

Exploring the Spatial Distribution of Low Income Housing Tax Credit Properties

Assisted Housing
Research Cadre Report



PD&R



Exploring the Spatial Distribution of Low Income Housing Tax Credit Properties

Prepared for:

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Author:

Casey J. Dawkins
University of Maryland

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DISCLAIMER

The contents of this report are the views of the contractor and do not necessarily reflect the views or policies of the U.S. Department of Housing and Urban Development or the U.S. Government.

Preface

Exploring the Spatial Distribution of Low Income Housing Tax Credit Properties explores whether the spatial distribution of Low Income Housing Tax Credit (LIHTC) properties exhibit higher than expected patterns of clustering?

Beginning in 1972 with the creation of the Section 8 rental housing assistance program, the U.S. Department of Housing and Urban Development (HUD) has placed increasing emphasis on dispersing the geographic pattern of housing assistance. Responding in part to decades of research pointing to the links between concentrated poverty, racial segregation, and barriers to economic opportunity, HUD programs now seek to enhance low income households' access to a wider variety of neighborhoods with more desirable public services and amenities.

While expanding housing choice through the dispersal of housing assistance has become a primary objective of HUD, it is not clear whether this objective is being met in the LIHTC program. The LIHTC program was created as part of the Tax Reform Act of 1986 and is jointly-administered by the U.S. Department of Treasury's Internal Revenue Service (IRS) (26 U.S.C. § 42) and local and state housing finance agencies. Since the IRS is primarily concerned with administration of the tax code, it may not have an interest or capacity to aggressively monitor the geographic distribution of LIHTC assistance to ensure consistency with HUD's housing assistance objectives. Furthermore, LIHTC provisions enacted in 1989 which increase a developer's credit eligibility if they propose developing units in high-poverty census tracts may actually encourage the concentration of LIHTC housing assistance within high-poverty areas.

This study uses HUD's publicly-available LIHTC database to examine the geographic pattern of the LIHTC properties themselves. For the nation's 10 largest metropolitan areas, the geographic pattern of LIHTC properties is examined to determine if the pattern of clustering is higher than what would be expected under conditions of "complete spatial randomness."

This research found an overall pattern of results that suggest that certain provisions of the LIHTC program may be contributing to the concentration of subsidized housing units within the nation's largest metropolitan areas. In all metropolitan areas examined, LIHTC properties are found to be more highly clustered than other housing units. The clusters tend to be located in more densely-developed central city locations that have higher poverty rates and lower shares of non-Hispanic whites.

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EXECUTIVE SUMMARY

U.S. housing policies promulgated by the U.S. Department of Housing and Urban Development (HUD) have placed increasing emphasis on dispersing housing assistance in order to de-concentrate poverty. The Low Income Housing Tax Credit (LIHTC) program, the nation's largest affordable housing subsidy program, is not administered by HUD and therefore not closely monitored for compliance with poverty de-concentration objectives. In fact, several provisions of the LIHTC enabling statute provide incentives to concentrate LIHTC properties within high-poverty census tracts.

This study examines the spatial distribution of LIHTC properties to determine if the units are being placed in a way that is in conflict with the goal of de-concentrating the spatial pattern of housing assistance. This is the first study to rely on the actual locations of individual properties to assess the extent of LIHTC clustering. The analytical approach employed is a variation of the Ripley's K function, a common technique used to characterize spatial point patterns. This study relies on a unique modification of the Ripley's K function which allows for comparisons between an observed point pattern and a simulated pattern generated from the underlying distribution of housing units. Using this comparison, it is possible to determine if LIHTC properties are more clustered than the average housing unit. Several analyses are performed, including a global clustering analysis, a local clustering analysis, a descriptive examination of the characteristics of clustered properties, and an analysis of space-time clustering, or "diffusion."

Based on these analyses, several findings emerge:

- In all metropolitan areas, LIHTC properties are more highly clustered than housing units, although the extent of clustering differs by metropolitan area.
- LIHTC clusters tend to be located in more densely-developed central city locations that have higher poverty rates and lower shares of non-Hispanic whites.
- Clusters are more likely to be located in Qualified Census Tracts (QCTs) and Difficult to Develop Areas (DDAs) in most metropolitan areas.
- The Houston metropolitan area is a clear outlier when its LIHTC spatial distribution is compared to other metropolitan areas. It exhibits lower levels of clustering, fewer clustered properties in QCTs and DDAs, few clustered properties in high-poverty areas, and few clustered properties in majority-Black neighborhoods. This finding is consistent with the objectives outlined in the State of Texas Qualified Allocation Plan (QAP).

These findings suggest that provisions of the LIHTC program may be contributing to the concentration of subsidized housing units within the nation's largest metropolitan areas. State policies outlined in the QAP may help to limit the concentration of affordable housing units in some states, but reform of LIHTC incentives, particularly the QCT provision, would go farther to ensure that LIHTC policy objectives are consistent with HUD's goals to disperse housing assistance.

INTRODUCTION

Beginning in 1972 with the creation of the Section 8 (Housing Choice Voucher) rental housing assistance program, the U.S. Department of Housing and Urban Development (HUD) has placed increasing emphasis on dispersing the geographic pattern of housing assistance. Responding in part to decades of research pointing to the links between concentrated poverty, racial segregation, and barriers to economic opportunity (see Ellen and Turner (1997) for a review), HUD programs now seek to enhance low income households' access to a wider variety of neighborhoods with more desirable public services and amenities.

This emphasis on de-concentrating affordable housing assistance was expanded in the 1990s with the creation of the HOPE VI program, which sought to replace severely-distressed public housing with new mixed income housing developments, and the Moving to Opportunity demonstration initiative, which provided rental housing assistance to those seeking to move out of high-poverty neighborhoods. HUD's FY 2011 budget proposes an expansion of these efforts with its "Transforming Rental Assistance" initiative, which seeks to expand housing choice and increase the share of HUD-assisted households living in low-poverty communities.

While expanding housing choice through the dispersal of housing assistance has become a primary objective of HUD, it is not clear whether this objective is being met in the nation's largest affordable housing subsidy program, the Low Income Housing Tax Credit (LIHTC). The LIHTC program was created as part of the Tax Reform Act of 1986 and is jointly-administered by the U.S. Department of Treasury's Internal Revenue Service (IRS) (26 U.S.C. § 42) and local and state housing finance agencies. Unlike affordable housing programs administered by HUD, geographic dispersal of LIHTC subsidies is not an explicit intent of the program. Since the IRS is primarily concerned with administration of the tax code, it may not have an interest or capacity to aggressively monitor the geographic distribution of LIHTC assistance to ensure consistency with HUD's housing assistance objectives. Furthermore, LIHTC provisions enacted in 1989 which increase a developer's credit eligibility if they propose developing units in high-poverty census tracts may actually encourage the concentration of LIHTC housing assistance within high-poverty areas (Freeman 2004).

Despite these apparent policy inconsistencies, little research has been done to evaluate the geographic pattern of LIHTC properties to determine if the spatial distribution of properties exhibits higher than expected patterns of clustering. A limited number of studies have examined the aggregate characteristics of census tracts where LIHTC units have been placed, along with the spatial relationships among LIHTC census tracts, but no study to date has taken advantage of HUD's publicly-available LIHTC database to examine the geographic pattern of the LIHTC properties themselves.

This study fills this gap. For the nation's 10 largest metropolitan areas, the geographic pattern of LIHTC properties is examined to determine if the pattern of clustering is higher than what would be expected under conditions of "complete spatial randomness." Local patterns of clustering within each metropolitan area are also examined, followed by a descriptive analysis of the average characteristics (e.g. number of units per property, percent new construction, location in

central cities, census tract poverty rates, census tract racial composition) of properties located within local clusters. The analysis concludes with an examination of patterns of spatial diffusion to examine whether neighboring LIHTC properties are constructed within a similar time frame, in years. Together, each of these analyses paints a picture of the geographic distribution of LIHTC properties and suggests possible policy responses to ensure that LIHTC policies are aligned with national poverty deconcentration objectives.

BACKGROUND

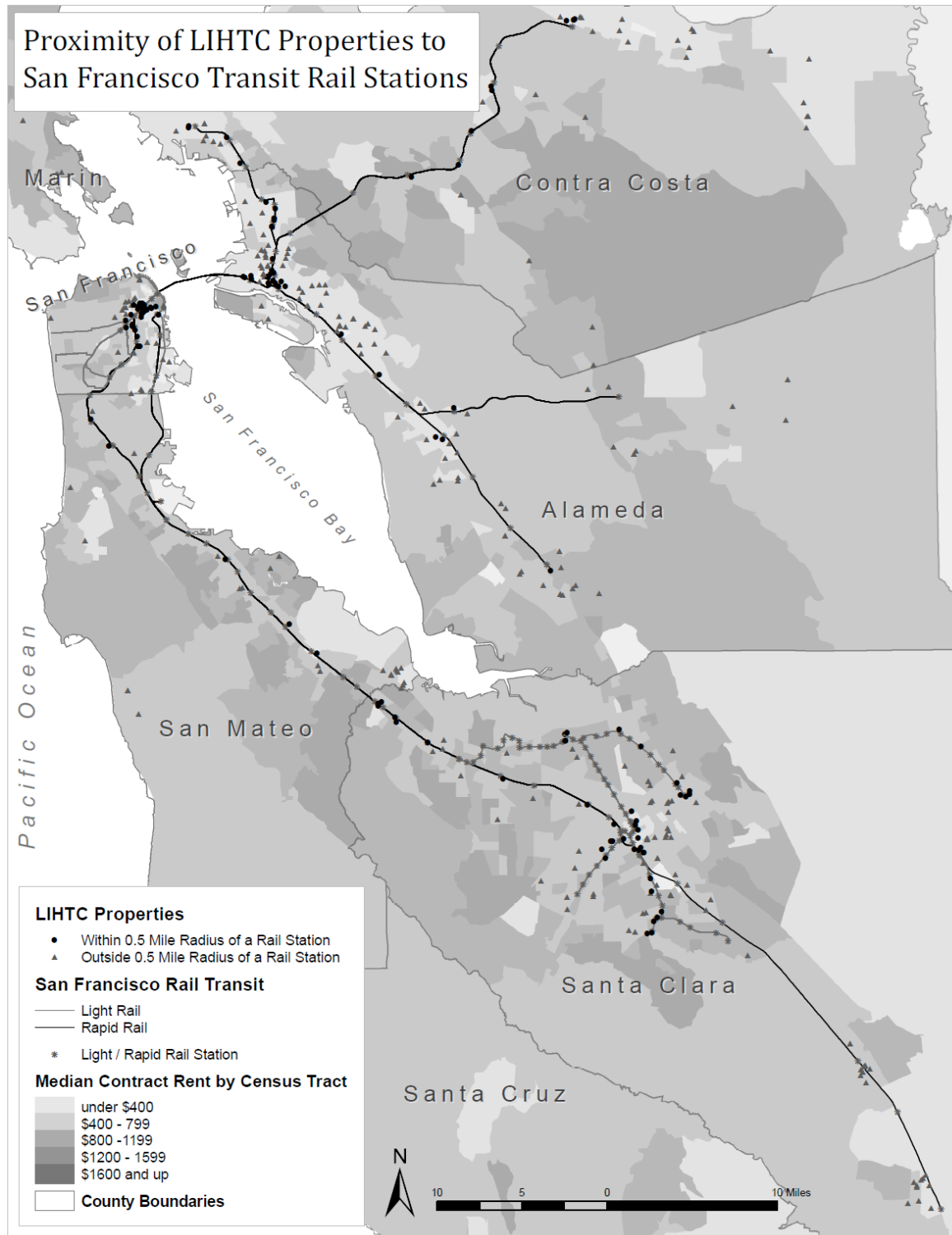
The Low Income Housing Tax Credit program was established to encourage the private construction of new affordable housing units. LIHTCs reduce a developer's federal tax liabilities and are usually sold to investors to raise equity for a development project. Since the credit lowers a developer's overall tax burden, less rental income is needed to finance debt service, and hence, rents can be made more affordable. Credits are awarded to states, and each state prepares a "Qualified Allocation Plan" (QAP) which identifies that state's priorities for allocating credits. Developers compete for a limited supply of credits and receive additional points or additional credits for proposals that meet the objectives outlined in either Section 42 of the Internal Revenue Code or the state's QAP.

Several provisions of the federal LIHTC statute may contribute to the concentration of LIHTC developments by design. The most important incentive is the qualified census tract (QCT) designation. Qualified census tracts are those with at least 50 percent of households earning incomes below 60 percent of the area median income or which have poverty rates of 25 percent or more (Hollar and Usowski 2007). Developers proposing projects in QCTs are eligible for 30 percent more credits than developments not located in QCTs, and states may award additional incentives for developments in QCTs. Since high-poverty census tracts are disproportionately located in higher density urban locations (and hence smaller in size since census tract boundaries are drawn to ensure that census tracts have roughly similar population sizes), the multi-family units built in these locations will tend to be built at higher densities and in closer proximity to one another. Furthermore, since the total number of designated QCTs in each metropolitan area or non-metropolitan county cannot exceed 20 percent of the area's population, fewer census tracts are designated than may otherwise qualify on the basis of poverty rates and median income alone. This implies that not only are QCTs likely to be smaller in area and have higher densities than non-QCT tracts, the total area covered by QCTs is likely to be small relative to the total area occupied by the region's low income population. Furthermore, since developers receive the additional credits only if their developments are entirely within a QCT, developers have an incentive to choose locations that are more centrally-located within the QCT tract.

Another incentive for concentration of LIHTC developments is that states may award additional credits for developments proposed in "difficult to develop" areas (DDAs). Since land costs cannot be included in the calculation of a developer's eligible credit basis, this provision is designed to provide an additional incentive to develop in areas where land costs constitute a large portion of a developer's total development costs. HUD defines DDAs as those areas exhibiting high land, utility, and construction costs. Since these areas tend to be the areas with the highest densities, awarding additional incentives to develop in these areas may further concentrate LIHTC properties.

State priorities over the geographic distribution of tax credits may also influence the spatial concentration of LIHTC properties. States often establish set-asides for the proportion of credits allocated to urban areas and / or the proportion allocated to high poverty areas (Gustafson and Walker 2002). Many states also award additional points or credits to developers proposing projects near transit stops. While this policy may help to increase the supply of affordable housing near transit, a laudable goal in and of itself, it may also serve to concentrate the affordable units that are located near transit. California, for example, awards points on a graduated scale depending on the distance to transit and the type and frequency of service. The map below of the San Francisco metropolitan area illustrates how such a policy may serve to concentrate LIHTC properties near transit stops.

Figure 1: Proximity of LIHTC Properties to San Francisco Transit Rail Stations



Source: Dawkins, Casey and Ralph Buehler. 2010. *Promoting Affordable Housing Near Public Transit: The Role of Planning*. Draft report prepared for the U.S. Department of Housing and Urban Development.

Few studies have examined the geographic distribution of LIHTC properties to determine if these provisions serve to exacerbate the concentration of LIHTC-supported affordable housing subsidies. The few studies that have examined this issue aggregate LIHTC counts to the census tract level and examine the characteristics of tracts with LIHTC properties compared to those without such properties. Freeman (2004) finds that while most LIHTC properties are constructed within central cities, the proportion of properties in the suburbs is larger than the proportion of other Section 8 project-based affordable housing units. He also finds that LIHTC neighborhoods tend to exhibit higher poverty rates, lower median incomes, and a higher share of black residents. McClure (2006) finds that the share of LIHTC properties constructed within the suburbs has increased over time as the value of the credits has risen, although this trend may have reversed following the housing market crash as the value of credits has declined. Khadduri, Buron, and Climaco (2006) examine the number of LIHTC family units located in low poverty census tracts and find that within large metropolitan areas, about 22 percent of LIHTC family units are located in low poverty neighborhoods. The authors also find substantial variation among states, which suggests that state QAPs may influence the distribution of LIHTC units within low poverty areas. Ellen et al. (2009) find that the largest share of LIHTC units are built in census tracts with poverty rates between 10 and 30 percent. Pfeiffer (2009) examines the educational opportunities available to LIHTC residents and finds that the majority of LIHTC units in California are located in high-poverty neighborhoods that feed into low-performing school districts.

None of the papers cited above examines clustering at a scale smaller than the census tract. Since census tracts are often very large, aggregate tract-level counts reveal little information about the extent to which properties are co-located at a scale that is relevant to neighborhood residents. Furthermore, the substantial variation in census tract size implies that even though large tracts may contain more LIHTC units, the units located in those tracts may be located farther apart than LIHTC units located in smaller tracts (Wang and Varady 2005).

Two recent spatial analyses are relevant to this paper. Oakley (2008) is the only study to examine spatial patterns of clustering among LIHTC properties. She relies on various measures of spatial autocorrelation to identify patterns of LIHTC clustering within four metropolitan areas. Her measures of clustering are based on census tract counts, however, and ignore the degree of clustering that may occur within tracts. Wang and Varady (2005) rely on hot-spot analysis to identify local patterns of clustering among Section 8 Voucher recipients living in Hamilton County, Ohio. Although their paper does not examine the spatial distribution of LIHTC properties, the authors demonstrate the advantages of point-based measures of clustering over those based on aggregate census tract counts. The authors demonstrate how census tract counts may produce a misleading picture of the degree of income-mixing that results from the movement of voucher holders. Furthermore, local hot spots were identified using the point-based method that were not identified using the census tract method.

METHODOLOGY

The descriptive analyses that follow rely on HUD's LIHTC database, which provides information on the location of all LIHTC properties by year of placement and by type of development. The full dataset include geocoded observations for all LIHTC projects placed in

service between 1987 and 2006. I exclude projects placed in service prior to 1995 to ensure consistency with 2000 Census data which were appended to the dataset. Geocodes prior to 1995 were also less precise and/or accurate, according to HUD. I omit observations which had potential geocoding errors due to being assigned to block group centroids rather than street addresses. There were actually few (less than one percent) inaccurate geocodes in the metropolitan areas examined, so deleting these observations has little impact on the final results. This was confirmed with an initial sensitivity analysis performed for the Washington, D.C. – Baltimore CMSA.

The analyses that follow were conducted for the 10 largest U.S. metropolitan areas as of 2000 over an approximately ten year period. These metropolitan areas include:

- New York--Northern New Jersey--Long Island, NY--NJ--CT--PA CMSA
- Los Angeles--Riverside--Orange County, CA CMSA
- Chicago--Gary--Kenosha, IL--IN--WI CMSA
- Washington--Baltimore, DC--MD--VA--WV CMSA
- San Francisco--Oakland--San Jose, CA CMSA
- Philadelphia--Wilmington--Atlantic City, PA--NJ--DE--MD CMSA
- Boston--Worcester--Lawrence, MA--NH--ME--CT CMSA
- Detroit--Ann Arbor--Flint, MI CMSA
- Dallas--Fort Worth, TX CMSA
- Houston--Galveston--Brazoria, TX CMSA

The Consolidated Metropolitan Statistical Area (CMSA) was chosen as the unit of geography to maximize the sample size of LIHTC properties included in the database. I rely on 1999 metropolitan area definitions to ensure consistency across the multiple data sources used to conduct the analyses.

The analyses rely on a variety of spatial analysis techniques, derived from spatial point pattern methods, to develop explicit models of the degree of clustering of LIHTC units. Most analyses are based on Ripley's K function, a descriptive measure of the number of points within increasing distances of a randomly selected point. The advantage of this technique compared to others is that it can be used to compare any given point pattern to a randomly generated pattern to quantify the degree of clustering and assess its statistical significance.

The Ripley's K function ($K(h)$) is defined as follows:

$$K(h) = (1/\lambda)E[\# \text{ of additional LIHTC properties within distance } h \text{ of an arbitrary property}]$$

Where λ is the density of points within the area being analyzed. One way to conceptualize $K(h)$ is to imagine randomly selecting a LIHTC property within the region and constructing circular buffers around the selected point that increase with distance h . The K function is then equal to the average number of LIHTC properties observed at increasing distances from each selected LIHTC property, scaled by the density of properties within the entire region. Distances are defined in terms of the Euclidian distances between LIHTC properties in miles. The distance bands are chosen by the analyst, but Smith (2009) recommends choosing distances such that the

maximum distance examined is one half the maximum distance between points. This approach helps to reduce the distortion induced by “edge effects” where distance bands are calculated over areas outside the region that do not contain points. To ensure that distance bands are small enough to detect meaningful small-scale clustering, I examine the K function over 100 distance intervals with the largest interval equal to one half the maximum distance between points. Since the maximum distance between points is different for each metropolitan area, due in part to differences in urban development patterns between metropolitan areas, the distance scale will differ by metropolitan area.

The K function is useful from a descriptive standpoint, but to determine if the degree of clustering observed is significantly different from a non-clustered pattern, the observed K function must be compared with the benchmark case of “complete spatial randomness” (CSR) to evaluate the observed pattern. The procedure for evaluating statistical significance involves a Monte Carlo simulation testing procedure, where the observed pattern is compared to repeated samples of points generated under the assumed random pattern. The simulated patterns are used to construct envelopes around the observed patterns, and these comparisons yield p-values that give the probability that the observed pattern is more or less dispersed than the randomly-generated envelopes. In all analyses that follow, I generate 999 simulations which allows for significance tests to the .001 level.

The trick to any K function analysis is to establish the appropriate CSR benchmark case. If the expected random pattern is poisson-distributed, then the K function under the assumption of complete spatial randomness reduces to a constant value that is equal to the density of points multiplied by a scale factor. Identifying deviations from a benchmark poisson distribution is not a very useful way to analyze most urban phenomena, because rarely would urban social and economic activities exhibit the poisson CSR pattern even if the spatial events themselves were not inherently attracted to or repelled from one another. For example, urban activities often cluster together to maximize access to transportation nodes or to minimize distance to resource extraction points or markets. Thus, in order to determine if LIHTC properties are clustering for reasons apart from forces which cause housing units themselves to cluster together, it is more useful to define a CSR pattern that would occur if LIHTC properties clustered in patterns similar to the distribution of total housing units. To perform this type of analysis, I rely on techniques proposed by Cressie (1993) and applied by Hillier (2003) to compare the observed LIHTC pattern to a non-homogeneous pattern generated from the following sampling procedure (Smith 2009):

1. Randomly sample a census tract from the analysis region, ensuring that the probability of selection is equal to the tract’s proportion of the total region’s housing units. (I also examined simulations using total rental housing units, rather than total housing units, as the reference population. The results are comparable to those reported below. One could also argue that the total number of multi-family units might be a more appropriate reference population, but this approach was not examined in this paper. Future research is needed to determine the sensitivity of results presented in this paper to alternative reference populations.)
2. Randomly locate a point within the chosen census tract.

3. Repeat (1) and (2) until a point pattern is generated with sample size equal to the observed pattern.
4. Repeat (1) through (3) 999 times to generate the simulation envelopes described above.

The Ripley's K function approach can also be extended to examine local patterns of clustering to identify points which are located in "hot spots." The local Ripley's K function is calculated similar to the procedure outlined above, but each point within the dataset receives its own localized K-Function that can be compared with the K-functions for other points.

The final test performed is a temporal indistinguishability test that is used to identify patterns of space-time clustering. This test identifies patterns of diffusion over time (in years), defined in this case as instances when LIHTC properties within close proximity tend to be placed in service within a short period of time from one another. The test relies on a version of the K function that incorporates the additional dimension of time. Conceptually, the distance radii are expanded over space and upward along a time axis to construct increasingly-large space-time cylinders within which point counts are examined (Smith 2009). P-values from the temporal indistinguishability test are constructed along the two dimensions of space and time to identify instances where clustered points emerge within a short time span of one another.

This paper relies on these techniques along with maps and descriptive statistics to examine several questions related to the spatial distribution of LIHTC properties, including the following:

- How spatially-clustered are LIHTC properties, compared to the distribution of housing units?
- Where are LIHTC "hot spots" located?
- How do clustered LIHTC properties differ from randomly-distributed and dispersed properties in terms of:
 - Unit size
 - Percent new construction
 - Percent located in the central city
 - Population density
 - Percent located in QCTs
 - Percent located in DDAs
 - Census tract poverty rates
 - Census tract racial and ethnic composition
- Do LIHTC properties exhibit patterns of spatio-temporal diffusion over time?

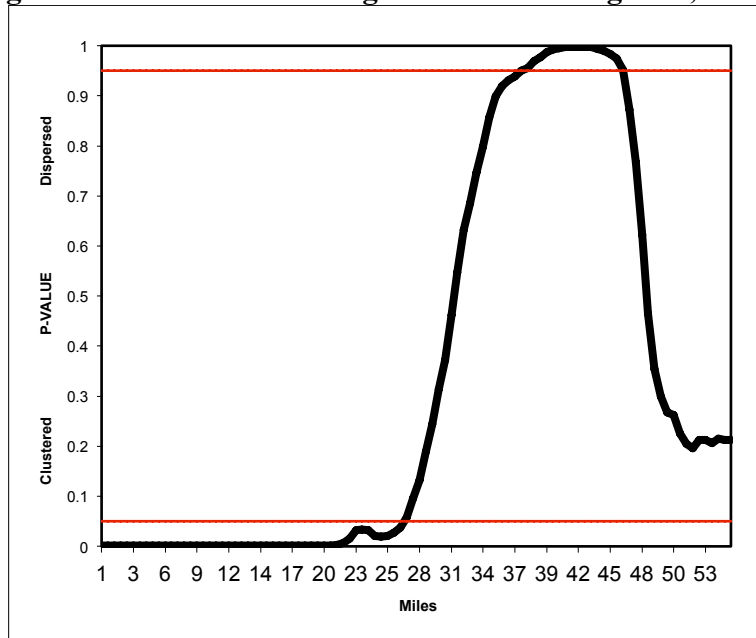
RESULTS

This study begins with an examination of tests for global non-homogenous clustering. In each graph below, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band. The most relevant pieces of information from these graphs are the extent of clustering at small distance bands and the degree to which clustering extends to

larger distances. Clustering over short distance intervals implies that a larger number of additional LIHTC properties are found near each randomly-selected property than one would expect to find given the distribution of housing units. From a policy standpoint, this would imply that households living in these LIHTC properties would be surrounded by relatively more LIHTC properties than housing units, if the number of total housing units was equal to the number of LIHTC properties.

As indicated in figures two through 11, all metropolitan areas exhibit statistically significant clustering at short distances. This implies that within a few miles (recalling that the distance bands differ by metropolitan area) LIHTC properties are surrounded by a larger number of additional properties than would be expected given the distribution of total housing units. The degree to which clustering is significant over larger distance bands differs greatly by metropolitan area. Within Dallas and Houston, clustering is no longer significant beyond three to four miles, and in the case of Dallas, significant dispersion is observed over distances of between approximately 19 and 33 miles. Within New York and Philadelphia, clustering is observed over all distance intervals. In terms of the policy questions of interest in this report, the most relevant clustering distances to consider are the first five distance intervals (which range from approximately one half mile to five miles in most metropolitan areas). In most metropolitan areas, it is unlikely that clustering at distances beyond five miles is a concern for policymakers.

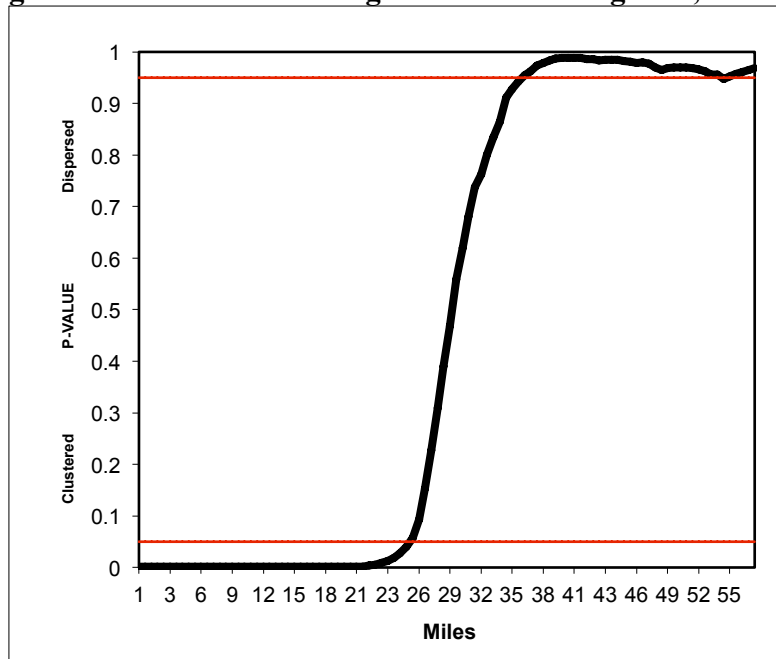
Figure 2: Global Non-Homogeneous Clustering Test, Boston



Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

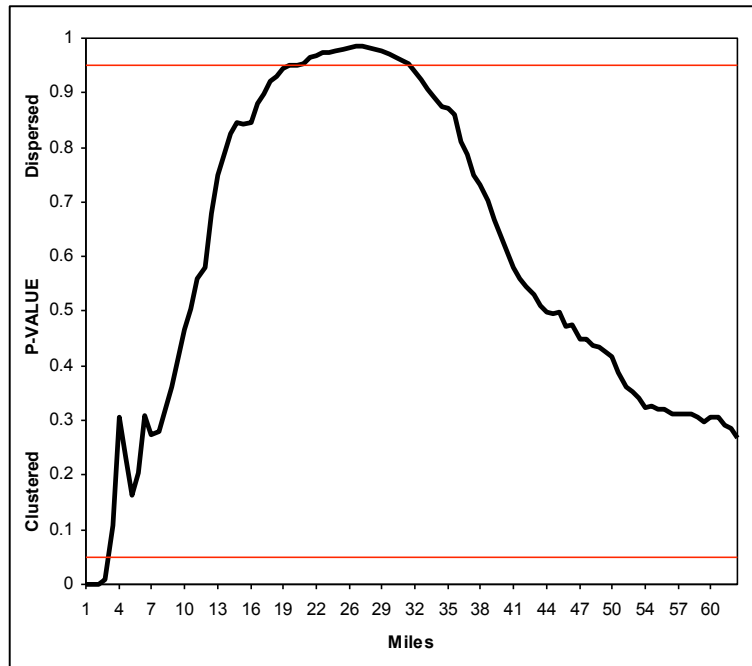
Figure 3: Global Non-Homogeneous Clustering Test, Chicago



Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

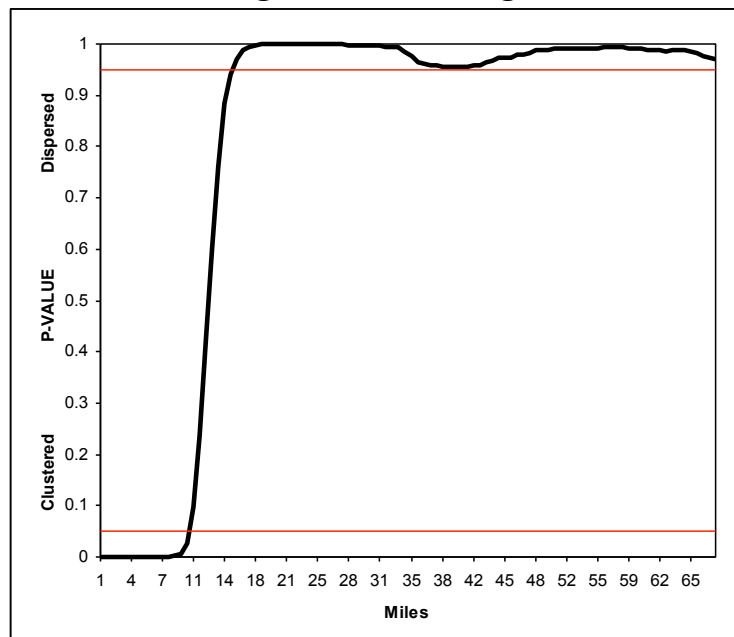
Figure 4: Global Non-Homogeneous Clustering Test, Dallas



Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

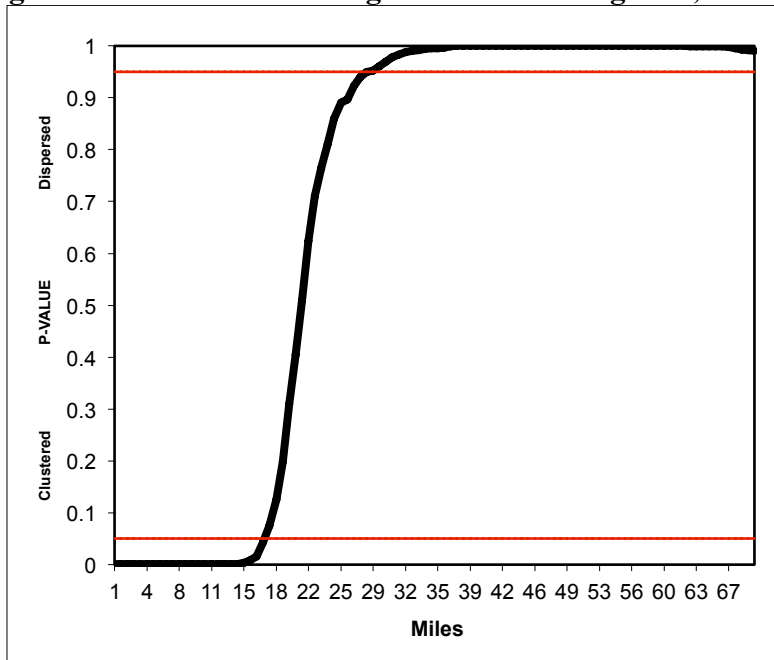
Figure 5: Global Non-Homogeneous Clustering Test, District of Columbia



Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

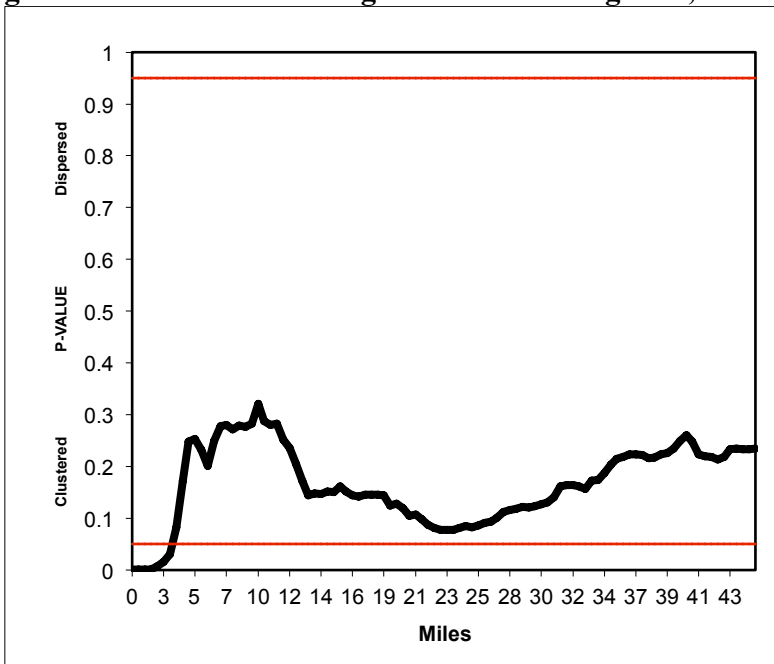
Figure 6: Global Non-Homogeneous Clustering Test, Detroit



Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

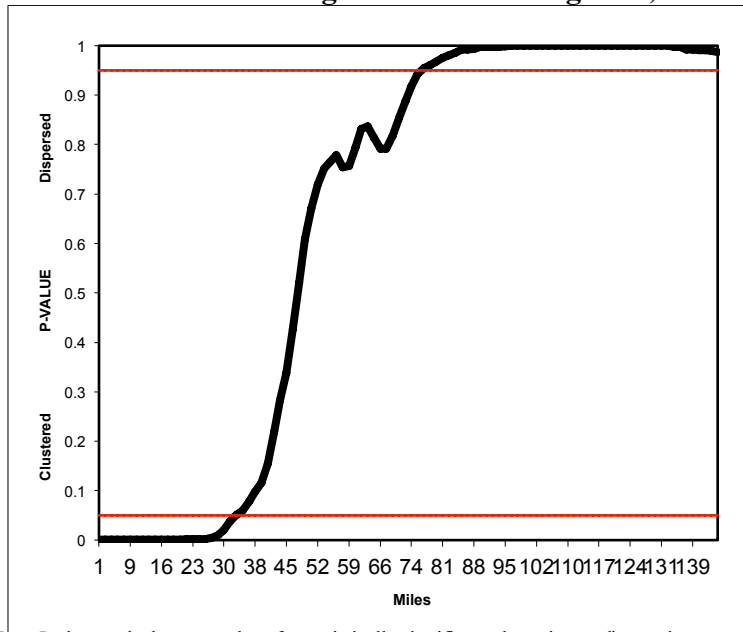
Figure 7: Global Non-Homogeneous Clustering Test, Houston



Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

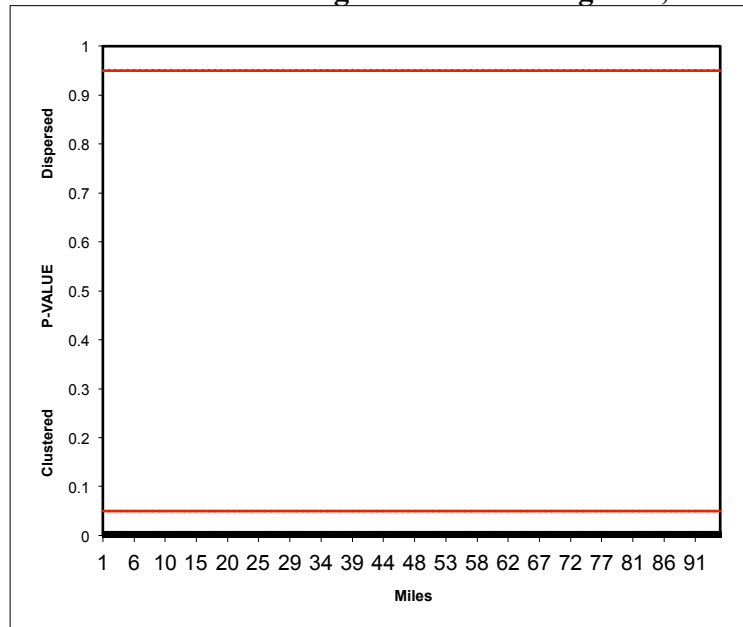
Figure 8: Global Non-Homogeneous Clustering Test, Los Angeles



Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

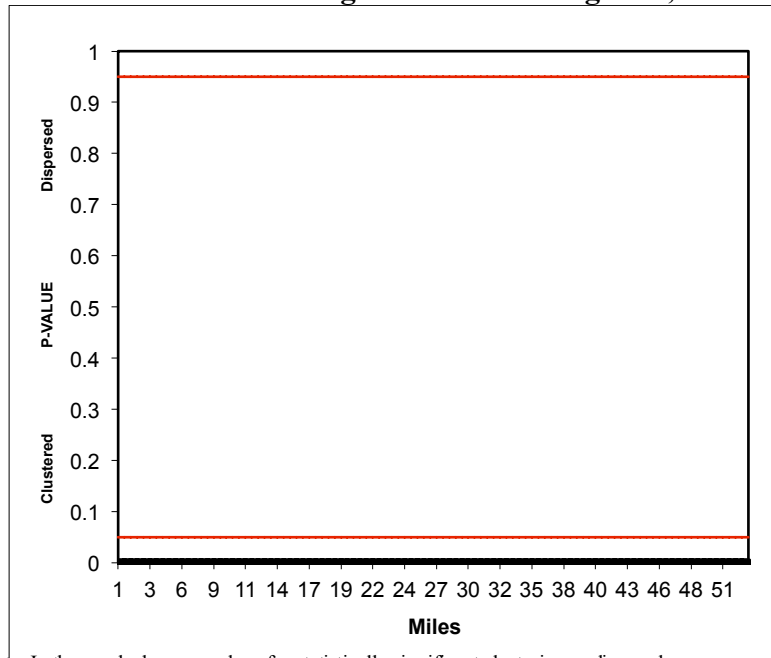
Figure 9: Global Non-Homogeneous Clustering Test, New York



Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

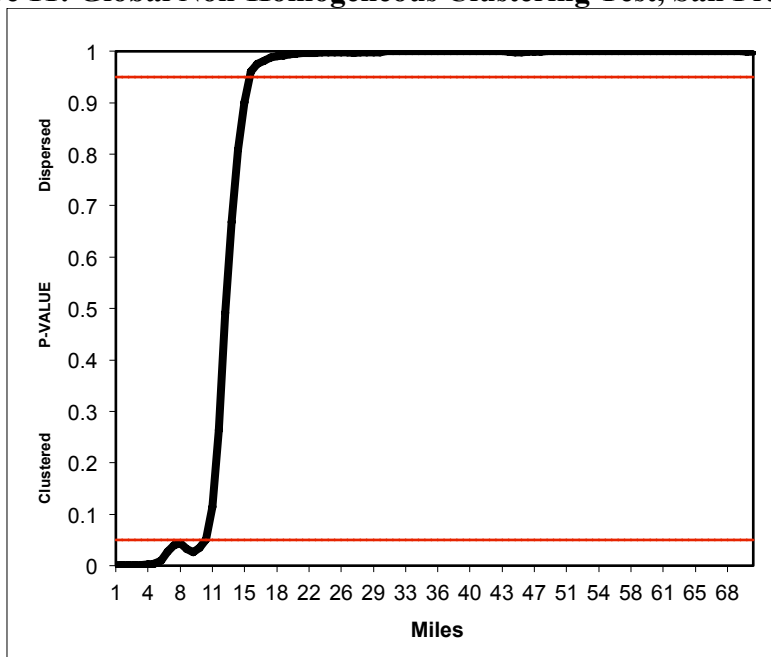
Figure 10: Global Non-Homogeneous Clustering Test, Philadelphia



Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

Figure 11: Global Non-Homogeneous Clustering Test, San Francisco



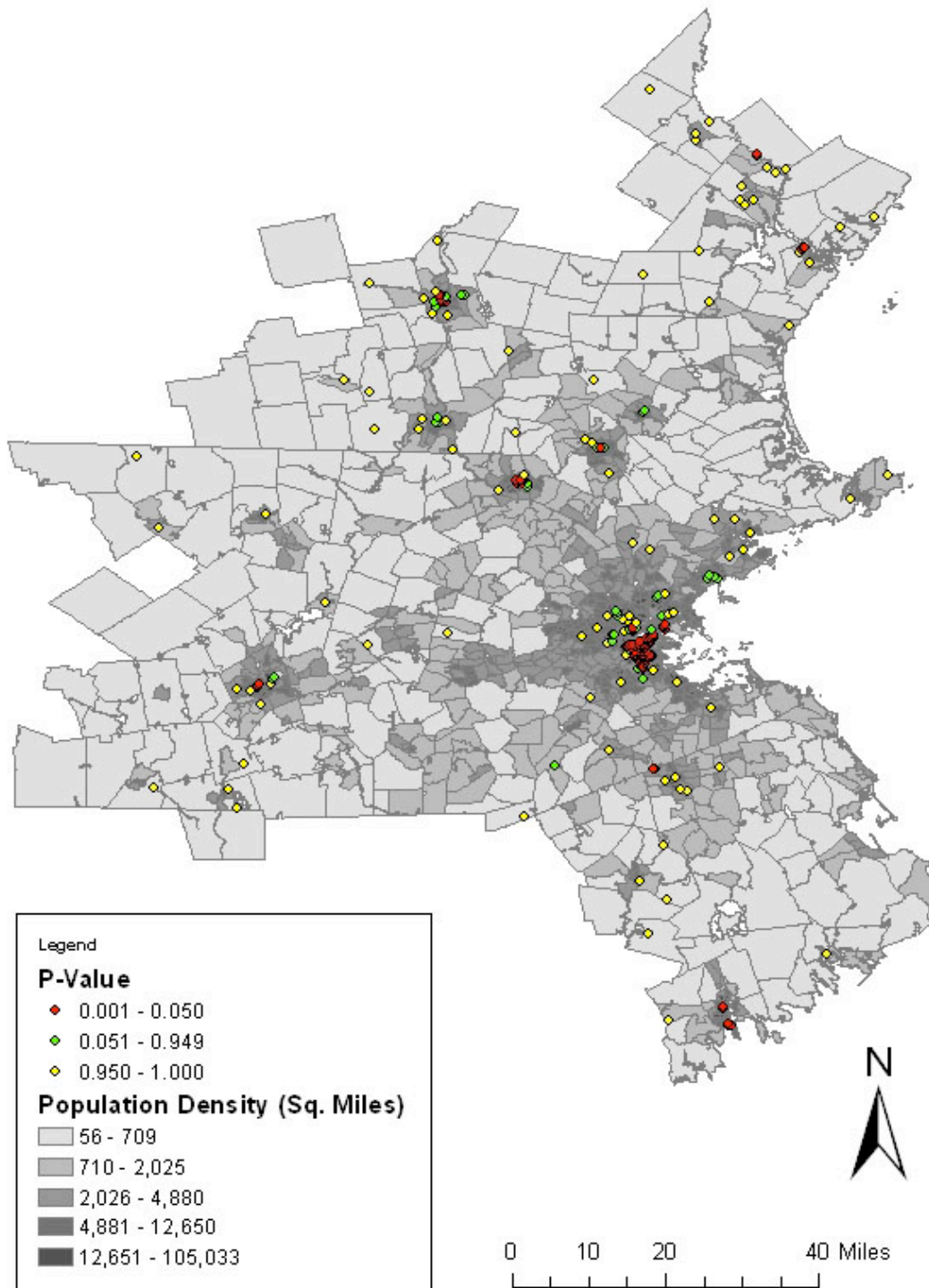
Note: In the graph above, p-values for statistically significant clustering or dispersal are plotted against increasing distance radii in miles. P-values below .05 indicate statistically significant patterns of clustering at that distance band, and p-values above .95 indicate statistically significant patterns of dispersion at that distance band.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1.

The maps displayed in figure 12 through figure 21 are derived from estimates of local K-functions. For each point, a K-function is calculated for each of 100 distance intervals along with corresponding p-values. The maps below display the location of each LIHTC property, color-coded according to the statistical significance of clustering at the smallest distance band. Points exhibiting statistically-significant patterns of local clustering are shaded red, points exhibiting statistically-significant local dispersion are shaded yellow, and dots exhibiting patterns of spatial randomness are shaded green. Census tracts are also shown, shaded from light grey to dark grey to indicate the location of low to high population densities.

Generally speaking, LIHTC clusters tend to be located in densely-developed central cities, although this is not always the case. Another thing to note is that while much of the degree of clustering can be “explained” by population density, some clusters emerge in low-density areas, and some dispersed properties emerge in high density areas. In the District of Columbia metropolitan area, for example, several small clusters can be identified in suburban areas located outside the region’s core. This is the advantage of the non-homogeneous test of spatial clustering. Without controlling for the density of housing units, the Ripley’s K function would reveal a much higher degree of clustering than what would be expected, given the underlying residential development pattern.

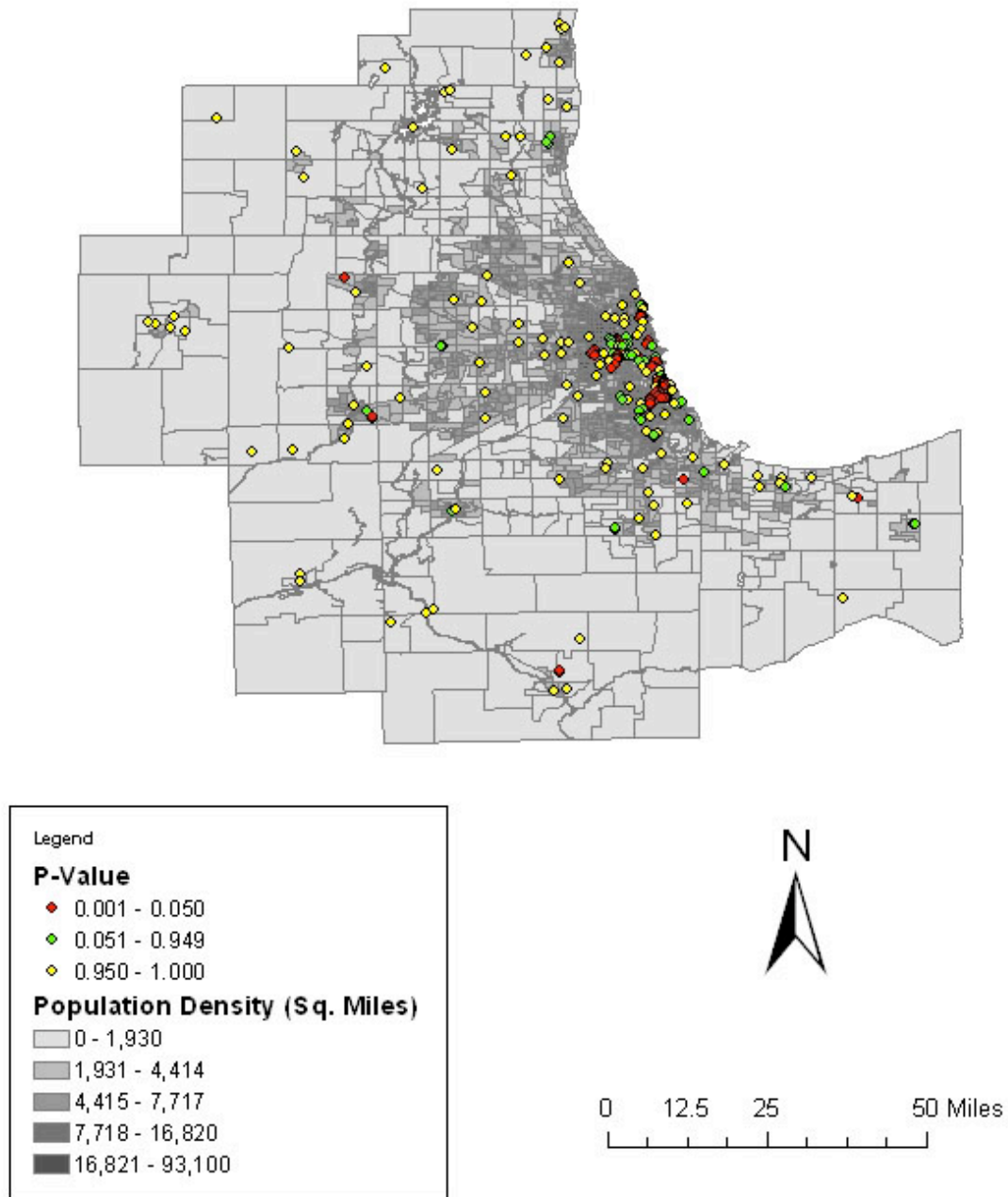
Figure 12: LIHTC Properties, Boston



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

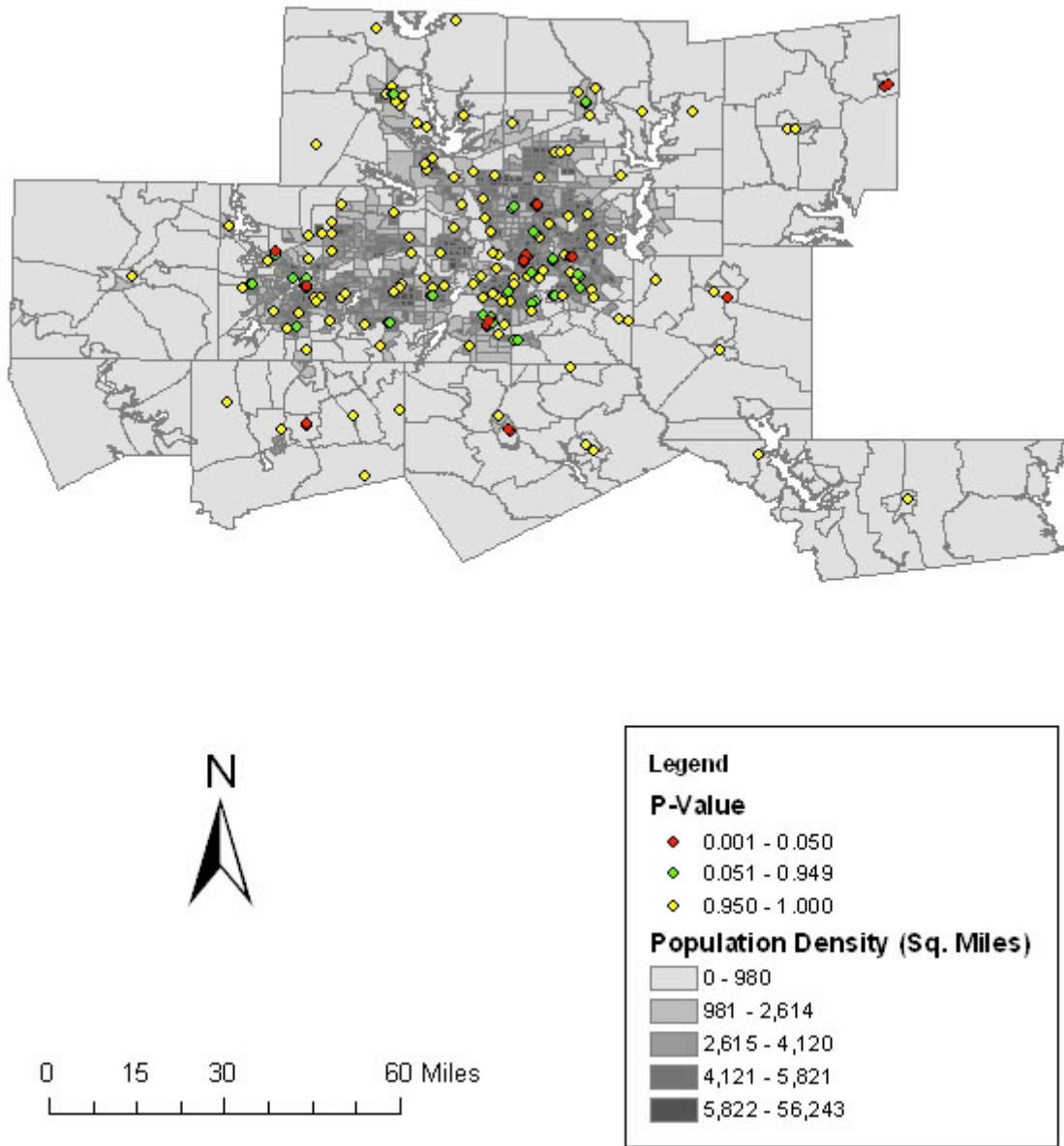
Figure 13: LIHTC Properties, Chicago



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

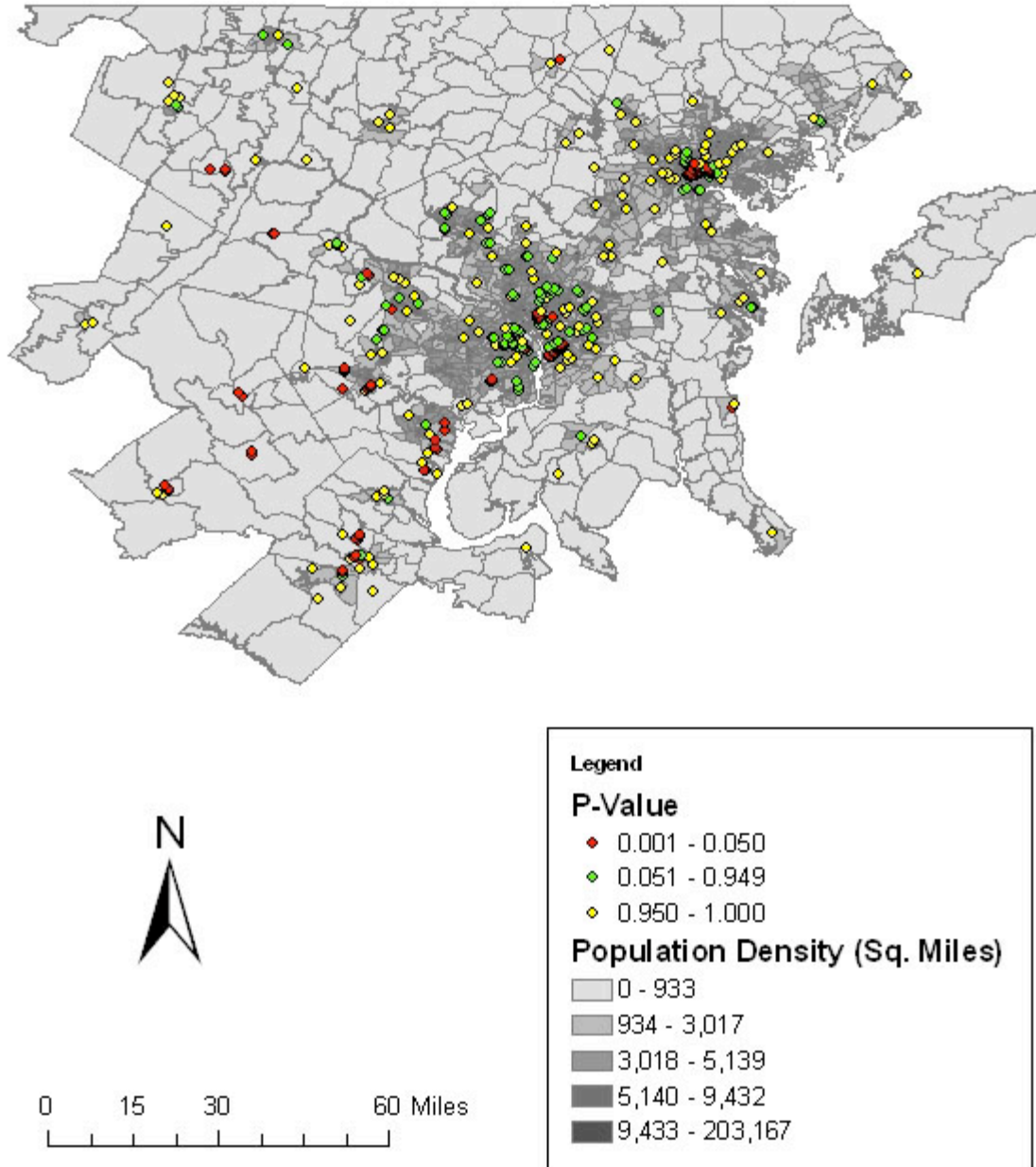
Figure 14: LIHTC Properties, Dallas



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

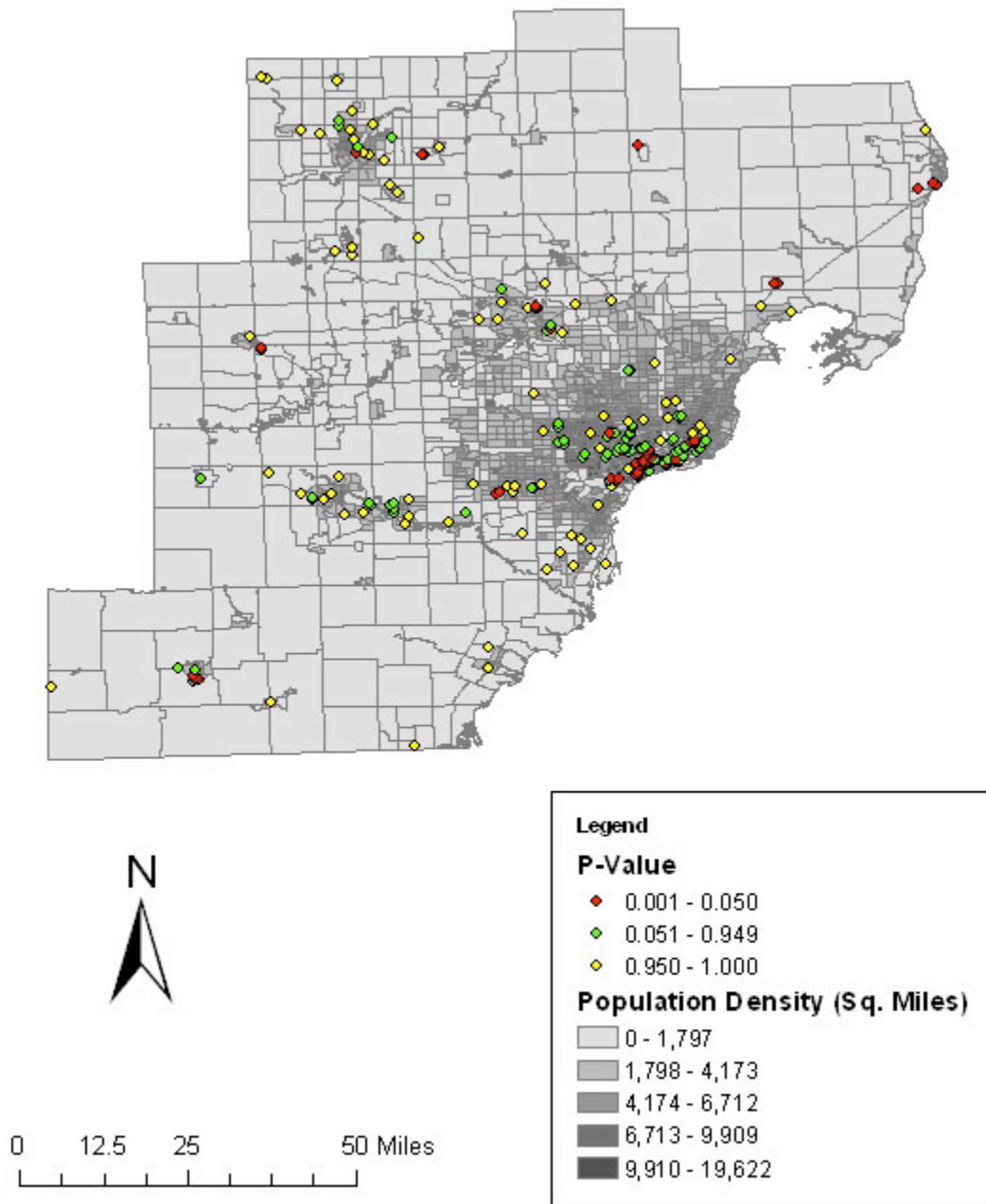
Figure 15: LIHTC Properties, District of Columbia



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

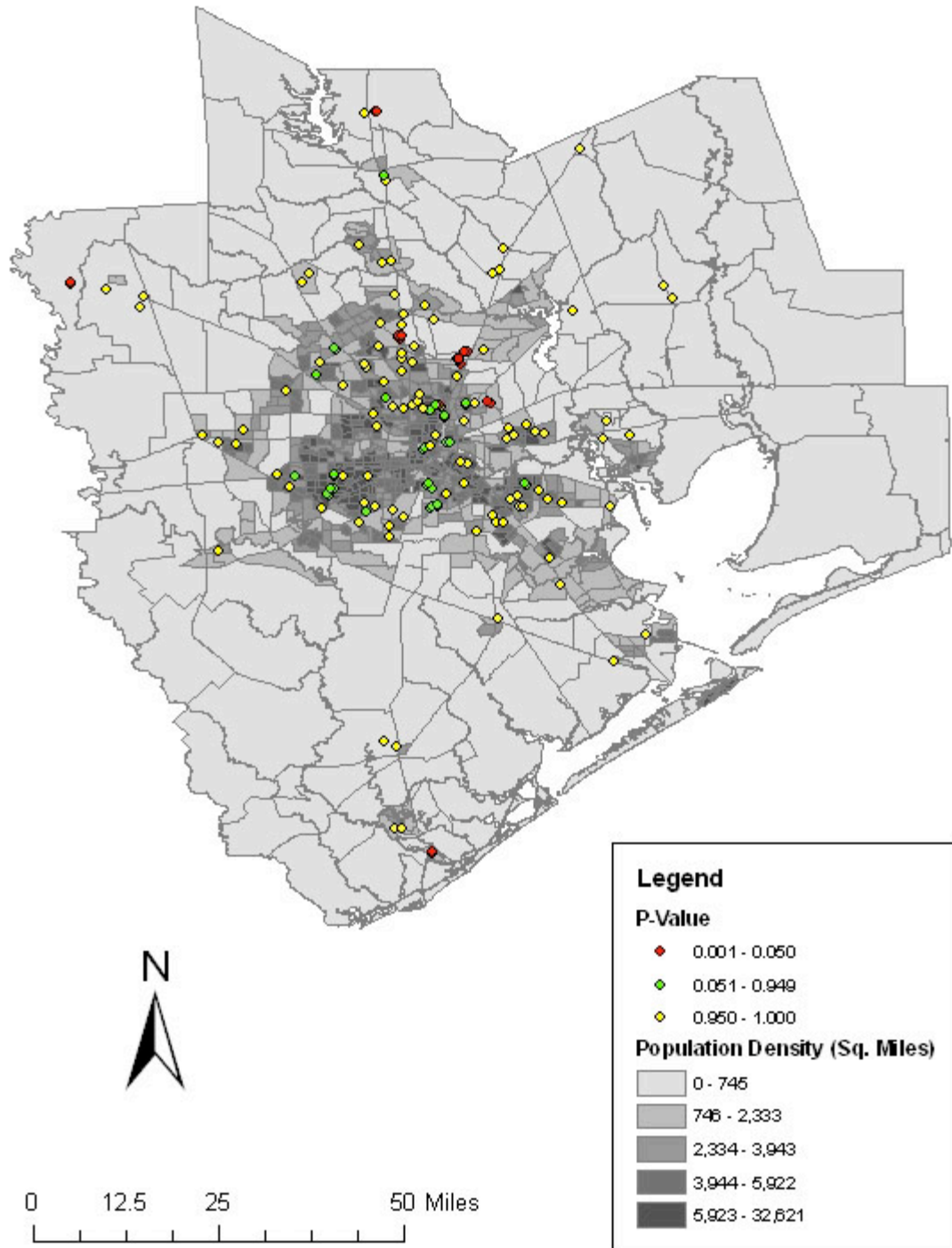
Figure 16: LIHTC Properties, Detroit



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

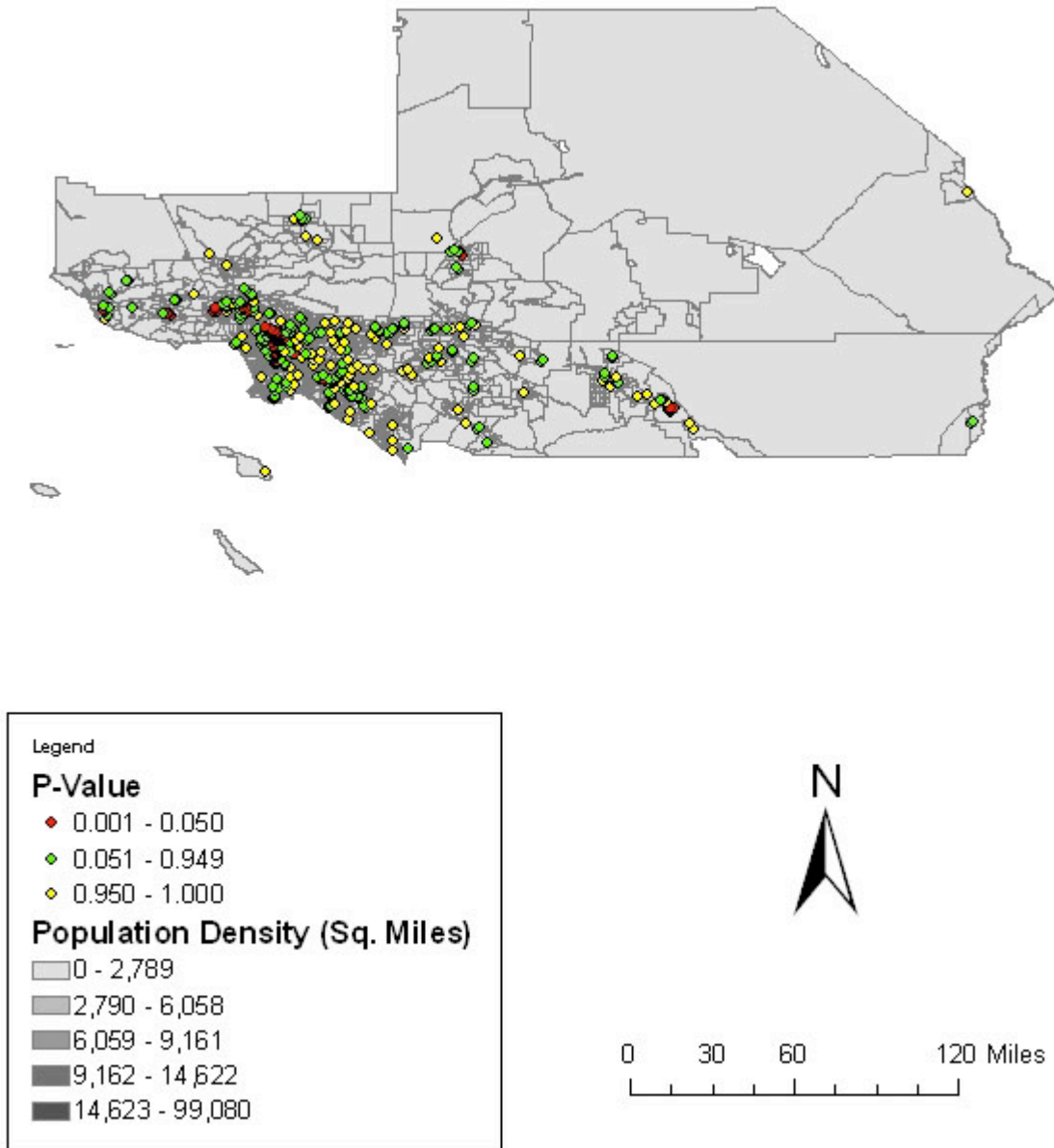
Figure 17: LIHTC Properties, Houston



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

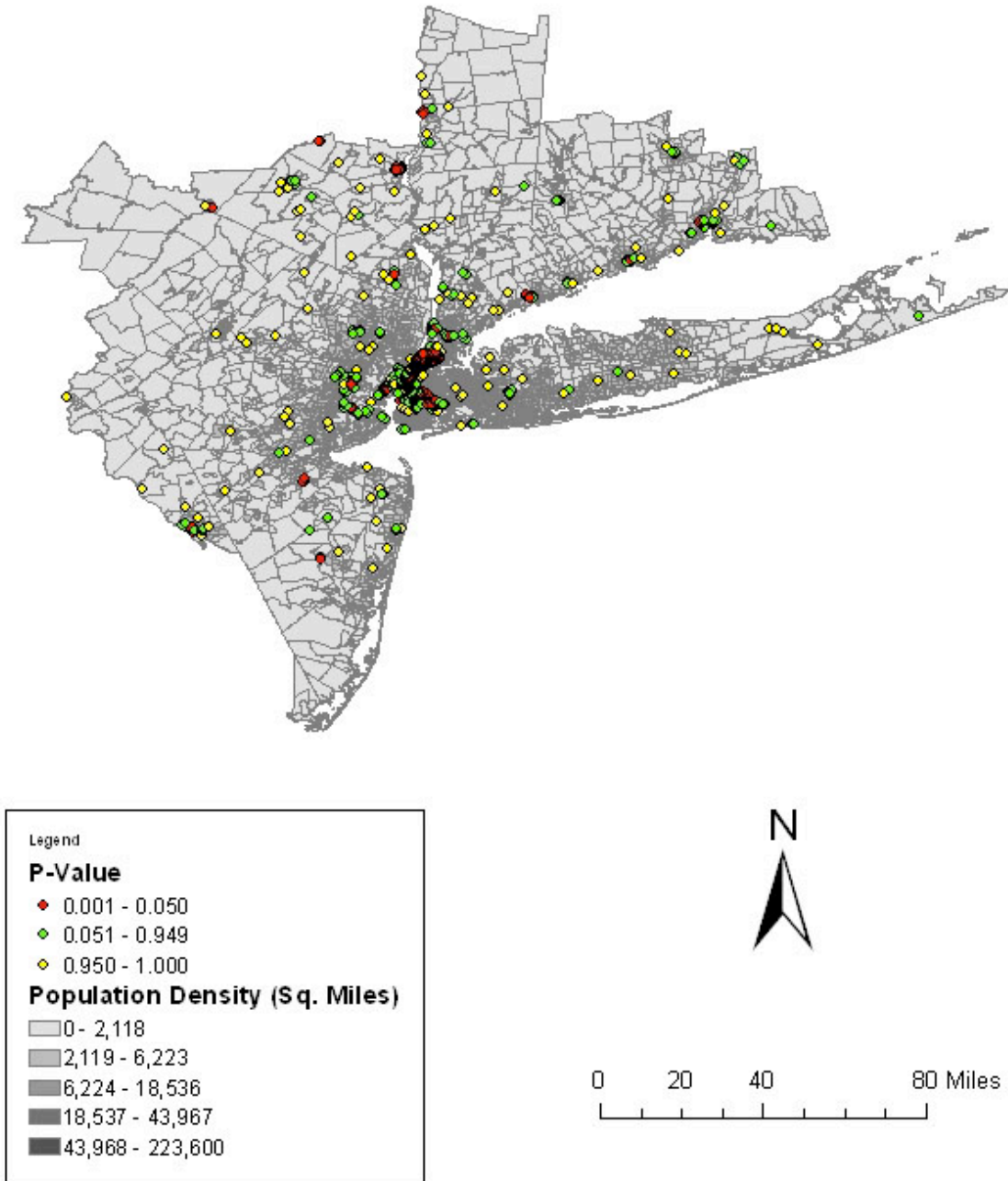
Figure 18: LIHTC Properties, Los Angeles



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

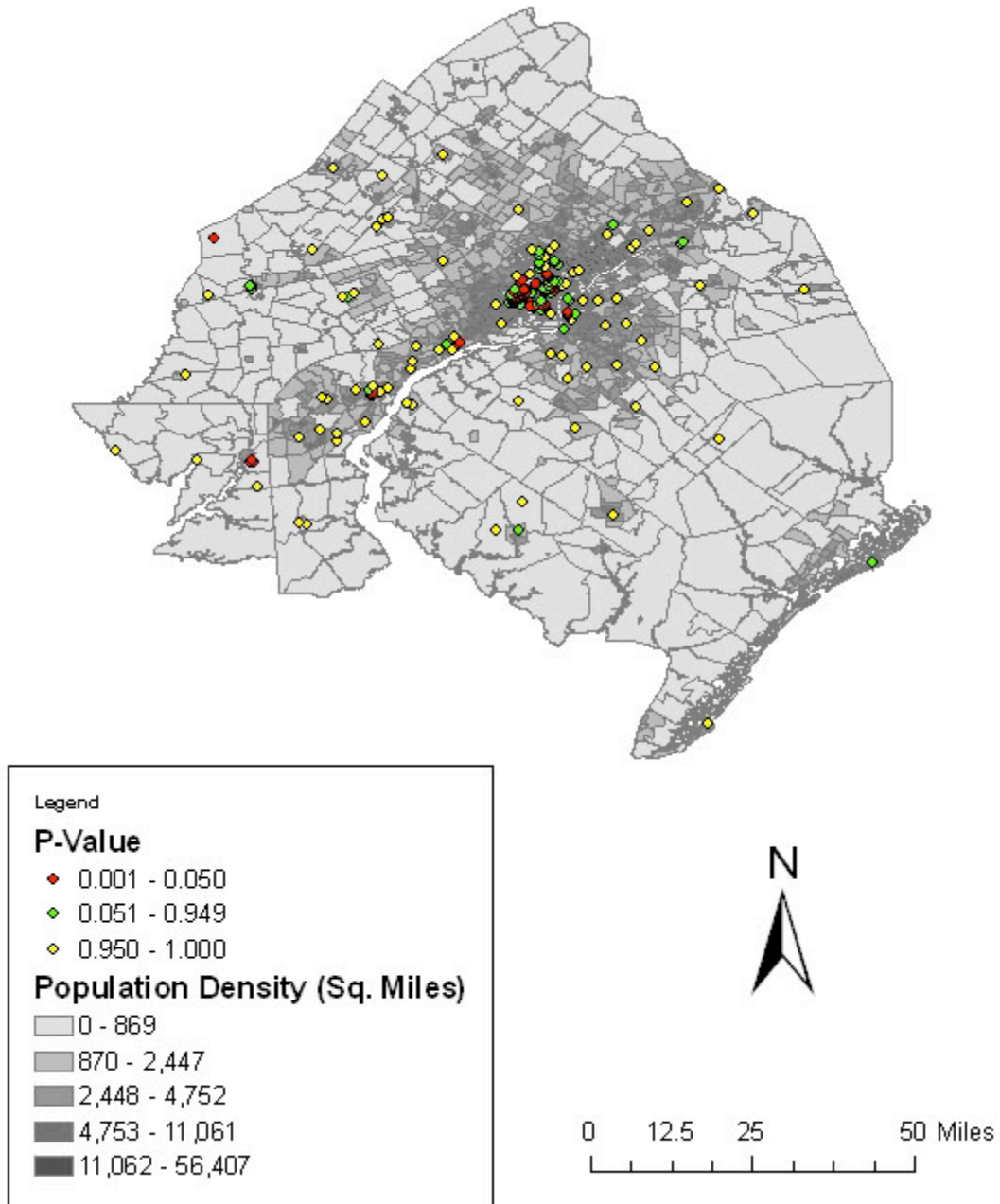
Figure 19: LIHTC Properties, New York



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

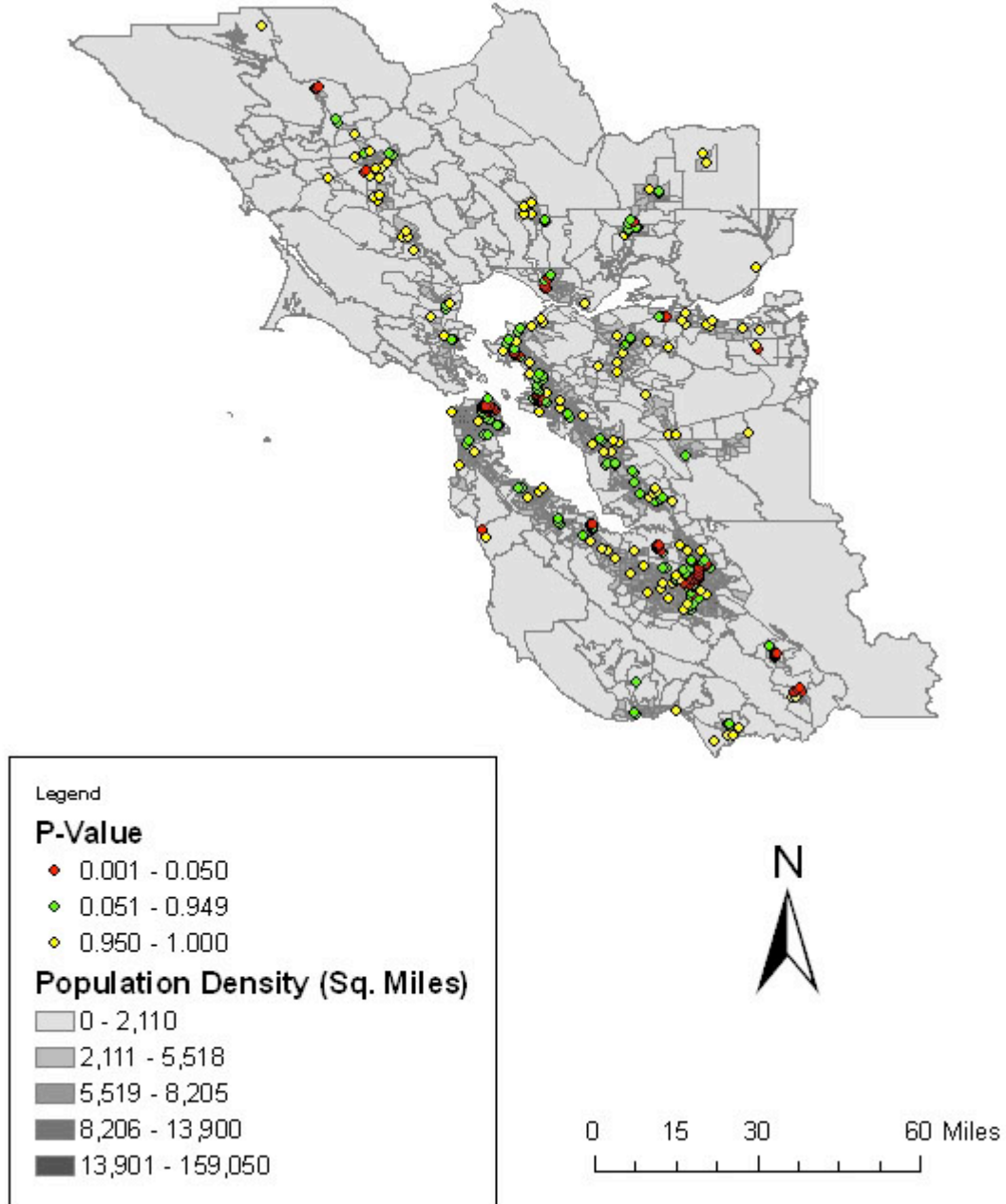
Figure 20: LIHTC Properties, Philadelphia



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

Figure 21: LIHTC Properties, San Francisco



Note: In the figure above, dots indicate the location of LIHTC properties. Red dots are those within local clusters; yellow dots are those exhibiting local patterns of dispersion; and green dots are those exhibiting a random spatial pattern. Census tract population density shown in gray, with low to high population density represented by light to dark gray.

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

An additional benefit of the local K-function analysis is that each point can be categorized in terms of its spatial relationship to other points within the region. Categorizing points in this way allows us to compare the characteristics of LIHTC properties that exhibit different spatial patterns. Table one displays the property-level characteristics of clustered, randomly-distributed, and dispersed LIHTC properties in each of the 10 largest metropolitan areas. The first few columns display the total number and relative frequency of points falling within each spatial category. The middle columns display the average number of units per property by the degree of clustering, and the last few columns display the percent of properties within each category that are new construction projects. The percentages shown in the last column along with all other percentages shown in the tables that follow do not add to 100 percent, because the percentages are calculated in terms of the percent of units within each spatial category that exhibit the particular characteristic. For example, the 18 percent shown under “clustered” and “percent new construction” for New York implies that 18 percent of the properties in the clustered category are classified as new construction.

Table 1: Average Characteristics of Clustered, Random, and Dispersed LIHTC Properties

Metropolitan Area	Properties						Units Per Property			Percent New Construction		
	Clustered		Random		Dispersed		Clustered	Random	Dispersed	Clustered	Random	Dispersed
	N	%	N	%	N	%						
New York	898	71%	246	19%	128	10%	46	79	90	18%	45%	61%
Los Angeles	161	35%	207	45%	90	20%	59	106	105	65%	59%	60%
Chicago	99	38%	49	19%	115	44%	91	122	106	48%	39%	55%
DC	146	35%	130	31%	146	35%	107	124	128	42%	38%	55%
San Francisco	105	30%	136	39%	108	31%	100	96	98	66%	67%	70%
Philadelphia	95	41%	57	24%	82	35%	45	69	79	53%	47%	62%
Boston	138	50%	45	16%	94	34%	83	78	86	25%	44%	40%
Detroit	87	35%	81	33%	79	32%	68	81	110	66%	57%	63%
Dallas	30	16%	43	23%	116	61%	139	195	164	57%	63%	66%
Houston	20	13%	40	25%	100	63%	170	182	184	70%	65%	73%

Source:

HUD LIHTC Database; 2000 U.S. Census, SF1

The percent of properties falling into local clusters varies by metropolitan area, with New York exhibiting the highest percentage and Houston exhibiting the lowest percentage. Within Chicago, Dallas, and Houston, the largest share of properties are those that exhibit patterns of local dispersion. Unit size differs by the degree of clustering, although the pattern of these differences varies by metropolitan area. In most metropolitan areas, dispersed LIHTC developments are more likely to be exclusively new construction, with the exception of Detroit and Los Angeles, which has the highest incidence of new construction in clustered properties. One would naturally expect LIHTCs used for rehabilitation purposes to exhibit a more spatially-concentrated pattern, because existing low income housing units, until recent changes in HUD policy geared towards dispersing the geographic pattern of affordable housing assistance, have tended to be located near other low income units.

Table two displays two geographic characteristics of clustered, randomly-distributed, and dispersed LIHTC properties: the percent of properties located in the metropolitan area’s central city and the average census tract population density.

Table 2: Geographic Characteristics of Clustered, Random, and Dispersed LIHTC Properties

Metropolitan Area	% in Central City			Population Density (Persons / Sq. Mi.)		
	Clustered	Random	Dispersed	Clustered	Random	Dispersed
New York	96%	59%	27%	64,278	31,299	20,474
Los Angeles	84%	48%	26%	22,120	10,785	7,561
Chicago	93%	78%	52%	16,577	19,030	7,720
DC	53%	40%	23%	10,618	9,651	4,754
San Francisco	78%	59%	44%	18,202	11,359	6,097
Philadelphia	89%	82%	21%	17,331	17,164	5,788
Boston	99%	80%	33%	20,118	13,300	5,222
Detrpit	70%	67%	28%	5,061	5,980	3,556
Dallas	73%	84%	52%	6,845	5,973	2,899
Houston	40%	90%	48%	1,210	5,616	3,211

Source: HUD LIHTC Database; 2000 U.S. Census, SF1

With the exception of Dallas and Houston, clustered properties are more likely to be located in central city locations. However, these areas are not always the areas with the highest population densities. In Chicago, Detroit, and Houston, randomly-distributed properties are located in tracts with the highest population densities.

Table three displays three census tract characteristics of clustered, randomly-distributed, and dispersed LIHTC properties in each of the 10 largest metropolitan areas: the percent of properties located in Qualified Census Tracts (QCTs), the percent of properties located in Difficult to Develop Areas (DDAs), and the average percent of the population in each census tract below the poverty line. Not all metropolitan areas designate DDAs, as indicated by the zero percentages in the middle columns in the table below.

Table 3: Census Tract Characteristics of Clustered, Random, and Dispersed LIHTC Properties

Metropolitan Area	% of Properties in QCTs			% of Properties in DDAs			% of Census Tract Pop in Poverty		
	Clustered	Random	Dispersed	Clustered	Random	Dispersed	Clustered	Random	Dispersed
New York	69%	37%	9%	94%	68%	59%	36%	22%	12%
Los Angeles	73%	31%	13%	87%	54%	54%	36%	22%	17%
Chicago	84%	53%	24%	0%	0%	0%	37%	27%	14%
DC	53%	22%	13%	0%	0%	0%	23%	14%	9%
San Francisco	48%	22%	9%	70%	64%	61%	19%	13%	9%
Philadelphia	82%	63%	11%	0%	2%	6%	33%	30%	12%
Boston	78%	42%	7%	66%	78%	73%	30%	18%	9%
Detrpit	75%	69%	23%	0%	0%	0%	29%	29%	14%
Dallas	87%	40%	33%	0%	0%	0%	26%	21%	17%
Houston	55%	63%	25%	15%	38%	42%	23%	31%	16%

Source:

HUD LIHTC Database; 2000 U.S. Census, SF1

In all metropolitan areas but Houston, clustered properties are more likely to be located in Qualified Census Tracts. Among those metropolitan areas designating DDAs, clustered properties are more likely to be found in DDAs within New York, Los Angeles, and San Francisco. In Boston, randomly-distributed properties are more likely to be located in DDAs, and in Houston, dispersed properties are more likely to be located in DDAs. The trends observed for QCT presence mirror the pattern of results for average poverty rates, with all metropolitan areas but Houston exhibiting higher poverty rates within more clustered tracts. This is an expected result given that poverty rates are one criterion used to designate QCTs.

Table four displays the average census tract racial and ethnic characteristics of clustered, randomly-distributed, and clustered LIHTC properties in each of the 10 largest metropolitan areas.

Table 4: Census Tract Racial / Ethnic Characteristics of Clustered, Random, and Dispersed LIHTC Properties

Metropolitan Area	% Non-Hispanic White			% Non-Hispanic Black			% Hispanic		
	Clustered	Random	Dispersed	Clustered	Random	Dispersed	Clustered	Random	Dispersed
	New York	7%	36%	64%	54%	32%	14%	36%	25%
Los Angeles	13%	30%	40%	13%	10%	6%	62%	48%	45%
Chicago	14%	25%	54%	74%	48%	27%	8%	24%	14%
DC	40%	43%	57%	51%	35%	31%	7%	14%	6%
San Francisco	32%	39%	55%	15%	13%	7%	32%	28%	23%
Philadelphia	15%	26%	67%	77%	60%	24%	6%	11%	6%
Boston	35%	61%	84%	31%	14%	4%	23%	18%	7%
Detrpit	38%	29%	69%	49%	67%	25%	10%	3%	25%
Dallas	30%	31%	50%	30%	37%	23%	36%	29%	24%
Houston	38%	15%	40%	30%	47%	21%	30%	32%	34%

Source:

HUD LIHTC Database; 2000 U.S. Census, SF1

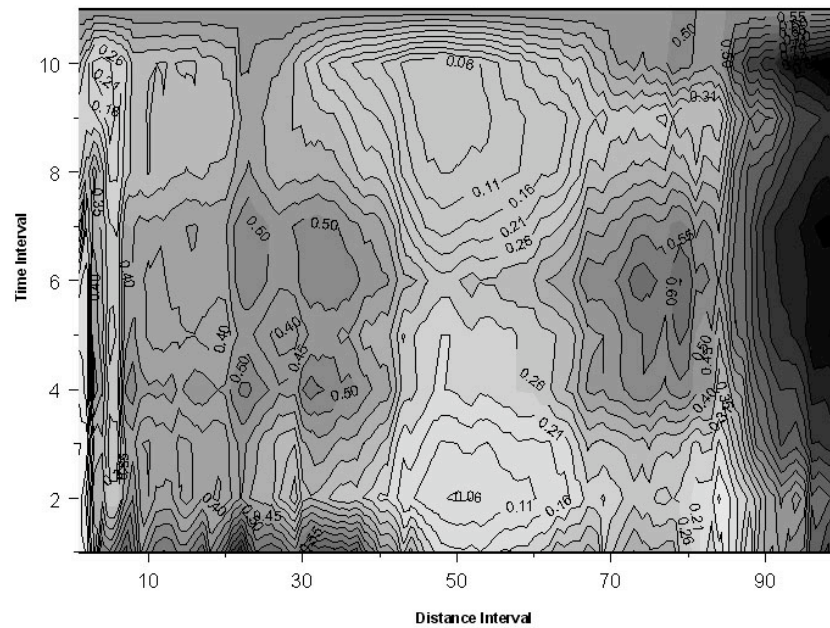
In all metropolitan areas, dispersed LIHTC properties are located in census tracts with a higher percentage of non-Hispanic Whites. Clustered properties in all metropolitan areas but Dallas, Detroit, and Houston are located in tracts that have higher non-Hispanic black percentages. The pattern of results for percent Hispanic exhibits considerably more inter-metropolitan variability.

The final analyses displayed in figures 22 through 31 are tests of space-time clustering based on a spatio-temporal variation of the Ripley’s K function. The shading in the figures below reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points. Statistically significant clustering over short distance and time intervals implies that properties which are spatially proximate are constructed within a short time span of one another, indicative of a pattern of spatial diffusion. Spatial diffusion implies that properties are “attracted” to one another, which points to another dimension by which clustering may occur. One possible explanation for LIHTC diffusion is that LIHTC properties may have spillover effects for the surrounding community. If a LIHTC development leads to an overall increase in neighborhood

quality, perhaps by replacing vacant and dilapidated properties with new development, then this may create incentives for further investment in the area (Baum-Snow and Marion. 2009).

As suggested by the figures below, patterns of diffusion differ quite dramatically by metropolitan area, with Boston, Washington DC, and Houston exhibiting little spatio-temporal clustering at short distance intervals. New York exhibits the highest degree of spatio-temporal clustering over the largest number of time and distance intervals. One possible contributor to these inter-metropolitan differences is the overall development pattern within the metropolitan area. In an area such as New York, where densities are much higher to begin with, the spillover effects of individual LIHTC developments may extend over a larger number of additional properties.

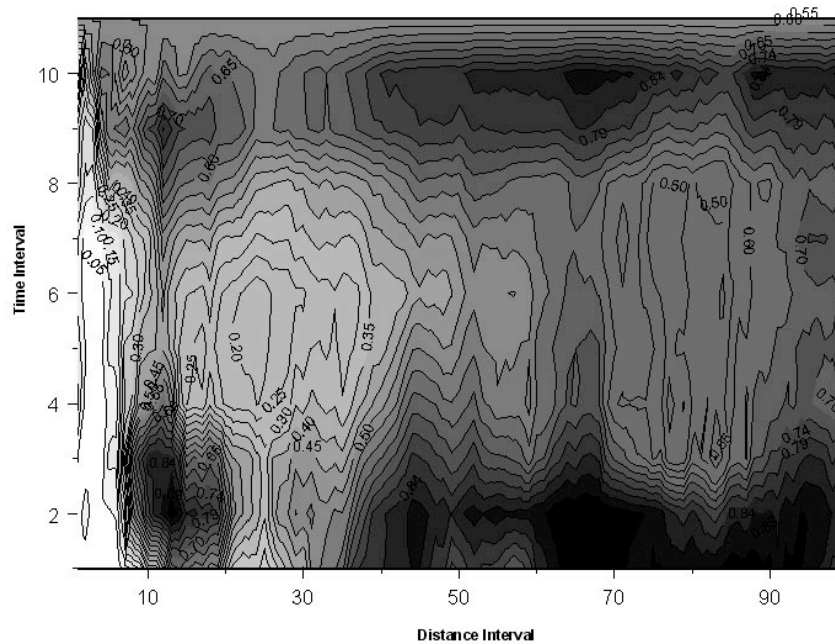
Figure 22: Space-Time Clustering Test, Boston



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

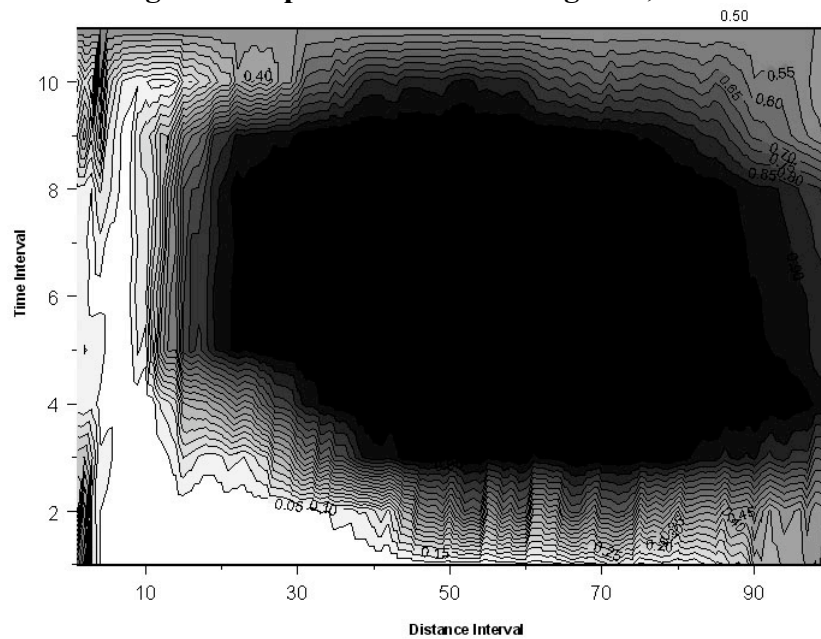
Figure 23: Space-Time Clustering Test, Chicago



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

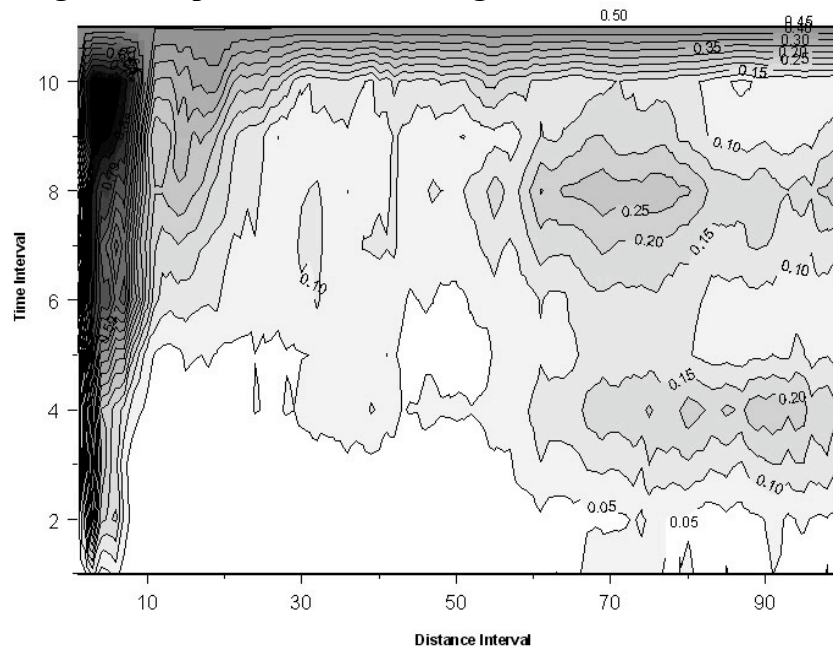
Figure 24: Space-Time Clustering Test, Dallas



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

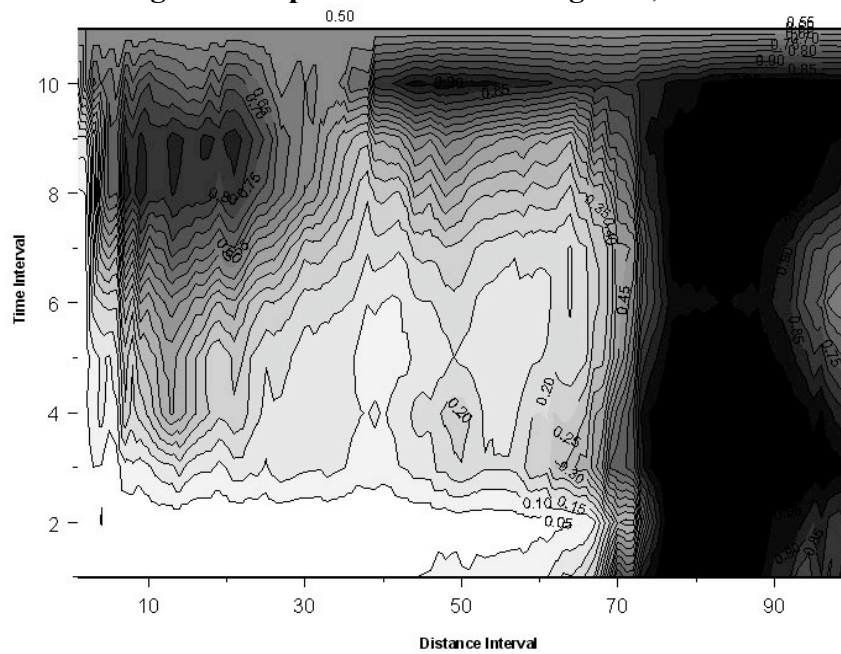
Figure 25: Space-Time Clustering Test, District of Columbia



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

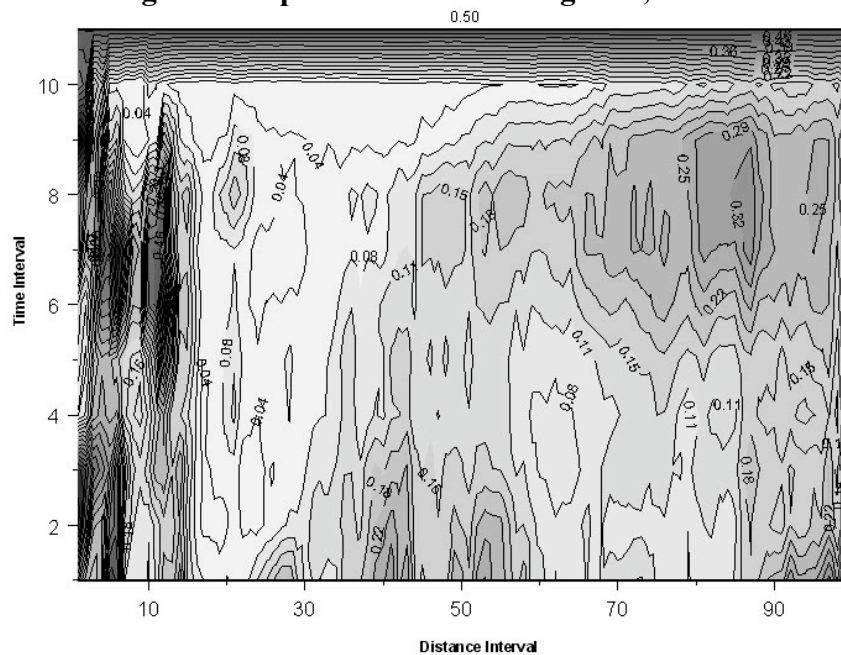
Figure 26: Space-Time Clustering Test, Detroit



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

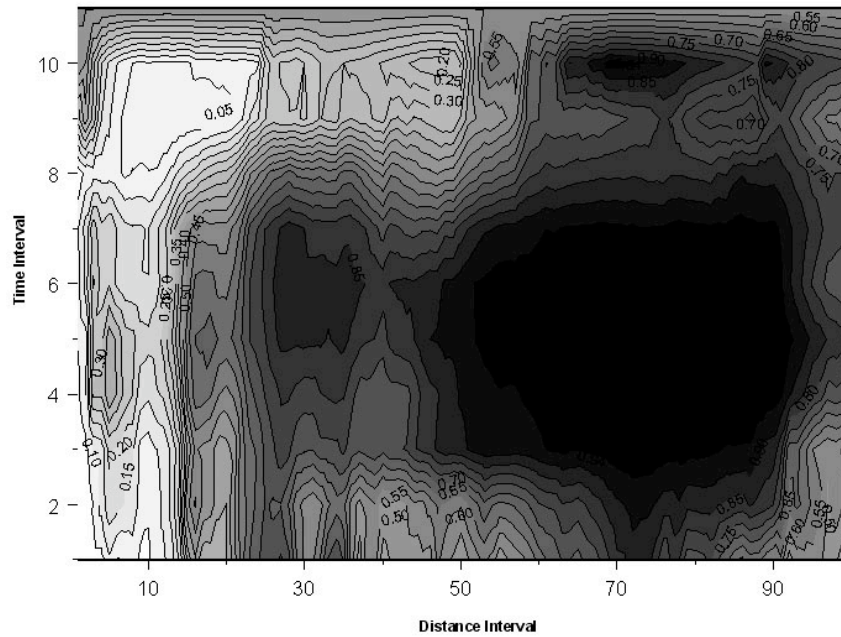
Figure 27: Space-Time Clustering Test, Houston



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

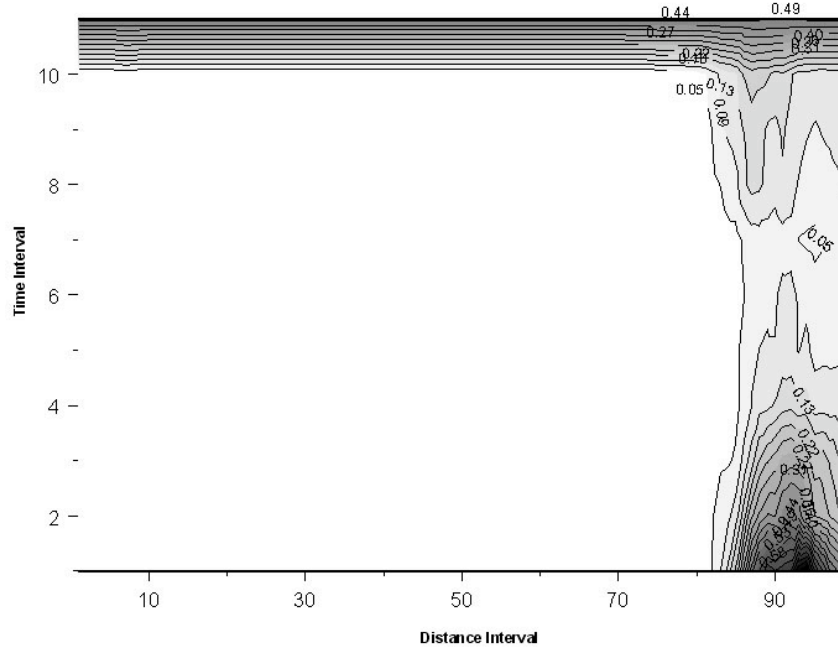
Figure 28: Space-Time Clustering Test, Los Angeles



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

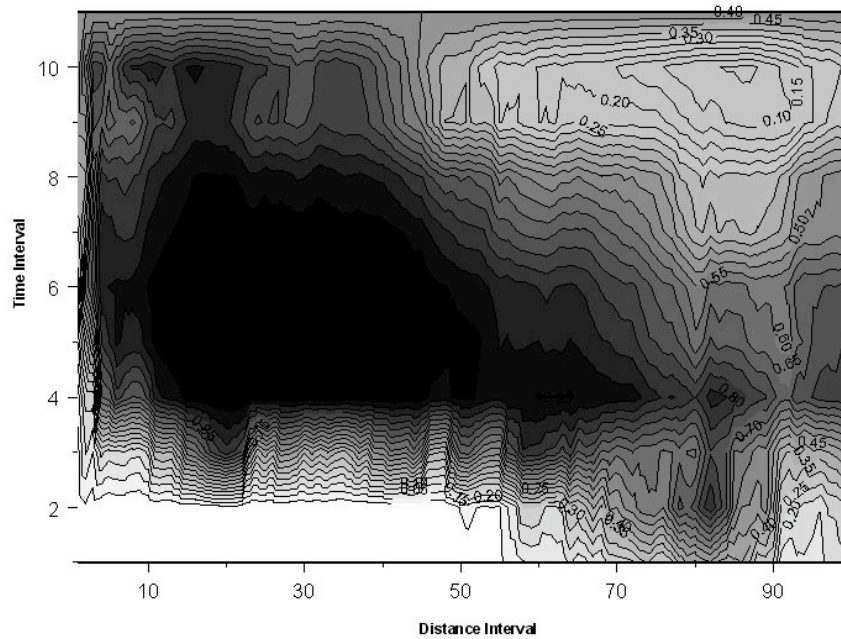
Figure 29: Space-Time Clustering Test, Space-Time Clustering Test, New York



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

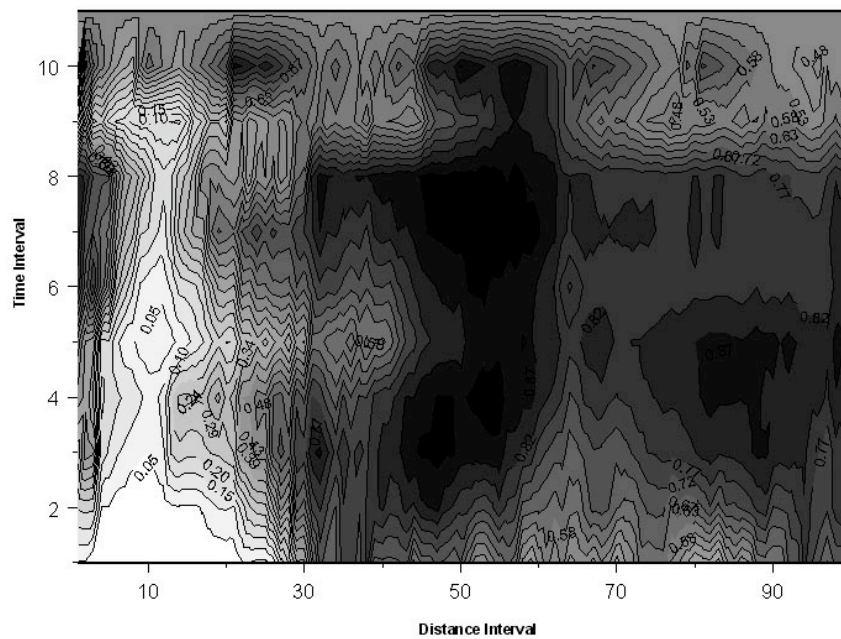
Figure 30: Space-Time Clustering Test, Philadelphia



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

Figure 31: Space-Time Clustering Test, San Francisco



Note: The shading in the figure above reflects the p-value associated with the significance of clustering / dispersion at a given distance / time interval. Time is reported in years, and distances are reported in terms of standardized distance intervals with the maximum interval equal to one half the maximum distance between points.

Source: HUD LIHTC Database

DISCUSSION

While the analyses performed in this paper offer an improvement over prior studies that ignore the spatial distribution of LIHTC properties within census tracts, there are a few caveats to consider when interpreting the results. First, simulations of the benchmark case of complete spatial randomness were performed using simulations from census tracts. As such, the simulations are only estimates of small scale (parcel-level) housing unit distributions. The census tract was chosen as the unit of simulation for this study, because earlier work validated the census tract as an appropriate unit of analysis for a similar application (see, for example, Hillier (2003)) and due to the fact that at any scale smaller, simulations would not be possible without additional computer processing capacity. An additional caveat is that LIHTC properties with inaccurate geocodes were omitted from the analysis. These omissions were less than one percent of the sample in all metropolitan areas analyzed, however, and sensitivity tests indicate that omitting such properties had little influence on the overall results.

In all metropolitan areas, LIHTC properties are more highly clustered than other housing units. The clusters tend to be located in more densely-developed central city locations that have higher poverty rates and lower shares of non-Hispanic whites. The pattern of results suggests that LIHTC programmatic rules may be contributing to these outcomes. Clusters are more likely to be located in QCTs and DDAs in most metropolitan areas, a clear result of incentives and according to the IRS, a successful outcome.

Apart from these overall trends, metropolitan areas exhibit different patterns of clustering at different scales. Generally speaking, LIHTC properties are clustered over much smaller distance radii in Dallas and Houston, compared to other metropolitan areas. These two metropolitan areas have the largest share of properties exhibiting dispersed local patterns (see figures four and seven and table one). Spatial patterns of diffusion also differ across metropolitan areas, with Boston, Washington DC, and Houston exhibiting little spatio-temporal clustering at short distance intervals (see figures 22, 25, and 27). In Dallas, Detroit, and Houston, randomly-distributed properties are located in census tracts with the highest non-Hispanic black percentage, and in the case of Detroit and Houston, dispersed properties are located in census tracts with the highest Hispanic percentage (see table four).

Among all metropolitan areas, Houston is the most unique. The low level of clustering over longer distance intervals and weak spatio-temporal clustering combined with the relatively lower share of clusters found in central cities and high density areas points to a more spatially-decentralized pattern of LIHTC placement. Houston also has fewer clustered properties in QCTs and DDAs. Randomly-distributed properties, not clustered properties, are the ones that exhibit the highest incidence of poverty and non-Hispanic black along with the highest concentration of non-whites. The finding of less clustering in high poverty tracts is consistent with Lopez and Di (2009), who observe that suburban counties in Texas have received higher LIHTC awards per person in poverty than central cities.

There are several possible explanations for the relatively lower degree of global LIHTC clustering in Houston and Dallas. First, the Texas Qualified Allocation Plan explicitly mandates that LIHTC developments be at least one mile from an existing LIHTC property. Furthermore,

LIHTC units cannot be located in census tracts with a large number of existing affordable housing units (Lopez and Di 2009). Another explanation is that with the lower development densities found in Dallas and Houston, there may be a larger supply of vacant developable land in a larger number of areas. Despite the incentives offered through the DDA provision, high land assembly costs can significantly reduce incentives to invest in LIHTC property development, particularly since land costs can not be included in a developer's calculation of eligible basis.

Although an investigation into the causes of inter-metropolitan differences in LIHTC placement patterns is beyond the scope of this study, there are several possible factors which may contribute to these inter-metropolitan differences. State-level differences in tax credit allocation priorities outlined in state QAPs may be one factor contributing to the differences observed, as suggested by the unique case of Houston. As noted by Gustafson and Walker (2002), states differ in their emphasis on "place-based" targeting of LIHTC resources. Among the metropolitan areas included in our study, the states of Texas, Virginia, Michigan, and Pennsylvania provide the largest number of place-based incentives.

Metropolitan differences in the identification of DDAs and QCTs may also contribute to differences in the patterns observed. As indicated in table three, DDAs were not designated in several of the 10 largest metropolitan areas. Each metropolitan area also has a different number of QCTs due to metropolitan differences in the number of low income neighborhoods, the extent of concentrated poverty, and the number of high poverty low income neighborhoods relative to the QCT population threshold requirement. The levels of clustering observed within DDAs may also be attributable to factors other than DDA status itself, particularly given that there is a built-in incentive to site properties within a DDA but choose locations with the lowest land costs in those areas. Furthermore, other local policies such as a policy of using LIHTCs to support redevelopment or local zoning codes may influence the distribution of properties within DDAs.

In addition to state-level differences in LIHTC policies, metropolitan differences in development patterns may also contribute to the differences observed. The metropolitan areas of Dallas and Houston exhibit much lower overall development densities than what is found in Chicago or New York. In more decentralized metropolitan areas, all development will be more spatially dispersed, thus we would expect LIHTC properties to be more dispersed as well. Inter-metropolitan differences in regulatory practices and the extent of citizen opposition to affordable housing developments may also influence the concentration of LIHTC properties. Since LIHTC properties do not have the traditional stigma often associated with public housing projects, it is possible that citizen opposition to LIHTC property development is less severe.

CONCLUSION AND POLICY IMPLICATIONS

The overall pattern of results suggests that certain provisions of the LIHTC program, inherent in the program design, may be contributing to the concentration of subsidized housing units within the nation's largest metropolitan areas. In all metropolitan areas examined, LIHTC properties are more highly clustered than other housing units. The clusters tend to be located in more densely-developed central city locations that have higher poverty rates and lower shares of non-Hispanic whites. LIHTC programmatic rules appear to be contributing to these patterns by

design. In most metropolitan areas, LIHTC clusters are more likely to be located in QCTs and DDAs. One suggestion is to change these incentives and provide points to developers choosing to locate LIHTC properties in high employment areas. The unique patterns observed in Houston and Dallas suggest that QAP provisions, such as the Texas mandate that LIHTC properties not be located within one mile of one another, may help to reduce the degree of LIHTC clustering.

I qualify these results with a few caveats. First, the pattern of clustering was examined conditional on the spatial distribution of housing units at the tract level. There are several other possible candidates for the reference population, including rental housing units and multi-family units, and I encourage future researchers to explore the sensitivity of the results presented to the variable used to measure the reference population. Second, the publicly-available indicator of QCT and DDA status indicates whether a LIHTC property is located in one of these two areas but does not identify whether the property actually received a basis boost from being located in one of these areas. The publicly-available data include a separate variable indicating whether a basis boost was provided, but there is no way to separately identify the policy incentive triggering the basis boost. Since states have some discretion determining the number of credits awarded for being located in QCTs and DDAs, the QCT / DDA indicator possibly overstates the number of properties actually receiving incentives from being located in either a QCT or DDA.

Additional research is needed to determine if these patterns observed are exacerbating local conditions of concentrated poverty and / or racial and ethnic segregation. Currently, HUD does not collect information on the race or income of LIHTC unit tenants, so it is not known whether the units placed in high-poverty areas or racially-segregated areas are altering local socio-economic patterns or helping to reinforce patterns that already exist. According to HUD, there are plans to include this information in future versions of the LIHTC database. Furthermore, even though the evidence from this study points to significant local clustering of LIHTC units, the effects of such clustering are unclear. On the one hand, local clustering of LIHTC units may increase the concentration of poverty-stricken households and limit the opportunities for such residents to build “bridging” social capital with higher income households (Putnam 2000). On the other hand, new LIHTC properties may replace vacant and dilapidated structures that previously existed in the neighborhood, and a concentration of new properties may enhance the neighborhood quality of local residents, even if the units are co-located in a concentrated fashion (Baum-Snow and Marion 2009). Future research should address these effects and explore the policy implications of the patterns identified in this paper.

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