.1176** (0.0440)	−0.0822* (0.0346)	−0.1317* (0.0574)	−0.1149** (0.0378)
Ln (population)	−0.0127*** (0.0029)	−0.0026 (0.0056)	−0.0138*** (0.0030)	−0.0019 (0.0059)	0.0017 (0.0045)	−0.0083 (0.0087)	0.0008 (0.0046)	−0.0089 (0.0098)
% African American	−0.0002** (5.52E-05)	−0.0010*** (7.22E-05)	−0.0001* (6.29E-05)	−0.0011*** (7.97E-05)	−0.0001* (7.09E-05)	−0.0003* (0.0001)	−0.0001 (7.42E-05)	−0.0004** (0.0002)
% Hispanic	3.44E-06 (6.90E-05)	−0.0006*** (0.0001)	0.0001* (8.26E-05)	−0.0006*** (0.0001)	−4.37E-05 (8.85E-05)	−0.0002 (0.0002)	−0.0001 (8.45E-05)	−0.0003 (0.0002)
Socioeconomically disadvantaged score	0.0005 (0.0005)	0.0005 (0.0010)	−0.0017 (0.0008)	−0.0022 (0.0012)	0.0020*** (0.0005)	−0.0041* (0.0019)	0.0015** (0.0005)	−0.0022 (0.0014)
Homeownership rates	0.0005*** (6.18E-05)	0.0010*** (0.0001)	0.0006*** (6.53E-05)	0.0006*** (0.0001)	1.66E-05 (0.0001)	0.0006* (0.0002)	−0.0002 (0.0001)	0.0004 (0.0003)
% bachelors or above degree	0.0003** (9.50E-05)	0.0027*** (0.0002)	0.0002 (0.0001)	0.0024*** (0.0003)	0.0006** (0.0002)	0.0029*** (0.0004)	0.0005* (0.0002)	0.0033*** (0.0005)
Vacancy rate	0.0008*** (0.0002)	0.0012*** (0.0003)	0.0008*** (0.0003)	0.0009** (0.0004)	0.0009** (0.0003)	0.0021*** (0.0006)	0.0005 (0.0003)	0.0021** (0.0007)
% of middle-age housing (20–30 years old in 2000)	−0.0004*** (8.47E-05)	−0.0010*** (0.0001)	−0.0004*** (8.91E-05)	−0.0010*** (0.0001)	−0.0005** (0.0002)	−0.0012*** (0.0003)	−0.0008*** (0.0002)	−0.0016*** (0.0003)
Intercept	0.0822*** (0.0233)	0.1297** (0.0498)	0.0850*** (0.0246)	0.1466** (0.0534)	−0.0276 (0.0389)	0.2640*** (0.0704)	−0.0060 (0.0393)	0.2628** (0.0807)
MSA-fixed effects	Yes							
N	58,972		53,799		5,713		3,868	

Note. Robust standard errors in parentheses.
*$p < .05$. **$p < .01$. ***$p < .001$.

income of the neighborhood, while lower than the MSA average household income as shown in the LDS model. One possible interpretation related to the different results between the 1990s and the 2000s is that LIHTC developments had negative implications in its early stages, but have gained more positive images during the 1990s. As a result, LIHTC developments in the 2000s promote a positive impact on neighborhood economic status. It may also be possible that new LIHTC tenants in a neighborhood during the 2000s had higher incomes than those of the households living in the neighborhoods before receiving LIHTC units, while that was not the case in the 1990s.

Third, several models consistently report that LIHTC units in any adjacent neighborhoods are associated with the economic ascent of the focal neighborhood especially for the LQ models during the period of 2000 to 2010. It is possible that the provision of LIHTC units in the adjacent neighborhoods absorbs the lower income households which would enter the focal neighborhood if there were no LIHTC developments in the adjacent areas. It is also possible that households who have lower income than neighborhood average income move into the adjacent neighborhoods in which LIHTC units were provided.

Conclusion

This study expands the literature by questioning the long-term spatial patterns of the LIHTC units and the impact of LIHTC developments on income segregation, measured at the neighborhood level that captures between-neighborhood inequality. This research also explores the possible heterogeneous effects of LIHTC units varied by the initial poverty rate and the long-term clustering pattern of LIHTC units in a neighborhood.

The descriptive analysis in this study shows that the construction of LIHTC units has been clustered in specific neighborhoods that have socioeconomically disadvantaged contexts. First, LIHTC units were located in a small portion of neighborhoods in metropolitan areas. Second, about 50 percent of census tracts with LIHTC units had at least one neighboring census tract that also received LIHTC units during the same period. Third, between 1990 and 2016, LIHTC developments took place in neighborhoods in which, or in any adjacent neighborhoods, LIHTC units had already been built in previous periods. Future studies may explore the process or mechanisms of selecting LIHTC development applications that promote the longitudinal clustering pattern of LIHTC units. Fourth, longitudinally clustered LIHTC neighborhoods have socioeconomically disadvantaged attributes than other neighborhoods within the same metropolitan areas.

In the multivariate regression analyses, this analysis uses the propensity score approach to control the self-selection of developers' decisions on the location of LIHTC developments, isolating the effects of LIHTC developments on neighborhood-level economic measures. The results indicate that LIHTC developments in a neighborhood are expected to increase the concentration of lower-income residents within the neighborhood who have a lower level of income than the average household income of the MSA. However, in poor neighborhoods in which the poverty rates are above 30 percent, the result suggests that LIHTC developments provide positive spillover effects on neighborhood economic status in the 2000s. After LIHTC units were provided in the poor neighborhoods, the households who moved into (or out of) the neighborhoods have incomes which are higher (lower) than the average household income of the poor neighborhood, even though the income of the households is lower than the average household income of the MSA. The findings suggest a more detailed explanation of why LIHTC units do not seem to further poverty concentration in high poverty neighborhoods, as reported by several researchers. Moreover, the LIHTC developments in poor neighborhoods in which LIHTC developments were already provided in the focal or any adjacent neighborhoods have positive effects on neighborhoods' economic status in the 2000s, while that was not the case in the 1990s. It is possible that positive aspects of LIHTC developments are recognized, and thereby attract households who have a higher income than residents in the poor neighborhoods. It is also found that LIHTC developments in adjacent neighborhoods, in general, improved the economic status of the focal neighborhood.

This study contributes to the literature by exploring longitudinal location patterns of LIHTC units and the spillover effects of LIHTC units by utilizing neighborhood economic variables that capture between-neighborhood inequality. However, understanding the circumstances in which LIHTC developments provide positive spillover effects and their background mechanisms needs more scholarly attention. Future studies can improve the finding of the literature by identifying how the socioeconomic and racial characteristics of tenants vary by the clustering patterns of LIHTC units or surrounding opportunities, such as access to school, retails, or jobs. With the tenant-level data, future studies can also expand the findings of this research by exploring how the effects of LIHTC units on neighborhood economic status vary by different income levels or sociodemographic attributes of new LIHTC tenants. Policymakers and scholars should reassess the LIHTC program in terms of its ability to create "a suitable living environment" by expanding their views beyond the traditional sociodemographic contexts in future studies. Incorporating the housing context with education, transportation, environment, and other important aspects of urban settings will promote our understanding of LIHTC developments and will suggest insights for providing subsidized housing.

Appendix: Propensity Score Model with Continuous Treatment

For an additional analysis, I utilize the propensity score method by using the numbers of LIHTC units, measured in 100 units, in a neighborhood as a continuous treatment. However, using the continuous treatment for this study has two nontrivial limitations. First, it is not easy to meet one of the important assumptions for using propensity score methods: one should consider all variables that influence the treatment selection (Cole and Hernán 2008). In the literature of LIHTC, scholars have mostly focused on the factors associated with the location of LIHTC developments by utilizing logistic regression, while the factors associated with the number of LIHTC units have been less explored. This suggests a high possibility of model misspecification due to the lack of evidence for predicting the number of LIHTC units. Secondly, checking the efficacy of the propensity score method to balance the observed covariates is not an easy task and less intuitive due to the continuous treatment (Fong et al. 2018).

While acknowledging these limitations, the generalized propensity score ($e_i = P(T_i = u|\mathbf{X})$) for each observation i is calculated after regressing the total number of LIHTC units, measured at 100 units (u), on the same observed covariates, used in the propensity score model of the binary treatment, by using OLS, $Z = \beta\mathbf{X} + \varepsilon$, where $\varepsilon \sim N(0, \sigma^2)$, and obtaining $\hat{\varepsilon}_i$ and $\hat{\sigma}$. Then, the generalized propensity score ($e_i = P(T_i = u|\mathbf{X})$) is estimated by the conditional normal density, $P\left(T_i = u|\mathbf{X}\right) = \frac{1}{\sqrt{2\pi\sigma^2}} exp[-\frac{\hat{\varepsilon}_i^2}{2\hat{\sigma}^2}]$ (Robins et al. 2000). Using the inverse-probability weighting for a continuous treatment (the number of LIHTC units) has an infinite variance issue. Therefore, stabilized weights were used without comparing the absolute standardized differences between treated and control groups of stabilized and unstabilized weighting samples, unlike the analysis of the binary treatment (Schuler et al. 2016).

While the results have to be taken cautiously, the results show very similar results to those based on the binary treatment. Additional LIHTC units, measured at 100 units, induced households whose income is lower than MSA average household income in all models. However, in poor neighborhoods, the provision of LIHTC units leads to an influx (outflow) of households whose income is higher (lower) than the average household income of the neighborhoods.

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Notes

1. HUD defines that QCTs "have 50 percent of households with incomes below 60 percent of the Area Median Gross Income (AMGI) or have a poverty rate of 25 percent or more." DDA refers to "areas with high land, construction and utility costs relative to the area median income."
2. LDS is a decomposition of DI since DI for an MSA *m* can be calculated by summing the absolute values of LDS_{mi} for all neighborhoods within an MSA *m* and divided by two.

$$DI_m = \frac{1}{2}\sum\left\|\left[\frac{k_{mi}}{K_m} - \frac{h_{mi}}{H_m}\right]\right\| = \frac{1}{2}\sum\left|LDS_{mi}\right| \tag{7}$$

   The value of DI can be understood as the share of household income that should redistribute to have an equal distribution of household income across neighborhoods within an MSA (Bailey et al. 2017). If many neighborhoods in a specific MSA are either overrepresented or underrepresented in terms of household income, DI would be high, indicating a higher level of income segregation. On the other hand, if many neighborhoods in another MSA are neither overrepresented or underrepresented, indicating that LDS would be close to zero, DI would be low, indicating a lower level of income segregation.
3. In general, two methods of utilizing propensity scores for addressing the selection bias have widely been used in social science. First, each subject in the treated group is matched to the control group, varied from one or more cases based on the methods of matching—such as kernel matching, caliper matching, and nearest neighbor matching. One drawback of this method is that a large number of the subjects, not included in the control group, has to be dropped from the analysis.

Another method, which was utilized in this study, is through performing a weighted linear regression analysis by employing the IPTWs. One advantage opposed to the matching is that all subjects in a data set can be used in the analysis (Olmos and Govindasamy 2015). Using IPTWs may also address the issue of choosing the control group based on arbitrarily decided matching methods or calipers.

4. The baseline probability of treatment, P(Z = 1), can be estimated by performing a logistic model without observed covariates.
5. This study explores how the means of the measured baseline covariates of treated groups differ from those of control groups by calculating the standardized difference (Austin and Stuart 2015). The standardized difference for each covariate in an unweighted sample is calculated as:

$$d = 100 \times \frac{\left(\bar{X}_{treatment} - \bar{X}_{control}\right)}{\sqrt{\frac{S^2_{treatment} + S^2_{control}}{2}}} \tag{8}$$

in which $\bar{X}$ and S^2 refer to the sample mean and the sample variance of X, respectively. The weighted sample mean and variance are calculated as $\bar{X}_{weight} = \frac{\sum w_i x_i}{\sum w_i}$ and $S^2_{weight} = \frac{\sum w_i}{\left(\sum w_i\right)^2 - \sum w_i^2} \sum w_i \left(x_i - \bar{x}_{weight}\right)^2$, respectively, where w_i is the weight for each observation i. The standard difference for each covariate in weighted samples (unstabilized and stabilized samples) can be calculated by applying the weighted sample mean and variance (Austin and Stuart 2015).

6. The absolute standardized difference between the treated group and the control group for each covariate presents the efficacy of the model used to estimate the propensity score. In general, if the absolute standardized difference is below 10 percent, it indicates that the propensity score model was effective for creating a pseudo-randomized sample outcome (Austin 2009; Austin and Stuart 2015). Since all of the absolute standardized differences were less than 10 percent in the unstabilized weighting sample (see Figure 2), this study utilizes the unstabilized weight in the multivariate analysis.
7. The decision of using a dummy variable which indicates whether a neighborhood *i* received a LIHTC development during a decade as an independent variable is because the weights are developed from the propensity score model which used the dummy variable as an outcome variable.
8. The mean of each variable in LLN and LIHTC neighborhoods was weighted by the number of LIHTC units, while that in neighborhoods without LIHTC units was weighted by the total number of housing units.
9. I also split the non-poor neighborhoods into three types of neighborhoods whose poverty rates are at and below 10 percent, between 10 and 20 percent, and

between 20 and 30 percent, and conduct the same analyses for each subsample. The analyses present identical results from that of non-poor neighborhoods.

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