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Subsidized Housing, Private Developers and Place: A Spatial Analysis of the Clustering of Low Income Housing Tax Credit Properties in the 25 Largest U.S. Cities

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Abstract

The Low Income Housing Tax Credit Program is the primary federal program for producing new units of affordable housing. The program provides financial incentives to private developers to develop and operate affordable rental housing. In recent years, evidence has emerged that the program has led to clusters of subsidized housing in some cities. It is hardly surprising that some clustering would exist in a program in which the housing is constructed and owned by private developers.

Despite the significant number of units produced by the program and despite the potential tendency for clustering of units built under this program, the locational patterns within the LIHTC program remain largely unexamined. Instead, most studies of the LIHTC program have focused on the national level rather than on individual cities. In contrast to previous studies, this study seeks to improve our understanding of variations in the LIHTC program across cities. The hypothesis of this study is that, because private developers produce housing in the LIHTC program and because the factors that influence private developers vary across cities, there is likely to be significant variation in the locational patterns of LIHTC developments across cities. The results of this study show, among other things, that clustering of LIHTC properties exists in the study cities, this clustering is extreme in some cases, and the clusters are associated with high poverty tracts in some cities. Given the LIHTC program's emphasis on market-driven policies and a similar emphasis in some other federal housing programs, such findings will likely be applicable to other affordable housing programs.

Keywords: Low Income Housing Tax Credit Program, affordable housing, spatial statistics, clustering analysis, GIS

Chapter 1 – Introduction

> *Tax credits in coordination with money have really done a great job of taking neighborhoods in Camden and Newark and making them among the best in those cities.*
>
> -Sean Closkey, Director of Neighborhood Investment Strategies for The Reinvestment Fund (Neuwirth, 2004)

> *In many parts of the country, the tax credit programs are producing the same kind of racism and economic discrimination that we saw in HUD programs 30 to 40 years ago.*
>
> -Philip Tegeler, former Legal Director of the Connecticut Civil Liberties Union (Neuwirth, 2004)

The purpose of this study to examine the advantages and disadvantages of using spatial statistics in housing and to investigate what spatial statistics can reveal about the locational patterns of Low Income Housing Tax Credit developments in different cities. Data on Low Income Housing Tax Credit (LIHTC) projects in the 25 largest U.S. cities are used to examine these issues.

This paper presents the results of a study of the distribution of LIHTC units using a clustering analysis. The locations of LIHTC properties in the 25 study cities are identified and analyzed for the presence of clusters. The characteristics of the clusters in all cities are examined and compared.

It is hypothesized that the locational patterns of LIHTC developments will vary across cities. Because the LIHTC program is a market-oriented program which relies on private actors, the patterns of LIHTC development should vary as housing markets vary.

This paper will consider the implications of clustering of the LIHTC program and whether other federal housing programs may exhibit similar patterns.

After the pattern analysis in the first stage of this research, the advantages of spatial clustering analysis over other measures are discussed. Because the statistical analysis in this study was done in a GIS environment, the analysis has the power of traditional statistical analyses while also taking advantage of the intuitive power in mapping and visualization techniques. It is argued that the single analytic method used in this study reveals the same information as several traditional measures of segregation combined.

Background

While housing policy research does not have a long history of using spatial statistics[1], housing policy practitioners and researchers have long been aware of the importance of spatial relationships to housing, especially affordable housing. One of the earliest major housing policy crises in the modern era was the problem of redlining. Redlining, the practice of denying mortgages to people trying to purchase houses on the basis of the location of the house under application, was explicitly spatial. In fact, the term *redlining* refers to the maps used by mortgages bankers that had certain neighborhoods outlined in red. Another major housing crisis in the 20th century – the problem of concentrated poverty in and around public housing projects – is also spatial in nature. While the problems found in the most notorious public housing projects had numerous causes, one of the major causes of the ills that plagued public housing was concentration of poverty. Concentration of low-income persons continues to be a concern for policymakers today. For example, a recent GAO report revealed that thirty percent of

[1] See Chapter 2 for a discussion of the limited cases where housing research has used spatial statistics.

the state agencies responsible for allocating tax credit indicated that excessive concentration of very low-income housing was a problem somewhere in their states (1997, 56).

Statement of Policy Relevance

This paper examines whether the forces that lead to concentrated poverty or other similar forces may lead to clustering of LIHTC properties. The LIHTC Program was created in 1986. It is a major federal affordable housing program and has created more than 1.5 million units in its history. Nationwide, almost two-thirds of all LIHTC projects placed in service from 1995 through 2000 were newly constructed (as opposed to rehabilitated units). In fact, the LIHTC program is the primary federal program for producing affordable housing. Beyond that, the LIHTC program is a major producer of housing even when compared to the unsubsidized housing market. The newly constructed units placed in service during the last half of the 1990s accounted for more than 20 percent of all multifamily rental unit construction – subsidized and unsubsidized - over that time period (Nolden, et al., 2002, ii).

While the LIHTC program has been very successful at encouraging the private development of new affordable housing, some residents (Houston Chronicle, 2004; Ramshaw, 2004) and advocacy groups (Neuwirth, 2004; Zimmerman, 2004) have recently argued that the LIHTC program leads to clusters of subsidized housing. Approximately 48 percent of all LIHTC units placed in service from 1995 to 2000 are located in central city neighborhoods (Nolden, et al., 2002). It is hardly surprising that some clustering would exist in a program in which the housing is constructed and owned by private developers and in which some allocating agencies even award extra points to the projects preferred by local officials (GAO, 1997).

Despite the significant number of units produced by the program and despite the potential tendency for clustering of units built under this program, the locational patterns within the LIHTC program remain largely unexamined (Oakley, 2008) and our knowledge of where units are located is limited (Deng, 2007). Most studies of the LIHTC program have focused on the national level. We know that LIHTC projects tend to serve moderate-income persons (as opposed to low-income persons); these projects tend not to be mixed-income; and they tend to be located in areas with relatively high concentrations of low-income persons (McClure, 2000).

In contrast to these studies, this study seeks to improve our understanding of variations in the LIHTC program across cities. The hypothesis of this study is that, because private developers produce housing in the LIHTC program and because the factors that influence private developers vary across cities, there is likely to be significant variation in the locational patterns of LIHTC developments across cities. The results of this study will show, among other things, that clustering of LIHTC properties exists in the study cities, this clustering is extreme in some cases, and the clusters are associated with high poverty tracts in some cities. Given the LIHTC program's emphasis on market-driven policies and a similar emphasis in some other federal housing programs, such findings will likely be applicable to other affordable housing programs. The emphasis on market-oriented policies in the LIHTC program can be found in other federal affordable housing programs. Accordingly, there is reason to believe that the findings about clustering in LIHTC developments may be partly applicable to other programs.

Research Questions

This study addresses the following research questions:

- What variation among cities in the distribution of LIHTC projects is revealed by local spatial statistics?
- What are the advantages and disadvantages of conducting research on housing using local spatial statistics?

The first question is a programmatic question while the second question is a methodological question. As discussed in Chapter 4, these two questions are symbiotic; because housing researchers have made little use of spatial statistics until now, the answers to one question provide insight to the other.

Overview of Methodology

Despite the clearly spatial nature of housing in general and subsidized housing in particular, spatial statistics have been underutilized in housing research. While many studies have examined spatial aspects of housing, only a handful of studies of housing policy have used methods that are explicitly spatial. This study employs spatial statistics to examine locational patterns of LIHTC units. Spatial statistics differ from classical statistics primarily in the underlying assumptions. Classical statistics assume that each data point is unrelated to every other data point. Spatial statistics assume the opposite. The assumption that all data are related in some way is expressed by Tobler's law, which is considered the first rule of spatial statistics: Everything is related to everything else, but near things are more related than distant things. The phenomenon of close things being related is known as spatial autocorrelation.

As will be discussed in detail later in this paper, there is reason to believe that much spatial autocorrelation occurs with the location of housing. Although much of the spatial analysis of housing has focused on single family houses (for example, see Fik et al., 2003, and Can and Megbolugbe, 1997), the results of these studies indicate that spatial autocorrelation exists in housing markets in general. With respect to the LIHTC program in particular, there are programmatic factors that might result in clustering of developments (Oakley, 2008).

This study uses a spatial statistic to measure clustering of LIHTC units in the 25 largest U.S. cities. Hot spots, or areas where relatively many LIHTC units are located, are identified for each city.

The analysis is performed at the Census tract level for each city. The number of LIHTC units in each Census tract is determined and analyzed using the spatial statistic G_i*. The G_i* statistic is able to measure clusters of relatively high values and relatively low values. In this study, the G_i* statistic shows where Census tracts with substantially higher numbers of LIHTC units are clustered.[2]

The analysis was performed in a Geographical Information System (GIS). All of the LIHTC properties in the study cities were plotted in ArcView and the analysis was performed using a combination of built-in features of ArcView and scripts for ArcView written in Avenue. The results of the analysis were returned in the form of maps and

2 Because the vast majority of Census tracts in each study city have zero LIHTC units, the ability of Gi* to shsow clusters of low values is not relevant to this study; too much of the study area has a zero value for those areas to be considered clusters.

tables. The advantage of conducting this analysis in a GIS is discussed in Chapters 5 and 6.

Definition of Terms

I use the term *hot spot* to refer to a group of Census tracts that are located close to one another and that all have relatively high G_i* values. The term *cluster* (along with variants such as *clustering* or *clustered*) is also sometimes used to refer to a hot spot. Unlike some other statistics, such as Pearson's Product-Moment Correlation Coefficient, the G_i* statistic does not have standard thresholds for determining what constitutes a hot spot. The threshold G_i* value for determining what constitutes a cluster is always determined by the researcher. The threshold used in this study is discussed in Chapter 4.

Limitations of Study

This study has several limitations that prevent the results from being broadly applied to the LIHTC program or subsidized housing in general. The first limitation is that this study looks at clustering of only one affordable housing program. There are several affordable housing programs currently in operation throughout the country, each with different rules and regulations about how the funding can be used, where housing can be located, and what populations can be served. Some subsidized housing is privately developed and owned, by for-profit or non-profit organizations, while other subsidized housing is owned by governmental agencies. Because housing developed under the LIHTC program was developed under a very specific set of rules and guidelines, findings about the nature of clustering of LIHTC properties do not necessarily reveal information about the nature of clustering of subsidized housing in general.

However, there are reasons to believe that the general findings of this study may be applied to other programs. The LIHTC program is a market-oriented program. As is discussed in depth in Chapter 3, federal housing programs have become increasingly market-oriented over the past few decades. The variations across cities in the patterns of LIHTC developments that are found in this study indicate that other market-oriented programs may have similar variations across cities.

Furthermore, the results of this study do not allow any broad generalizations about the LIHTC to be drawn because this study examines LIHTC units in only the 25 largest cities in the country. Large cities were selected for this study in an effort to select cities with relatively many LIHTC units. It was assumed that a large population would be closely correlated with a high number of units in most cases. Thus, the cities in this study are not necessarily representative of even large cities, much less all of the areas where LIHTC properties are developed. Certainly there is reason to believe that locational patterns of rural developments will be quite different from those in the study cities.

Organization of This Study

After this introductory chapter, Chapter Two presents a review of existing literature. This chapter has two focuses: the literature on affordable housing and the literature on spatial statistics and GIS. Chapter Three looks at the Low Income Housing Tax Credit program in depth. It places the program in the context of other federal affordable housing programs and looks at the ideological trajectory of federal housing programs over the past several decades. Given the LIHTC program's reliance on private developers, some of the factors that influence private development are also discussed. Chapter Four explains the data and methodology used in this study. Important methodological limitations of this study are discussed at the end of Chapter Four. Chapter Five contains a discussion of the results of the analysis. Chapter Six includes a discussion of the implications of the findings in Chapter 5, policy recommendations, the methodological findings, and possible avenues for future research. Maps showing the locations of all LIHTC properties in the study and all hot spots identified through the analysis are included in the Appendices. Also included in the Appendices is a brief description of the plans that govern the allocation of tax credits and data about the number of tax credit properties and units in each study city.

Chapter 2 - Literature Review

The research questions addressed by this paper combine the fields of traditional housing research and spatial analysis in a GIS environment. Because relatively little housing research has taken advantage of the power of GIS[3], there are few previous studies to guide future research in terms of specific research design. This literature review joins together research from a broad spectrum of research to present the context for this study.

Housing Policy[4]

For many decades, the only type of federally subsidized rental housing was public housing. In the 1937, Congress created the public housing program, and in the post-World War II years, the program began to grow significantly in size. Under the public housing program, the government acted as the developer, owner and operator of rental housing for low-income persons. The public housing program as it was designed included several elements (e.g., a target population that was the poorest of the poor, limited funding for operation) that led to the problems that would plague the program

[3] Michael P. Johnson has looked at how to use GIS as a tool to help families make relocation decisions under the Section 8 Housing Assistance Program (Johnson, 2001). While this such a support system takes advantage of some of the more advanced capabilities of GIS, it does really use GIS to analyze housing. Rather, it provides a way of finding a best fit for an individual family on a series of neighborhood characteristics.

Another type of housing research that has begun to incorporate GIS is hedonic models (Geoghegan, et al., 1997; Paterson and Boyle, 2002). As is to be expected with hedonic models, however, these studies focus more on the economic aspects of the housing market, rather than policy.

[4] This brief discussion is focused on how the history of federal housing affordable housing policy has developed over time with respect to racial and economic concentration. For a more in-depth history of federal housing policy, see Hays (1995).

over the next several decades. One of these features created particularly long-lasting negative impacts; this feature was site selection.

Because local officials were allowed to choose the location of public housing projects, the potential for problems was always present. As early as the 1950s in some cities, the tensions created by the process of selecting sites for public housing began to have serious implications for the success of the program. Officials in many cities, under pressure from middle-income residents and white residents, resorted to tactics to minimize the resistance from these groups to public housing projects. These tactics included locating public housing projects in areas that were undesirable (often because of proximity to undesirable land uses), using public housing as a tool for slum clearance, restricting public housing to certain areas of town, and enforcing segregation at the project level to keep blacks out of certain neighborhoods.

The problems created by the local site selection process, along with other problems that were built into the public housing program, led to public housing projects that were economically and racially segregated. Recognizing that economically and racially segregated public housing not only led to poor living conditions but also violated the law in some cases, a new movement that sought to disperse residents began. The first programs designed to disperse subsidized housing began in the 1960s. The first major dispersal program, Section 23, was enacted in 1965. It allowed local public housing authorities to lease scattered-site, private homes to public housing residents. In 1974, the Section 8 program was created, allowing low-income families to receive certificates to use toward rent for existing rental units. The Section 8 program became an important component of the remedy for the precedent-setting *Gautreaux* lawsuit (Rubinowitz and

Rosenbaum, 2000). In this lawsuit, the courts found that the Chicago Housing Authority had discriminated in the site selection process and assignment of residents to public housing projects. While the initial lawsuit involved racial discrimination, a Supreme Court decision in a related case indicated that the case had implications for economic discrimination as well (Rubinowitz and Rosenbaum, 2000). The Gautreaux program created as a remedy under the lawsuit provided the opportunity for families to move out of the inner city and into the suburbs.

Since the 1970s, when the goal of deconcentrating poverty gained popularity among housing reformers (Hays, 1995: 144), the emphasis on deconcentrating poverty has grown. Today, HUD regulations state that one of the main goals of the Consolidated Planning Process is to reduce "the isolation of income groups within a community or geographical area through the spatial deconcentration of housing opportunities for persons of lower income and the revitalization of deteriorating or deteriorated neighborhoods" (Code of Federal Regulations, 2003). This emphasis on deconcentration is the result of the lessons learned throughout the history of modern affordable housing.

However, because it is authorized primarily as a tax program, the LIHTC program to a certain extent operates outside of the arena of affordable housing. That the LIHTC program is not subject to HUD's regulations concerning deconcentration and, in fact, is not even operated by HUD, makes it all the more important that researchers and administrators understand the dynamics of location selection in the LIHTC program. The LIHTC program is largest federal program to fund the development and rehabilitation of low-income housing (GAO, 1997; Abt Associates, 2002). For the years

1995 to 2000, the LIHTC program was responsible for the creation of 80,762 low-income units per year on average. Over 60 percent of these were newly constructed units (Abt Associates, 2002). Housing researchers and practitioners should monitor the LIHTC program to ensure that the lessons learned from previous housing programs are not lost on this important program. As the analysis in later in this paper shows, local spatial statistics such as those used here can be provide a picture of the execution of the LIHTC program that is rich in detail.

Previous Analysis of the Low Income Housing Tax Credit Program

As stated above, Congress created the LIHTC program 1986. By the mid-1990s, enough units had been placed in service that researchers were able to begin examining the program both in terms of how the program compares to other housing programs and how well the program achieves its goals.

McClure (2000) has combined the results of several other studies of the LIHTC program in an effort to develop a comprehensive picture of the program's first 10 years. He finds that the LIHTC program has tended to produce housing for moderate-income households, defined as households below 60 of area median family income. Few projects produce low-income units or market-rate units despite program rules that allow for such development. Few low-income households are served because the program provides no incentives for developers to serve this population over moderate-income persons; that is, the benefits to the developer from the tax credits are no higher for low-income units. Since LIHTC projects are developed by private developers, most developers choose to target moderate-income persons in order to charge higher rents. McClure (2000) also finds that the program fails to promote mixed-income development, that is, development with some market-rate units. The LIHTC program was intended to promote mixed-income developments by allowing a certain percentage of units in each project to be leased at market-rates. However, of all units places in service from 1995 through 2000, only four percent were not set-aside low-income units that qualified for tax credits (Abt Associates, 2000:11). One possible explanation for this outcome is that developers seek tax credits for all of the units if the project is being developed under circumstances in which financing would not otherwise be available (McClure, 2000).

Especially important to any spatial analysis of the LIHTC program is the finding that LIHTC projects tend to be located disproportionately in certain areas known as Difficult Development Areas (DDAs) or Qualifying Census tracts (QCTs). Beginning in 1990, larger tax credits could be awarded for any project developed in a DDA, defined as a county with high construction, land, and utility costs relative to the income levels of the area, or a QCT, defined as a tract where at least 50 percent of the households have an income that is less than 60 percent of the area median family income. Abt Associates (1996) found that 37 percent of LIHTC projects were developed in these areas. Based on this, McClure (2000:98) concludes that the incentives to develop in these areas seem to be working since DDAs and QCTs can comprise at most 20 percent of a jurisdiction's area[5]. However, LIHTC projects tend to be located in low-income areas generally: 64 percent of projects are located in neighborhoods where the median family income is below 80 percent of the area median family income (McClure, 2000:99).

[5] Actually, under the LIHTC statute, DDAs and QCTs can each comprise 20 percent of a jurisdiction's population (Department of Housing and Urban Development, 2002). McClure is unclear on this point in his work. When the fact that DDAs and QCTs are calculated and capped at 20 percent of the population independently, McClure's conclusion about the incentives working does not seem to follow. In fact, in a later study Abt Associates (2002:25) found that 19 percent of projects are located in DDAs and 24 percent are located in QCTs, for a total of 38 percent in designated areas (once double-counted properties are accounted for).

Since QCTs are low-income areas, it is possible that the tendency of LIHTC projects to be located in QCTs is caused in part by the tendency of LIHTC projects to be located in low-income areas in general. Thus, it is not clear how effective the incentives to develop in such areas have been.

Other factors influence the location of LIHTC projects. LIHTC developments tend to be located in areas with high concentrations of poor households and racial minorities (McClure, 2000). However, the tendency of tax credit projects to be located in high poverty areas varies greatly depending on whether the project is in a central city. On the one hand, Newman and Schnare find that only 10 percent of LIHTC projects nationwide are located in census tracts where over 40 percent of the households are poor (1997:724). However, Abt Associates find that 31 percent of all LIHTC units located in central cities are located in Census tracts with poverty rates of greater than 30 percent while less than five percent of LIHTC units in suburban areas are in such tracts (2002:32).

Another influence on the location of LIHTC projects is the nature of the developer. Nonprofit community development corporations (CDCs) tend to be more willing to develop in high-cost, low-income areas (McClure, 2000). Thus, the number of CDCs in a city could potentially have an impact on the location of LIHTC projects developed there. Cities with fewer CDCs will likely have fewer properties located in riskier neighborhoods.

While much is now known about the national patterns of LIHTC development, less is known about the program at a smaller scale. This is because most of the major studies of the LIHTC program that have been undertaken have focused on the outcomes of the program at the national or regional level. However, the program regulations allow individual state allocation agencies much flexibility in developing program guidelines. Because of this flexibility, there is no reason to believe that national averages provide an accurate picture of how the program is administered at the local level. In fact, given the wide variation that the GAO found in states' Qualified Allocation Plans (GAO, 1997), there is every reason to believe that there is much variation in the final results of the LIHTC program across states and cities.

Concentration of Poverty and Concentration of Affluence

There was a dramatic increase in the number of people living in concentrated poverty during the 1970s and 1980s. The number of census tracts in which at least 40 percent of the residents lived in poverty more than doubled between 1970 and 1990, and the number of persons living in such areas increased from 4.1 million to 8.0 million (Jargowsky, 1997:30). These changes led to many important studies of concentrated poverty during the 1980s and 1990s (Wilson, 1987; Massey and Denton, 1993; Jargowsky, 1997). Macroeconomic changes (Jargowsky, 1997; Wilson, 1987), changes in the composition of inner city neighborhoods (Wilson, 1987), residential racial segregation (Massey and Denton, 1993), and discrimination (Wilson, 1987) have all been presented as causes of the rise of concentrated poverty in U.S. cities.

Variations across cities have long been part of studies of concentrated poverty. Indices of dissimilarity and isolation are two ways that researchers have measured the level of concentrated poverty across metropolitan areas (Coulton, et al., 1996; Massey and Denton, 1993). A dissimilarity index can be interpreted as the proportion of the poor populations who would have to move to achieve an even distribution throughout the metropolitan area. An isolation index can be interpreted as the percentage of poor people living in the census tract of an average poor person. In 1990 the dissimilarity and isolation indices for poor persons in the largest 100 MSAs in the U.S. ranged from .22 to .62 and from .08 to .34, respectively (Coulton, et al., 1996). Thus, in all large cities poor people are concentrated to some degree, but there is much variation across cities.

Much has been written about concentrated poverty in U.S. cities. Less has been written about concentrated affluence. Although there is empirical evidence that there is spatial concentration of affluence in the U.S. (Coutlon, 1996; St. John, 2002), this phenomenon has received little attention by researchers.

When concentrated affluence has been studied, the same indices described above have been used. For example, according to one survey, in 1990 the indices of dissimilarity and isolation for affluent persons in the 100 largest MSAs in the U.S. ranged from .26 to .52 and from .11 to .45 respectively (Coulton, et al., 1996). One important aspect of such studies of concentrated affluence is the lack of a widely-used definition of affluence. Most research on poverty uses the federal definition of poverty; however, no analogous standard exists for affluence. Thus, studies of affluence vary in their definition of affluence. The Coulton, et al. (1996) study cited above defined affluent families as those with incomes in excess of approximately $75,000, which is slightly more than twice the national median family income (192). In contrast, another major study used four times the poverty threshold, which is equal to $50,696, as the definition of affluent (St. John, 2002:504). Thus, despite the existence of accepted indices or concentration, the results of different studies of concentration of affluence cannot always be easily compared.

The Relationship between Concentrated Poverty and Affordable Housing Policy

The relationship between concentrated poverty and affluence in the U.S and housing development is a complex one. However, some of the effects of this relationship are widely known. For example, the relationship between public housing and concentrated poverty has been well studied. Other effects are perhaps less obvious. For example, Goetz (1993) has found an interesting link between income disparity and housing policy. While this finding does not relate directly to levels of spatial concentration of poverty and affluence, Goetz points out that high levels of such concentration tend to occur simultaneously with high levels of income disparity. Goetz finds that cities with high levels of income disparity tend to pursue more progressive affordable housing policies than cities with lower levels of income disparity do. He argues that, in cities where income inequality is highly visible, pro-growth coalitions that argue in favor of subsidies for business have a hard time maintaining political support. Thus, there are many ways that the nature of concentrated poverty and affluence in cities is important to any study of the patterns of development of assisted housing.

While few studies of affordable housing have a specifically spatial focus, the spatial ramifications of affordable housing policy are directly addressed in some studies of concentrated poverty. Numerous researchers have found links between concentrated poverty and subsidized housing. The complex relationship between subsidized housing and concentrated poverty runs in two directions: affordable housing policy has been shown to have an effect on concentrated poverty and concentrated poverty has been shown to affect the implementation of affordable housing policy.

The most glaring example of the ability of affordable housing policy to influence the concentration of poverty in certain areas is public housing policy. In conjunction with urban renewal and redevelopment in the middle decades of the twentieth century, many cities developed large public housing projects. Cities and housing authorities faced public opposition to locating these projects in neighborhoods that were primarily white and/or middle-class. As such, these projects were often located in areas with high concentrations of minorities and/or poor persons. Researchers have found that this tendency of public housing to concentrate poverty continued well after the initial period of construction.

Massey and Kanaiaupuni (1993) found that public housing in Chicago substantially increased the concentration of poverty years after the projects were built. Holloway, et al. (1998) extended the research of Massey and Kanaiaupuni (1993) to a city that is less well-known for public housing problems. Their study of public housing in Columbus, Ohio, found evidence that public housing concentrates poverty in that city. The authors conclude that it is not only the most notorious public housing projects in the largest cities that concentrate poverty.

Holloway, et al. (1998) find two mechanisms through which public housing concentrates poverty: by attracting economically vulnerable persons and by negatively affecting the neighborhood housing market. If lower housing values are one part of the process of concentrating poverty, subsidized housing in general, not just public housing, may play a role in concentrating poverty. Section 8 certificates and vouchers and

LIHTC projects have a significant negative effect on housing values in the neighborhood (Lee, Culhane, and Wachter, 1999). Although the evidence is mixed, scattered-site public housing may also have negative effects: Lee, Culhane, and Wachter (1999) find that such housing has a negative effect on neighborhood housing markets while Santiago, Galster, and Tatian (2001) find a positive effect in some neighborhoods. At the same time, Briggs, Darden and Aidala (1999) found no short-run effects on the sales prices of houses close to scattered-site developments in Yonkers, New York. As all of these findings show, evidence suggests that traditional public housing affects concentration of poverty and there is reason to suspect that other types of subsidized housing may as well.

There is also reason to believe that concentrated poverty influences the execution of affordable housing policy. Concentrated poverty likely has effects on both tenant-based and project-based housing assistance. With tenant-based assistance, concentrated poverty may limit areas where recipients are likely to live. This is because recipients of Section 8 vouchers and certificates tend to cluster in distressed neighborhoods (Pendall, 2000). Distressed neighborhoods are defined in part by a relatively high percentage of persons below the poverty. Furthermore, Hartung and Henig (1997) have shown that even when voucher and certificate recipients leave the inner cities, they reconcentrate in suburban neighborhoods with lower median incomes.

Neighborhood socioeconomic status also influences some project-based assistance. Low Income Housing Tax Credit properties tend to locate in areas with high concentrations of poor persons (McClure, 2000). That this tendency exists despite program rules that allow properties to have a certain percentage of market-rate units indicates that there are strong pressures on the location of these projects that bias them towards poorer neighborhoods. If LIHTC properties tend to be located in high poverty areas, it seems likely that properties built under other project-based programs that do not allow for any market-rate units will most likely also be concentrated in poor areas. The results of the studies discussed here indicate that the location of assisted housing, whether project-based or tenant-based, will be limited in part by the location of the poor population within a city.

Need Local Understanding

In her study of the demographic polarization in six cities, Withers (1997) says that the "urban housing market is the arena that links poverty and geography." Indeed, the links between concentrated poverty and subsidized housing policy discussed suggest possible new avenues for studies of affordable housing. In recent years some researchers have changed the way they look at concentrated poverty. Rather than looking for nationwide trends in concentrated poverty, they have begun to focus on how concentrated poverty varies from place to place. The evidence that these researchers provide about the variations in concentrated poverty suggests that subsidized housing might likewise have significant spatial variation across cities.

Many of the best-known studies of concentrated poverty have looked at poverty at the macro level. Works by Wilson (1987), Massey and Denton (1993), and Jargowsky (1997) seek to explain the increase in concentrated poverty that occurred during the 1970s and 1980s. All of these works find that macro-level forces are the cause of concentrated poverty. Wilson (1987) argues that economic restructuring and class-based residential segregation led to concentrated poverty. Massey and Denton (1993) argue that the main cause was race-based residential segregation. Jargowsky (1996) finds evidence that macroeconomic changes are behind much of the increase in concentrated poverty.

Recently, some researchers have argued that poverty studies need to focus on the local circumstances of concentrated poverty. One early study of poverty at the local level was conducted by Kodras (1997). While the emphasis of her work was not on arguing in favor of a micro-level approach, her work nevertheless demonstrates that an understanding of the mechanisms of concentrated poverty based on a macro-level perspective does not provide much information about poverty in individual cities. She looks at the "genesis of poverty" in five different places and shows that the mechanisms identified by the major studies mentioned above operated differently in each place. While she looks at both urban and rural examples, the impacts of different causes of poverty are different in all of the places she studies.

Other researchers have argued more directly that studies of poverty should focus more on the local contexts. Holloway, et al. (1999) look at the effects of neighborhood changes and city-wide changes on the level of poverty concentration in cities. They argue that the impacts of different forces that concentrate poverty vary across cities and the authors call for future research to study this hypothesis empirically. Cooke's (1999) study of the geographic context of concentrated urban poverty in the U.S. is just such a study. The results of his cluster analysis on all high-poverty urban census tracts in the U.S. show that the effects of racial composition of tracts, lack of economic opportunity, and class-based segregation are different in different locales. Based on his results, he cautions against “an overreliance on macro-level explanations” that “may result in the formation of public policies that may not be appropriate for specific metropolitan areas” (554-555).

These recent studies of concentrated poverty present the idea that an understanding of a phenomenon that is based on the aggregated experiences of several places is lacking in certain ways. Especially in areas that involve public policy, it is important to look at variations across space. One recent study of assisted housing has demonstrated that this idea is applicable to housing as well. Pendall (2000) looks at voucher and certificate holders in all MSAs in the U.S. Using Kasarda’s (1993) definition of distressed tracts, he looks at the percentage of voucher and certificate holders who live in distressed tracts in all MSAs in the U.S. He finds great variation across cities. For example, the percentage of metropolitan-area voucher and certificate users living in mildly distressed tracts ranges from zero in some cities to more than 50 percent in others. He concludes that this variation is due to several factors. The percentage of rental units city-wide that are in distressed areas, the level of racial disparity between assisted households and other households in the city, and the metropolitan poverty rate all affect the degree to which voucher and certificate users concentrate in distressed tracts.

Need Appropriate Local Statistics

Recent trends in the field of spatial statistics correspond to the emphasis on local understanding that is developing in study of the concentration of poverty (Anselin, 1995; Ord and Getis, 1995; Fotheringham, 1997; Fotheringham and Brunsdon, 1999). In the past spatial statistics have usually been applied at the global, rather than local, level. Global spatial statistics return one result for the entire study area and assume that this value is valid for all points within with study area. For example, a global clustering statistic would return one value for an entire study city, such as a city, indicating whether clustering was present in that area; it would not indicate where the clustering was located or whether it occurred uniformly across space. While this approach is appropriate for certain phenomena, it is not appropriate in the study of many phenomena that vary across space. Fotheringham and Brunsdon (1999) give the example that often applying global statistics provides information that is akin to knowing the average annual rainfall of the entire U.S. – a statistic that is not very useful for most common purposes. The new class of local statistics returns results for each data point within a study area. These statistics are interested in identifying differences across space (Fotheringham, 1997), and for many studies in the social sciences, such an approach is preferable to one that aggregates disparate data.

One important difference between global and local statistics is that they do not always return the same results when used to measure clustering. It is possible for some local clustering to exist but not enough to be picked up by a global indicator (Anselin, 1995; Craglia, Haining and Wiles, 2000). For example, Getis and Ord (1992) identify the presence of clustering of SIDS deaths in North Carolina using a local test even though global tests do not clearly identify spatial autocorrelation. On the other hand, a significant result for a global test may obscure pockets where there is no clustering. For example, O'Loughlin, Flint and Anselin (1994) find evidence of clustering of votes during the 1930 elections in Germany using a global test despite the presence of many areas where no clustering occurred.

Spatial Analysis and GIS

Spatial analysis

Tobler's law states that points that are close together are more likely to have similar values than points that are far apart. Colloquially stated, Tobler's law says that all things are related but near things are more related. Tobler's law points to the fundamental difference between classical statistics and spatial statistics. Classical statistics usually assumes independence between observations; in spatial statistics, the assumption is that all observations are dependent to some degree. Special statistics should be used to analyze data that has a strong spatial component because of the likelihood of spatial autocorrelation, or dependence between observations.

Spatial data have unique problems that must be considered by anyone undertaking an analysis using spatial statistics. One of the main problems facing any researcher using spatial data is the Modifiable Areal Unit Problem (MAUP). This problem is particularly relevant to social science applications of spatial statistics (Bailey and Gatrell, 1995). The modifiable areal unit problem refers to the fact that sometimes the units into which data are aggregated are arbitrarily drawn. For example, census tracts are arbitrarily drawn in that they do not follow any boundaries that exist independently. Analyses that have been performed on data that have been aggregated into arbitrary units, or into areal units that could be modified, might yield different results if the data were aggregated into different units. Different results might be reached if the boundaries of the units were shifted (zone changes) and/or if the size of the units were changed (scale changes). Although the modifiable areal unit problem comes up in social science often because of the nature of social data, there is often little that can be done to solve the problem because the data that is available is already aggregated into certain areal units. Rather, researchers must be aware that the problem exists and that arbitrary areal units do not tell the only possible story in the data.

Another set of issues arises from the nature of the space being studied. One such issue is that of edge effects. Points near the edge of a study area are going to have fewer neighbors. This can influence the results of analyses that rely on nearest neighbor analysis. Other peculiarities of spatial data that can have an effect on spatial analysis are natural and human structures. In studying housing development, geographical features, such as mountains and rivers, or human constructions, such as highways or very large building complexes, could affect the analysis. Another interesting aspect of spatial data deals with the detection of patterns. A pattern that is clear at one scale can be lost at another scale; for example, a pattern that is clear at a neighborhood scale might not be observed at a city scale. Thus, the study area boundaries are very important to spatial studies. Also, visual detection of patterns is not always reliable (Bailey and Gatrell, 1995). Even under conditions of complete spatial randomness, there are usually areas in which data points appear to be clustered. The unreliability of visual detection of patterns is one reason that tests of significance are so important in spatial studies.

Geographic Information Systems (GIS)

GIS offers many different ways to handle spatial data. Maguire (1991) identifies three categories of GIS functionality. In order of increasing complexity and sophistication, these categories are map support, spatial database management, and spatial analysis. The first function, map support, is largely the use of maps to present data. The second function, spatial database management, handles many of the same functions as traditional database management; however, it organizes both locational (e.g., address, census tract) and attribute (e.g., type of building, age of building) information. The third function, spatial analysis, includes both exploratory and confirmatory examination and analysis of patterns of data.

These categories are useful because they allow us to identify areas of research in which increased application of GIS could be useful. For example, the sector of the housing industry that is currently using GIS most widely is the mortgage finance sector. Most firms in this sector are using GIS in ways that do not make use of the analytical functions of GIS (Belsky, Can, and Megbolugbe, 1998).

Although most of the focus on GIS and housing has been in the mortgage finance area, GIS is also appropriate for broad use in both housing research (Can, 1998*b*) and in the housing industry (Can, 1998*a*). However, GIS has not been widely used in either capacity yet (Can, 1998*a*; Can, 1998*b*).

One reason that has been presented to explain why GIS has not been widely used in housing research is that researchers must have relatively current data (Can, 1998*b*). Because housing research has traditionally relied heavily on Census data, which is gathered only every ten years, the availability of data is problematic. However, this same problem faces all housing researchers, not only those using GIS. Furthermore, research such as that undertaken in this study is less constrained by the limitations of Census data than other types might be because this study will be using data about funding for housing. Such data is available from funding agencies in a more-timely manner than is Census data. Housing research using GIS seems to face no constraints beyond those faced by other types of housing research, and GIS seems to offer a unique, useful way of analyzing housing data, which has a clear spatial component.

Chapter 3 – The LIHTC Program: The Intersection of Policy, Politics, and Business

The LIHTC program provides tax credits to developers as an incentive to develop affordable housing. The recipients of the tax credits sell them to raise equity, which lowers the overall cost of production of the housing. This reliance on private actors means that the decision about where to locate LIHTC units, how many to build, and what type of units (e.g., small or large units) to build is in the hands of many private developers with little to no influence from government agencies. The government's role in this program is limited to scarcely more than providing funding streams and monitoring the financial aspects of the developments to monitor compliance with requirements in the tax code.

Other than the intervention through tax credits, the development of an LIHTC development is just like the development of any other residential multifamily housing. Because LIHTC projects are developed by private developers who maintain their position as private actors within the market, the broad patterns of urban residential development and land use should have an influence on the locations of the developments. To understand the LIHTC program and the locations of LIHTC projects, it is important to understand the patterns of urban development.

This chapter examines the intersection of policy, politics, and the business of development. First, the history of affordable housing programs is presented and the shift from government-directed programs to market-driven programs is discussed. Next, in light of the LIHTC program's reliance on private developers, forces that may influence development patterns in cities are discussed. Finally, the specifics of the LIHTC program are discussed in this context.

Overview of Major Federal Affordable Housing Programs

As part of the Reagan era shift toward privatization, the LIHTC program was created in 1986 as a way to provide incentives to private developers to build and manage affordable housing. The success of this shift toward private provision of affordable housing is underscored by the fact that the LIHTC program, the largest production program of affordable housing in the country today, relies on private actors operating within the marketplace, as opposed to government agencies operating outside of the marketplace. This is not surprising when the trajectory of federal affordable housing programs over the past several decades is considered.

Before exploring the political and ideological history of housing programs, a brief overview of the major federal programs operating today is warranted. Three key programs – the Housing Choice Voucher program, public housing, and the HOME Investment Partnership – are discussed below. These three programs are the federal affordable housing programs that receive annual appropriations in excess of $1 billion. After that, the political and ideological trajectory of affordable housing programs over the past several decades is discussed.

Housing Choice Vouchers

The largest federal affordable housing program in terms of cost is the Housing Choice Voucher (HCV) Program, previously known as the Section 8 voucher program. For

2008, the HCV program received $16.4 billion in federal appropriations to cover the cost of approximately 1.8 million vouchers.

Housing vouchers bridge the gap between the amount that a low-income family can afford to pay in rent and the market rent in each housing market in the country. Generally, voucher recipients are required to pay 30 percent of household income toward rent. Vouchers are used to rent private housing units. They can be used on units with rents up to the 40th percentile of all rents in a given housing market.

The HCV program is one of the few federal programs that results in what is known as a "deep subsidy" to extremely low income families. (Public housing is the only other major federal programs that targets extremely low-income families.) All HCV recipients must earn no more than 80 percent of the area median family income, and 75 percent of new voucher recipients each year must have incomes no more than 30 percent of the area median family income.

Public housing

Public housing is government owned and operated housing. Created by the U.S. Housing Act of 1937, it is the oldest federal affordable housing program in operation today. Public housing units across the country are operated by public housing authorities, which are governmental agencies created by states to serve cities and counties. The U.S. Department of Housing and Urban Development regulates public housing authorities.

As with the HCV program, public housing residents are generally required to contribute 30 percent of household income toward rent. The federal government provides subsidies to cover the gap between rents collected by public housing authorities and the cost of operating the housing. In 2008, public housing received $6.6 billion in federal appropriations.

There are approximately 1.2 million units of public housing today in approximately 14,000 developments across the country. While there has been some redevelopment of public housing over the last decade, there has been no net increase in units in the last decade. Federal law caps the number of units that a public housing authority may own and operate at the number that it operated as of October 1, 1999.

Public housing, along with the Housing Choice Voucher program, is one of the only federal housing programs that results in a “deep subsidy” to extremely low income families. All public housing households must earn no more than 80 percent of the area median family income, and 40 percent of new public housing tenants each year must have incomes no more than 30 percent of the area median family income.

HOME Investments Partnership Program (HOME Program)

The HOME Program is essentially a block grant designed to increase the supply of affordable housing for low-income persons through a variety of means. HOME program funds can be used to construct new units, rehabilitate existing units, assist with down payments, and provide tenant-based rental assistance (i.e., housing vouchers). HOME funds are distributed to states and localities on the basis of a formula. Cities, metropolitan counties, and states receive allocations of HOME funds, which they then award to developers, community development corporations, and other for-profit and non-profit entities for specific projects. In 2008, federal appropriations for the HOME program equaled $1.6 billion.

Since 1992, the HOME program has resulted in the development of approximately 800,000 units. Less than half of these units - 300,000 - have been rental units; more than 160,000 have been existing, owner-occupied units; nearly 340,000 have been units being purchased by a low-income homebuyer.

Evolution of Federal Housing Programs

In addition to the LIHTC program, the three programs described above are the major federal programs to increase access to affordable housing for low-income persons. Now that they key programs have been identified, it is instructive to look at how they developed and changed over time.

With passage of the U.S. Housing Act of 1937, the federal government created the first major federal programs to provide subsidies for affordable housing. The Housing Act of 1937 established the public housing program and these same statutes govern the program today. A little more than a decade after the 1937, the next major piece of federal housing legislation was passed, the U.S. Housing Act of 1949. The Housing Act of 1949 laid the foundation for a greatly expanded public housing program by creating the urban renewal program (Hirsch, 1983; Bauman, 1987). The 1949 Act also included an important goal: to ensure a "decent home and a suitable living environment for every American family" (42 U.S.C 1441a). (This statute remains in place today, even if the goal has been scaled back slightly. HUD's Strategic Plan 2006-2011 lists as one of five overarching goals to "promote decent affordable housing;" however, the idea that every family should have such housing seems to have been scaled back.)

From its beginning, public housing has been completely government-directed. The federal government provided funding for construction while local governments selected the locations for individual developments.[6] The federal government also provides operating and capital subsidies so that rents can be set at affordable levels.

The public housing program was the primary federal affordable housing program during the mid-20th century. Due in part to urban renewal programs, significant numbers of public housing units were constructed throughout the country during the 1950s and 1960s. In fact, two-thirds of all public housing units were constructed before 1970 (Harvard Graduate School of Design, 2003).

However, the 1960s also saw the rise of a new type of federal housing program. In contrast to public housing, which was constructed, owned, and managed by the government, these new programs provided financial incentives to private developers to construct, own, and manage affordable housing. The Section 221(d)(3) program and the Section 236 program both took this approach to increasing the affordable housing supply.

Another program that deviated from the public housing model even further was created in 1974 – the Section 8 voucher program (today known as the Housing Choice Voucher program). HUD began an experimental voucher program in 1972, and in 1974 the program was made permanent under Section 8 of the U.S. Housing Act. Housing

[6] The ability of local governments to select the sites for public housing developments led to many developments being located in undesirable locations and being geographically segregated in many cities (Hays, 1995).

vouchers require the recipients to find and rent private housing units. The government's role is largely limited to providing subsidies to landlords.

In the space of barely more than a decade, the range of federal affordable housing programs moved from consisting exclusively of government-run programs for the development and operation of affordable housing to including privately-run production programs and demand-side programs that do not directly create any new units but rather rely on those private units already in the market.

The spectrum of federal affordable housing programs began to shrink in the late 1990s. In 1999, a federal law capped the number of public housing units to those already in existence. Since then, there has been no net gain in the number of public housing units across the country. Government support of this production program continued to erode throughout the 2000s: HUD and Congress have fully funded the operations of public housing only twice since the cap was put in place (Fischer, 2006).

The Low-Income Housing Tax Credit program was created in the midst of the transformation of federal affordable housing policy. Throughout the 1980s and 1990s, policies favoring the marketplace and privatization became increasingly popular politically. Tax credits for the development of affordable housing are very typical of these policies (Ruben, 2001).

The specifics of the LIHTC program, which are discussed in greater detail later in this chapter, show how thoroughly this program privatizes the provision of affordable housing. Private developers control every aspect of the production and management of housing under this program from site selection to screening potential residents for eligibility. This is a completely different approach than that of the public housing program. In the case of public housing, government - local public housing authorities - decided what, where, and how much to build and managed the operation of the housing once it was built.

In some respects the LIHTC program takes the “market-based notions of consumerism, responsibility, initiative, and entrepreneurship” (Maskovsky, 2001) of neoliberalism one step further than the Section 8/Housing Choice Voucher program, the first major market-oriented federal affordable housing program. Housing vouchers rely on the private market to provide housing units; the vouchers merely provide funding to close the gap between the amount a low-income family can pay in rent and market rents. The Housing Choice Voucher program relies on the ability of low-income families to navigate the housing market on their own and it rewards those people who are able to do so. Families that are unable to be successful in the market, even with additional funding, are penalized by not being able to participate in the program. In fact, in 2006 the Housing Choice Voucher program had a utilization rate of 92 percent (Center on Budget and Policy Priorities, 2007), which means that approximately 1 in every 12 families that was issued a voucher was forced to turn the voucher back to the issuing housing authority because they were not able to use the voucher for some reason.

The LIHTC program likewise rewards low-income families that can navigate the private market. Because the housing produced under the program is entirely private housing, potential residents must find the housing on their own and meet application requirements. In addition, the program subsidizes and enhances developers, who fit into the category of what Hays calls “market winners” (1995). The recipients of tax credits are market winners because allocation of tax credits signals a “green light” for a project to move ahead. While the tax credits awarded under the program do not create windfall profits for developers (McClure, 2000), these credits do allow projects to move forward. Since developers of residential housing can only make money when they complete projects, the benefits of tax credits to the developers is that they able to close another deal and reap and standard rate of return on the project.

Influences on Private Development Patterns

With the LIHTC program, the political decision was made to put the private market in the driver's seat with respect to the creation of affordable housing. Thus, in order to understand the patterns of LIHTC development, it is critical to consider the factors that influence residential development of all types. In the mid 20th Century, economists began developing urban land use models to explain U.S. cities.[7] These models, later labeled bid-rent models, largely assumed an urban core that was the employment center for the city with development extending outward in concentric circles. While these models were initially helpful in discussing patterns of development, it is clear today that they do not accurately describe the pattern of development in many U.S. cities as it actually happens.

The concept of spatial interruption allows us to develop a more realistic picture of residential development in cities than the early urban spatial models that theorized development in a circular pattern across a featureless plain. Liu (2005) examines some of the ways that development can be interrupted by a variety of factors. Spatial interruption occurs when development is not continuous but rather is disrupted in some

[7] The first urban land use model, developed in the 1920s by Robert E. Park and Ernest W. Burgess of the University of Chicago, was widely used by researchers in the following decades as a simplified model of urban development.

way. Liu identifies three main causes of spatial interruption: topographical barriers, land use regulations, and blighted areas. While these three causes develop in different ways and must be addressed through different means, they all are likely to have a stifling effect on development in certain areas.

The first cause of interrupted development that Liu identifies is topographical barriers. Liu focuses primarily on the natural barrier that water presents. Throughout history, proximity to water was a crucial factor in the decision about where to locate towns. The historical importance of water explains why almost half of the 40 most populous cities in the U.S. are located along major bodies of water – the Atlantic, the Pacific, the Gulf of Mexico, or one of the Great Lakes (Rose, 1989). It is easy to see how large water bodies limit the direction of development in cities. Development must stop at the water's edge. However, smaller bodies of water, such as rivers and canals, can also have an impact on the pattern of development in cities. Development, as it is explained by bid-rent models, is necessarily interrupted by these features. Other topographic barriers exist as well. Low-lying areas that are prone to flooding and areas with extreme slopes are often less attractive to people looking to develop land. In other cases, topographical characteristics can combine with land use regulations to restrict development. Examples of this interruption are habitat areas and natural hazard areas. In both cases, there is nothing inherent in the topography that would prohibit development; however, regulations relating to the topography of the land may lead to spatial interruption. If an area is the habitat of a protected species, it may be developed later than surrounding areas or not at all, as developers must mitigate the impacts of development if they want to build on the land. Natural hazard areas will likely also be developed later or not at all.

The second cause of interruption development that Liu identifies is “location-specific dis-amenities.” These disamenities can include brownfield sites and blighted neighborhoods. Large-scale development may avoid blighted areas if developers believe it may be hard to rent or sell the newly developed units. Brownfield sites may have the additional disincentive of increased development costs if remediation of the land is required. It is important to note that “blight” does not always work to curb development. “Blighted areas” were targeted for development under urban renewal. Even today, developers may be attracted to the lower land values in blighted areas. However, low land values are not in and of themselves sufficient to attract developers. Blighted areas that are redeveloped often have other characteristics that make them appealing to developers, such as proximity to downtown or transit nodes.

Liu also classifies “vacant land” as a location-specific disamenity. He presents evidence that vacant land tends to be concentrated. He argues that concentration of vacant land indicates possible variations in land markets that create high expectations on the part of landowners, leading them to hold onto land in some areas while development continues in other areas of the city. If speculative holding of land is responsible for concentrations of vacant land, then it seems that nearby vacant land is not a direct cause of spatial interruption; rather, the variations in the land market that led to the high expectations are the cause.

Liu’s third cause of spatial interruption is land use regulation. Zoning, decisions about greenbelts and open space, and transportation decisions are specific types of land use regulations that impact development. To the extent that this paper is focused on variation across cities, zoning is one type of regulation that clearly has an important influence on development. In cities with strict limitations on where certain types of development, such as multifamily residential properties, are allowed and not allowed, development will almost necessarily be influenced by these regulations. Likewise, it is easy to see that set-asides for open space or green space will lead to interrupted development.

The causes of spatial interruption identified by Liu explain why residential development in U.S. cities does not proceed as predicted by bid-rent models. Topography, disamenities, and regulations have considerable impact on the pattern of development. The impact of interrupted development on LIHTC development is discussed below.

Low Income Housing Tax Credit - Background

The Low Income Housing Credit Program was created in 1986 to increase the supply of affordable housing. Today, the program is the primary means of promoting private investment in the affordable housing market. The LIHTC program does not provide direct funding for construction; rather, the tax credits provide financial incentives for private developers to develop affordable housing. Because the program involves tax credits, the Internal Revenue Service has oversight of the program at the federal level. The U.S. Department of Housing and Urban Development (HUD) has no role in administering the LIHTC program. At the state level, each state has an allocation agency that is responsible for administering the program.

The program authorizes states to award income tax credits to be used toward federal income taxes. Developers may use the tax credits themselves or they may sell the tax credits. Most often, the developers sell the tax credits and the money raised by selling the credits is used to offset the costs of development.

The LIHTC program was developed because Congress recognized that low-income rental property frequently did not provide enough return on investment to ensure that the private sector would produce an adequate supply of such housing. The LIHTC program provides an incentive for private developers to create affordable housing by increasing the financial rewards to private investors. Each year, the IRS allocates a certain amount of tax credits to state housing agencies. Prospective developers of low-income housing apply to their state housing agency for tax credits to build or renovate specific low-income projects. Successful bidders are awarded tax credits in an amount equal to the minimum amount deemed necessary to ensure the project's financial feasibility for the compliance period (i.e., the amount of time that the property must remain low-income by law). Developers who are awarded tax credits usually sell them to syndicators. The syndicators are groups of investors who buy the tax credits to offset their income tax. The money from the sale of tax credits provides the developers with the additional funds necessary to make the housing project financially feasible.

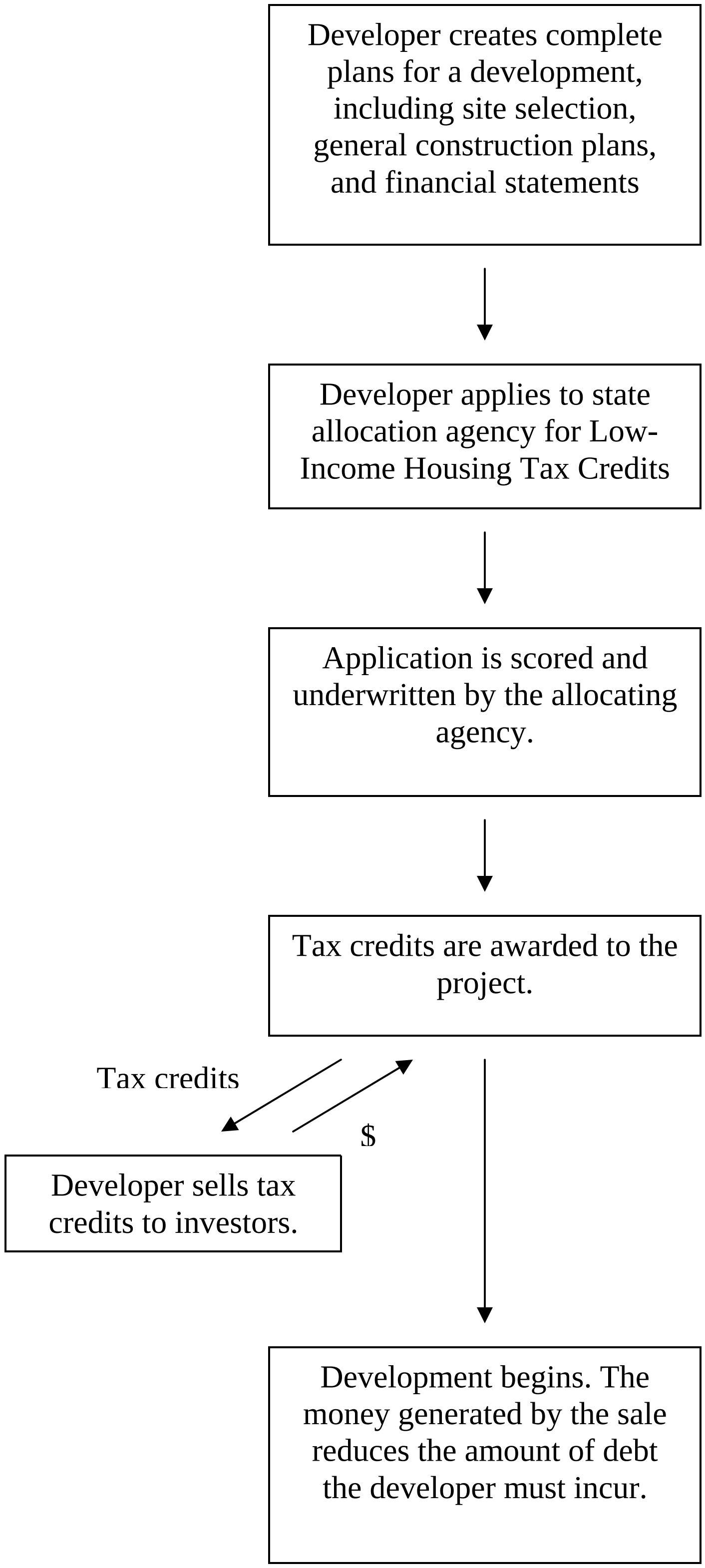

Figure 1: The LIHTC Allocation Process
(source: author)

As of 2007, each state has a total allocating authority equal to $1.95 per each resident of the state.[8] Tax credits can be awarded for developments that involve new construction or substantial rehabilitation of affordable units. The amount of tax credits that can be awarded per affordable unit is set by statute. Developers are eligible for tax credits worth nine percent of the eligible basis of the project, which is roughly the depreciable costs of constructing or rehabilitating the building and the depreciable costs of the land. To be eligible for any tax credits, a development must include a certain percentage of units that are set aside for low income renters. Specifically, the development must meet one of the following requirements:

> (1) Twenty (20) percent or more of the units in the development must be rent restricted and occupied by persons whose income is no more than 50 percent of the Area Median Family Income, OR
>
> (2) Forty (40) percent or more of the units in the development must be rent restricted and occupied by persons whose income is no more than 60 percent of Area Median Family Income.

Furthermore, the set-aside units must operate under the rent and occupancy restrictions for a certain amount of time, usually 30 years.[9] Tax credits may be awarded for all such set-aside units. Developers can set-aside 100 percent of units in a project if they desire.

A formula is used to determine the maximum allowable rent on the set-aside units. Rents are set so that persons/families earning the maximum income to qualify for the

[8] Unlike some other affordable housing programs, the amount available to each state is not weighted by measures of need.

[9] In 1989, Congress changed the compliance period from 15 to 30 years. However, developers may still convert set-aside units to market rate units after a period of 18 years in some instances.

set-aside units pay no more than 30 percent of their income for housing. For example, if the developer opted to set aside 20 percent of the units for persons/families earning no more than 50 percent of Area Median Family Income (AMFI), the maximum rent would be 30 percent of the monthly income of a person/family earning 50 of AMFI. This method of setting rents means that all families earning less than the maximum income will pay more than 30 percent of their income if the rents are set at the highest allowable level. That is, the rent that a family earning 40 percent of AMFI pays is not adjusted for the fact that they earn less than the maximum income.

State allocating agencies are given much latitude by federal statute in determining which properties receive tax credits. All allocating agencies are required to develop an allocation plan that identifies the state's priority housing needs and defines the criteria that will be used in scoring proposals for tax credits. However, states are given flexibility in establishing these criteria beyond the fact that they must address the identified priority housing needs. Furthermore, some states use discretionary judgment in the allocation process in addition to the criteria in the allocation plans (GAO, 1997).

The amount of tax credits that can be awarded to any project depends on the amount and type of additional funding sources, the total amount of qualified development costs associated with the project, and the percentage of units in the development that will be set aside for low-income tenants. States are required to determine the reasonableness of development costs associated with any project and to consider the sources and uses of project funds. Thus, LIHTC properties are sometimes developed with layered funding from other sources such as bonds or Rural Housing Service programs.

The Development Process

The philosophical and political underpinning of the LIHTC program is that traditional economic forces of supply and demand can be used to encourage the private market to provide affordable housing. In this case, tax credits should increase the supply of affordable housing because they decrease the cost to private developers. By selling the tax credits they are awarded under the application process, developers raise capital early in the development process. This capital helps to decrease the amount of debt a developer must incur for a property. Lower debt allows a developer to charge less each month in rent while still having enough revenue to repay debt and take a profit equivalent to that from a market-rate development. By providing developers with something of value (tax credits) that they can sell to raise money and thereby lowering the cost of financing the project, the LIHTC program is subsidizing the costs of production. Following the basic laws of supply and demand, lowering the costs of production will result in an increase of supply at a given price, all other things equal.

Aside from the lower costs of production, the development of tax credit properties is much the same as the development of unsubsidized developments. As described above, the LIHTC program is administered by the Internal Revenue Service at the federal level. Thus, at the federal level, the program is really a tax program, not a housing program. The federal government does not exert any influence over where LIHTC properties are built or what they look like. At the state level, the LIHTC program is usually administered by the state housing or housing finance agency. To the extent that these agencies set the scoring preferences for LIHTC applications for their states, they are able to exert some influence over the properties that are developed. But in the end the individual developers make the final decision about what gets built where under the LIHTC program.

Therefore, since LIHTC developers are private developers, the same factors that influence the location decisions of developers of unsubsidized developments should exert some influence over LIHTC developments; the only difference between LIHTC developers and other private developers is that LIHTC developers have lower costs of production. The causes of interrupted development that Liu (2005) identifies can help explain why developers of LIHTC properties, like developers of unassisted properties, may focus on some areas for development and avoid others.

One of the most influential factors in determining where developers may choose to locate a multifamily project is zoning and land use regulations. With only one exception[10], all major U.S. cities have zoning codes that restrict certain types of land use to certain neighborhoods, corridors, or areas of town. Among other things, zoning codes typically identify areas where multi-family housing can and cannot be developed. All developers of multi-family housing, subsidized or unsubsidized, are limited by local zoning codes in terms of where they can propose to build a new development. Cities directly influence the spatial pattern of the development of such housing through zoning codes. In cities where a relatively small proportion of land is zoned for multi-family housing, all multi-family housing, including LIHTC developments, will likely be more clustered than in other cities.

[10] Houston is widely known to be the only major U.S. city without zoning. However, even Houston has land use regulations in its city code that govern aspects of development such as minimum lot size and amount of parking required. Regulations such as these will influence developers' decisions about where to build because they influence the cost of land.

Other regulations that may influence development include regulations that would require mediation of negative impacts of development. For example, areas that lie within important watersheds may be covered by regulations that require significant design elements to deal with storm water runoff. Another example is habitat areas for protected species. Developers will be slower to develop these areas if they are required to mitigate the effects on the species.

Some of the causes of interrupted development identified by Liu address the marketability of the units that are ultimately developed. According to Liu's analysis, sites that are located close to blighted areas or brownfields are often skipped over as development progresses. Because developing in these areas does not cost more, and in fact may cost less if land values are lower, it is likely that developers avoid these areas because demand for housing or other units in these locations is low.

While developers of LIHTC properties will consider many of the same factors as developers of unsubsidized properties in deciding where to locate properties, tax credit developers will also face additional pressures on where to locate properties because of the scoring procedures for LIHTC applications at the state level. Many states give preference to disadvantaged areas in their allocation plans. Of the 25 study cities, ten are located in states that award extra points for proposed developments that are located in qualified Census tracts (QCTs), difficult development areas (DDAs), or areas that the local community has officially targeted for revitalization. Six of the study cities are located in states that give extra points for developments located near amenities such as retail or grocery stores, hospitals, schools, parks, or transit routes. Only three of the study cities are located in states with plans that specifically mention other LIHTC developments. Of these, only one, Texas, explicitly awards points to projects that would be located in a Census tract with no other LIHTC units; the other two give the awarding agency latitude to consider the proximity of other LIHTC projects. Two states, Texas and Indiana, actually subtract points for developments that would be located near disamenities. In these states points are subtracted from applications for projects that are located near places such as junkyards, railroad tracks, landfills, and vacant buildings. Because these scoring preferences are announced by the states prior to the application round, developers who wish to increase the competitiveness of their applications may take these scoring preferences into account when selecting locations for possible developments.

All of the factors that influence locational decisions by developers discussed here - topographical barriers, disamenities, regulations, and scoring of LIHTC applications – vary from city to city. Some cities have many topographical barriers spread throughout; for example, some cities have many waterways, such as rivers and canals, while others have very few. Location-specific disamenities will vary from city to city depending in large part on the historical patterns of industrial and commercial uses (in the cases of brownfields) and the population (in the case of blighted areas). In major U.S. cities, regulations governing development run the gamut from no zoning at all (such as in Houston) to more restrictive urban growth boundaries (such as in Portland, Oregon). Some state allocation plans award points to applications for projects located near certain amenities or subtract points for developments near disamenities. Other state plans do not consider the characteristics of the individual sites where projects would be located.

Developers of tax credit properties are subject to the influence of all these factors. Because of the emphasis on privatization and market-oriented strategies in federal affordable housing policy for the past 20-30 years, the options of low-income families who are eligible for the LIHTC program are constrained by the factors outlined in this chapter. As these factors vary from city to city, the pattern of LIHTC developments should vary from city to city as well. In some places the construction of LIHTC units outpaces the production of market-rate rental units (*Commercial Appeal*, 2006). To the extent that there are intense pressures on the locations of LIHTC developments, the locational choice of low income residents may be greatly affected.

Chapter 4 – Data Sources and Methodology

Purpose of the Study

This study examines two research questions: one dealing with methodology and one dealing with the program analyzed, the Low-Income Housing Tax Credit program. These two questions work in concert; the analysis undertaken for this study provides answers to both questions, and the answers to each provide a deeper understanding of the answers to the other. Applying spatial statistics to federal affordable housing data has the potential to uncover new information about what happens when federal affordable housing programs are put into action and to enrich what we already know about the patterns of affordable housing development. However, for a variety of reasons, using spatial statistics with housing data can be difficult. For that reason, this study seeks to further the basis knowledge about which circumstances are appropriate for spatial statistics, both in terms of inputs required and the outputs desired.

Programmatic Research Question

This study seeks to answer the following question about the LIHTC program:

> *what variation among cities in the distribution of LIHTC projects is revealed by local spatial statistics?*

As discussed in Chapter 3, the factors that influence decisions about where to locate LIHTC projects vary from city to city. As these factors vary, the locations of LIHTC projects themselves should vary. This study looks at how much variation there is across cities and what the nature of the variation is through a local spatial statistic, G_i*.

This study moves current research in a different direction than it has traditionally gone. Studies of the LIHTC program (and other affordable housing programs) have traditionally sought to identify the general location tendencies of the program being studied (Abt Associates, 2000; Abt Associates, 2002; McClure, 2000). Specifically, these studies have looked at the demographic and socioeconomic characteristics of the neighborhoods that LIHTC properties are located in at a nationally aggregated level. In contrast, my study asks whether there are reasons that we should look at the differences among LIHTC properties and LIHTC programs at the state level. As discussed in Chapters 2 and 3, research from related fields, such as recent poverty research, and the nature of housing development in general suggest that there is likely to be noteworthy variation across cities. This study begins to determine whether the data on the LIHTC program reveal such variations.

Methodological Research Question

This study seeks to answer the following question about local spatial statistics:

> *what are the advantages and disadvantages of conducting research on housing using local spatial statistics over using traditional methods?*

This study begins identifying how spatial statistics can be used in housing research given the constraints that are common in housing research. As discussed in Chapter 2, spatial statistics can provide much richer results than classical statistics can in some cases, but few housing studies have taken advantage of spatial statistics. While spatial statistics can provide far more complex information about phenomena that are inherently spatial, such as housing, than classical statistics can, spatial statistics have their own set of assumptions and conditions that must be met if they are going to return useful, valid results. This study uses the LIHTC program database to begin investigating how well housing data fulfills these requirements.

Exploratory Spatial Data Analysis

This study uses exploratory spatial data techniques. Exploratory spatial data analysis (ESDA) can be defined as “the collection of techniques to describe and visualise spatial distributions, identify atypical locations (spatial outliers), discover patterns of spatial association (spatial clusters), and suggest different spatial regimes and other forms of spatial instability or spatial non-stationarity” (Anselin, 1999:258). ESDA “examines an observed distribution and attempts to infer the process that produced it” (Unwin, 1996:541). In spatial statistics, analysis is frequently divided into exploratory and confirmatory analyses (Getis, 1999; Unwin, 1996; Anselin, 1999). The figure below shows the how different stages of spatial analysis fit together.

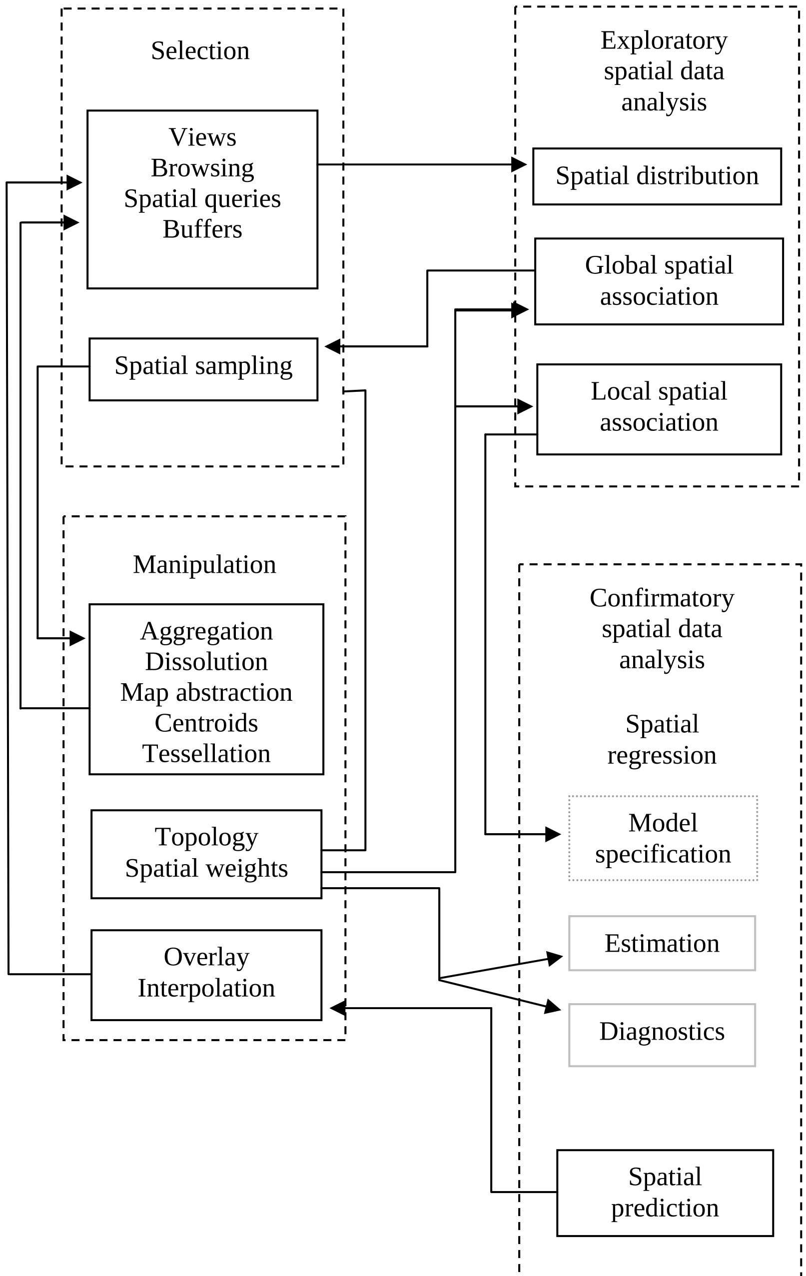

Figure 2: Spatial Analysis in GIS
(Figure adapted from Anselin, 1999)

While this figure is quite complex, it shows that spatial statistical analysis does not proceed in as linear fashion as traditional statistical analysis. Analysis with spatial methods is a much more iterative process. Another critical aspect of spatial analysis illustrated by Figure 2 is that exploratory and confirmatory analyses are split apart in spatial statistics, unlike classical statistics. This division is due to the fact that the emphasis of spatial statistics is different from that of classical statistics. Classical statistics assume independence between observations. In fact, where there is significant dependence between observations, technical corrections must be employed as part of the analysis. Things are quite different with spatial statistics. The first rule of spatial statistics is that all things are related and near things are more related than far things. Spatial statistics focus on non-stationarity across space. In order to analyze non-stationarity, one must first find it. As explained above, the role of ESDA is to do just that.

ESDA is considered a distinct stage of research in spatial analysis for a couple of reasons. First, ESDA by itself usually consists of a full-blown analysis with its own results. Although Figure 2 does not show all of the linkages between the different major and minor stages of spatial research, many of the techniques on the left side of the diagram must be employed prior to conducting the actual analysis. All of the analysis that leads up to and is part of ESDA - selecting the data, manipulating the data, running the actual statistical analysis - is a necessary step in the process and that manipulation reveal information about the phenomenon being studied. After these initial steps, an analysis using ESDA produces actual results. Although the results do not attribute causality, which is often the goal in traditional statistical analysis, the results do provide concrete information about the process studied. Second, spatial analysis is usually divided into exploratory and confirmatory steps because “relatively few new methods have been offered to allow for the confirmation of hypotheses, which is well behind [ESDA] in the race for new understanding of spatial phenomena” (Getis, 1999). In particular, few confirmatory analyses are available that are robust enough to handle problems associated with changing scale (as it pertains to the Modifiable Areal Unit Problem), boundary effects (where observations are near a boundary, which necessarily limits the number of other observations that will be nearby), and the effects of spatial weights (where dependence may be a function of many things other than nearness).

The importance of detecting spatial non-stationarity is easily understood in the context of research on affordable housing. A traditional analysis of the locations of LIHTC projects would focus on all projects and would analyze the characteristics of the areas where they are located. In fact, much of the research that has been conducted on the LIHTC program to date (see Chapter 2) has been of this nature. However, such analysis does not address the issue of concentration. As discussed in Chapter 2, the national policy on location and affordable housing favors deconcentration. A deeper analysis of the effectiveness of the LIHTC program must not group all LIHTC projects together but rather must focus on those projects that are particularly concentrated. To the extent that concentration, or spatial non-stationarity, of affordable housing is a problem with affordable housing to be addressed through policy, policies based on the results of studies that focus on concentrated or clustered developments will be better than policies based on the results of studies that combine all developments together.

Therefore, in keeping with the principles of ESDA, this paper does not seek to draw firm conclusions about the LIHTC program that can be generalized to all LIHTC projects. Rather, this paper analyzes data about the locations of LIHTC properties in several cities to reveal possible patterns, associations, and causalities that can be investigated through confirmatory analysis at a later date. The results of this study make future confirmatory analysis of clustered properties possible.

Unit of Analysis and Study Area

While the choices of the unit of analysis and the study area have important consequences for any study, these decisions are especially important for a study that involves clustering. One of the central concerns when analyzing clusters is that clusters that are very pronounced at one scale may seem less pronounced at another scale. For example, a study that uses quadrants of a city as a unit of analysis may, through aggregation of observations, obscure clusters that would be present if the unit of analysis were Census tracts.

Various regulations could also have an effect on the appropriate unit of analysis and study area. First, for any study of a federal affordable housing program, program regulations could have an impact on the choice of unit of analysis and the study area. The program regulations of federal affordable housing programs determine the areas in which the subsidies can be used. Some areas may be excluded or specifically targeted. In the case of the LIHTC program, however, the impact of regulations is difficult to determine. Each state is given the authority to award tax credits to properties anywhere within the state. If an individual state wants to target certain areas, it can award extra points during the scoring of applications for projects based on the locations of the projects. However, such policies vary from state to state and can even vary from year to year. Second, local regulations could influence the choice of unit of analysis and study area. For this study, zoning regulations could have a significant impact on the location of LIHTC properties (because they are multifamily housing). A study area that is too small could leave out the areas most likely to include LIHTC properties

Keeping in mind the significance of scale issues and regulations, cities were chosen as the study areas and Census tracts were chosen as the unit of analysis. Specifically, this study looks at Low-Income Housing Tax Credit projects in the 25 most populous U.S. cities according to the 2000 Census. Table 1 shows the cities that are included in this study.

Table 1: Cities Included in Study

Austin	El Paso	Philadelphia
Baltimore	Houston	Phoenix
Boston	Indianapolis	San Antonio
Chicago	Jacksonville	San Diego
Columbus	Los Angeles	San Francisco
Dallas	Memphis	San Jose
Denver	Milwaukee	Seattle
Detroit	Nashville	
District of Columbia	New York City	

The most populous cities were selected as the study cities in an effort to include cities with relatively high LIHTC development. It is assumed that the general trend will be for there to be more LIHTC developments as city population increases.

I selected cities as the study area instead of counties for two reasons. First, using cities as the study areas reduces the number of tracts in the analysis with no LIHTC units. In most cities, LIHTC projects are disproportionately located in the central cities. From 1995 to 2000, nearly one-half of all LIHTC units placed in service were located in central cities (Nolden, et al., 2002). Furthermore, in the specific cases of the study cities, well over half of all LIHTC projects located in the central *county* are located within the central *city* in most cases. Because the analysis used in this study relies on a measure of proximity, including large areas that include no LIHTC properties would not result in significantly more hot spots detected. Second, a few of the counties that contain the study have a few very large tracts on the outer edges of the county. The centroids of these tracts are not within one mile, the distance used in this analysis, of any other centroids and, therefore, would not register as hot spots unless there were an extremely large project in the tract. (See Figure 3 below.)

Although I originally selected as the study area, I made some modifications to the actual boundaries of the cities due to the fact that the analysis was conducted on Census tracts. The actual unit of analysis does not completely correspond to the incorporated city limits in all cases because Census tracts boundaries in some cities are not coterminous with the city limits. In cases where there was a mismatch between city boundaries and Census tract boundaries, edge tracts were selected or deselected manually in ArcView. The following rules were used when selecting tracts for inclusion in the unit of analysis manually:

- Tracts where the overlap with the city was at least 25 percent of the tract's entire area were selected. (The assessment of percent of overlap was made visually, so this is an approximate measure.)
- Tracts that contained LIHTC properties and that overlapped with the city to any extent were selected.
- Tracts where the overlap with the city was less than 25 percent of the tract's entire area were kept in cases where the tract being evaluated was the only tract connecting another tract that would be selected according to other rules

- Tracts that overlapped with the city to any extent and were bordered on most sides by selected tracts were selected.

The final study area in all cases closely matches the incorporated city limits. In the interest of readability, throughout this paper when I refer to the study cities by name I mean the areas created according to the rules above.

Data Sources

The primary source of data for this study was the Low-Income Housing Tax Credit database maintained by HUDUser. This database lists all LIHTC properties that were placed in service from the beginning of the program in 1987 through 2000.[11] It includes a wealth of information about each project, including latitude and longitude of the project, the total number of units in the project, the number of low-income units in the project, and a breakdown of the units by number of bedrooms.

The LIHTC database was created for HUD by Abt Associates, Inc., which is also responsible for periodic updates. The addresses of the LIHTC properties in the database were collected from the state allocating agencies. The addresses were geocoded by Abt Associates and their contractors to obtain the latitude and longitude for each property. Overall, 78 percent of all units in the database were successfully geocoded and have geographic indicators included in their record in the database.

[11] The LIHTC program was created by the Tax Reform Act of 1986; however, the first units were not placed in service until 1987. Furthermore, the LIHTC database maintained by HUDUser is occasionally updated and today has information on all units placed in service through 2003. The version of the database that was used in this study contained information on all units placed in service through 2000.

The other sources of data for this project were the Census TIGER/Line files available from ESRI, Census data, and information on the location of Housing Choice Voucher (also known as the Section 8 Voucher) holders. TIGER/Line files are data files that serve as the base for maps in a Geographic Information System (GIS). The files are based on the Census Bureau's TIGER (Topologically Integrated Geographic Encoding and Referencing) database. Periodically, the TIGER files are released into the public domain in the TIGER/Line format. These files are not maps; rather, they contain digital information describing geographic features, including census statistical boundaries. ESRI, the company that produces ArcView, provides these files in a format that is compatible with ArcView. TIGER/Line files make it easy to import demographic Census data and use it in a GIS.

Information about Census tracts was used as part of a follow-up analysis for some cities in this study.[12] One of the questions raised by the initial analysis of the clusters concerned the poverty rates of neighborhoods with particularly intense clusters of LIHTC housing. Census data on poverty[13] was used in this phase. Poverty rates per Census tract were calculated directly from Census data and matched with the Census tract files in ArcView.

Another aspect of clustering investigated during the second phase of the analysis is the extent to which LIHTC properties are located relative to the general stock of affordable housing in cities. One of the difficulties in answering this question is

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[12] See Chapter 5 for a discussion of follow up analysis as part of Exploratory Spatial Data Analysis.

[13] 1990 Census data was used so that the presence of LIHTC units did not affect the Census data for a tract. The presence of one large or several small LIHTC projects built during the 1990s in one tract could have an effect on the poverty rate data for that tract in 2000. In an effort to prevent this, 1990 Census data was used and only properties placed in service in 1990 or later were used. See below for more information about the inclusion of properties based on the year placed in service.

determining where affordable housing units are located. Different housing programs use different definitions for "affordable."

The LIHTC program defines low-income units on the basis of tenants' income. The program rules state that at least 20 percent of the units in any property must be affordable to families with incomes no more than 50 of Area Median Family Income (AMF) or at least 40 percent of the units must be affordable to families with incomes no more than 60 percent of AMFI. Affordable in this case means that families pay no more than 30 percent of their incomes on rent. Thus, affordability in the LIHTC program is defined entirely by tenants' incomes.

Other programs, especially tenant-based programs such as housing vouchers, also take into consideration the rental market in the city. For example, the Housing Choice Voucher Program considers both tenants' incomes and the cost of rental housing in an area. To help assess the market conditions for rental housing in an area, HUD determines Fair Market Rents for cities and counties throughout the country. While the limits on how much tenants must pay out of pocket are tied to their incomes, with Housing Choice (or Section 8) Vouchers affordable units are defined by the price of housing in a given area.

Information on the number of voucher holders per tract was taken from *A Picture of Subsidized Households – 1998*. *Picture* is a database that contains information on nearly five million households receiving subsidies through several affordable housing programs, including the Section 8 Voucher, Section 8 Project-Based, and Public and Indian Housing programs. The information in *Picture* on Section 8 voucher holders was extracted from submissions by local housing agencies and HUD's own internal databases. The information on Section 8 voucher holders used in this study is from May 1998 and is reported by Census tract.

Data Collection

This study looks at LIHTC properties placed in service from 1990 to 2000. The LIHTC database from HUDUser provides the project address, including city and zip code, the latitude and longitude, and the Census tract for each project. LIHTC projects in the database were extracted according to the following method. Because the unit of analysis for this study is defined by Census tracts (see above), Census tract numbers were used to as the first criterion to identify the LIHTC projects to be included in the study. Thus, the first step was to identify all properties in the LIHTC database that are located within the counties of the study cities. Once these properties were identified, they were all plotted in ArcView according to the latitude and longitude provided in the database. This resulted in all LIHTC properties within a county being plotted. To select only those properties within the central city (as defined above), the Select by Theme feature in ArcView was used.

Methodology

To detect clustering of LIHTC properties in the study cities, the G_i* statistic was used. G_i* is a measure of spatial association that takes into account both the location and the attribute value of the data points. In this case, the attribute values of the data points are the number of low-income set-aside LIHTC units in each Census tract included in the study. (As is discussed in Chapter 2, not all units in an LIHTC development must be income-restricted and set aside for low-income residents. Only those set-aside, income-restricted units are eligible for tax credits, however.) The ability of G_i* to measure the number of units in addition to the location is important for a study of clustering of affordable housing. In setting policy goals, whether they address choice of neighborhoods for program participants or the neighborhood effects of the properties, a property with five units is very different from a property with 150 units.

The G_i* statistic is

$$G_i^*(d) = \frac{\Sigma_j\, w_{ij}(d)\, x_j}{\Sigma_j\; x_j} \qquad ,$$

where *d* is the specified search radius around a given point *i*; w_{ij} is a spatial weights matrix with a value of one for all points *j* that are within distance *d* of point *i* and zero for all points that are not within distance *d* of point *i*; and x_j is the attribute value for *j*. The numerator is the sum of the attribute values for all points that are within distance *d* of *i.* The denominator is the sum of all attribute values. Thus, G_i* really measures the proportion of all attribute values that lie within the specified distance of a given project. The statistic is performed on every point *i* in the study area. (The asterisk in G_i* indicates that the attribute value for point *i* is included in the numerator. Another statistic not used here, G_i, allows the researcher to eliminate the attribute value for *i*.)

With the G_i* statistic, the researcher determines the specified search radius, *d*. In this case, I chose a search radius equal to one mile. Previous studies of the impacts of affordable housing units have used radii of one-eighth to one-mile generally (Lee, Culhane, and Wachter, 1999; Santiago, Galster, and Tatian, 2001; Guhathakurta and Mushkatel, 2002). However, these studies all used individual properties as inputs. My study, on the other hand, uses Census tract centroids. Thus, the search radius needs to be slightly larger so that the buffer created around centroid at the distance, *d*, picks up other centroids. One mile is still a small enough distance that things within one mile of each other can be thought of as close to one another. Also, the relatively large search radius used by this study is acceptable because of the nature of the analysis. The G_i* statistic measures proportionality. Because the value *d* is the same for every point analyzed, a smaller *d* would reveal the same hot spots; this is because the proportion of units in close proximity to a given centroid will not change. With a small *d*, the resulting values of G_i* may change, but the same areas would be identified as hot spots.

The next step in this study was creating the data points that would become *i* and *j*: the centroids of all Census tracts in the study areas were chosen as the data points for the analysis. Because the analysis is only performed at a given distance from each data point, using the centroids of Census tracts was a way to ensure that the entire study area would be analyzed. The locations of the LIHTC properties were not appropriate data points because using them would leave out large areas of the study cities. One mile buffers created around each LIHTC project in a city would not come close to covering the entire city for any city in this study. Furthermore, using the locations of the LIHTC properties would result in clusters being defined in terms of how they compare to other clusters in intensity. That is because every area analyzed would register as a cluster of LIHTC units. Using Census tract centroids allows for comparison of areas with LIHTC units to all other areas of the city.

Centroids for each Census tract in the study areas were created using an extension in ArcView.[14] (See Figure 3.) Next, all LIHTC properties in the study area were plotted based on the latitude and longitude information provided by the LIHTC database. ArcView was used to add the total number of low-income LIHTC units within each Census tract. The total was attached to each centroid as the attribute value.

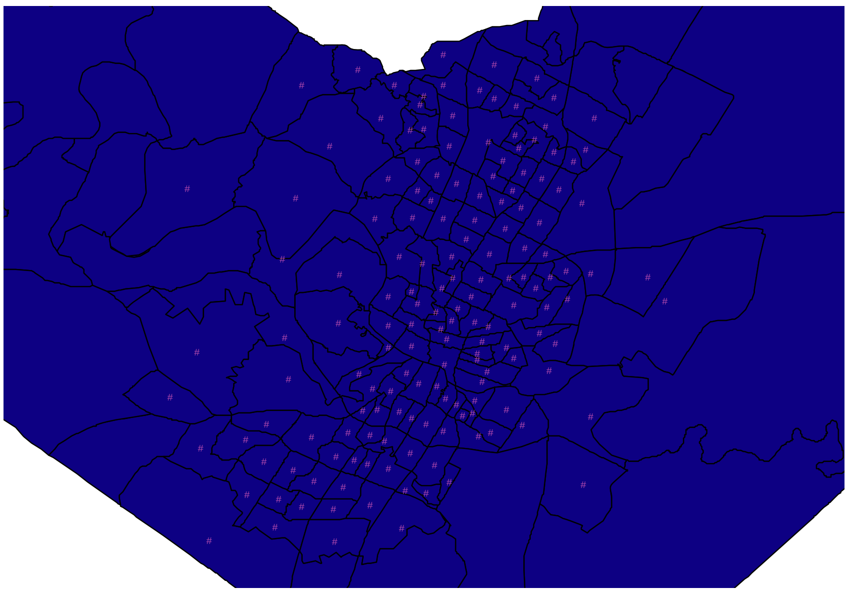

Figure 3: Examples of Census Tract Centroids – Austin

The G_i* statistical requires that the input of LIHTC units be standardized by area. The number of units per square mile was calculated for each Census tract and this value was attached to each centroid. (See Limitations of Study for a discussion of the possible impacts of the standardization process.) Next, an extension in ArcView was used to draw buffers around each centroid. The radius of each buffer was one mile,

[14] The centroids calculated by ArcView are not true centroids in some cases. A true centroid can lie outside its polygon. However, ESRI, the company that created ArcView, has written the centroid algorithm so that an ArcView centroid is always contained with its polygon.

which is the distance *d* in the formula above. As discussed above, one mile was selected as the search radius as a compromise between the distances frequently used in housing studies that use proximity measures and the requirements of the G_i^* statistic. On the one hand, housing studies that use proximity measures frequently use distances that range from several hundred feet to one-half mile (Guhathakurta and Mushkatel, 2002; Lee, Culhane, and Wachter, 1999; Santiago, Galster, and Tatian, 2001). On the other hand, the G_i^* statistic will only detect clustering to the extent that enough data points are within the search distance of each other. Because Census tract centroids were selected as the data points, it was important to select a search distance that was large enough that multiple centroids would be within that distance of one another. One mile was selected as the best distance to balance these two concerns. The distance of one mile also was satisfactory because it is a distance that corresponds well to what many people would consider their local environs.

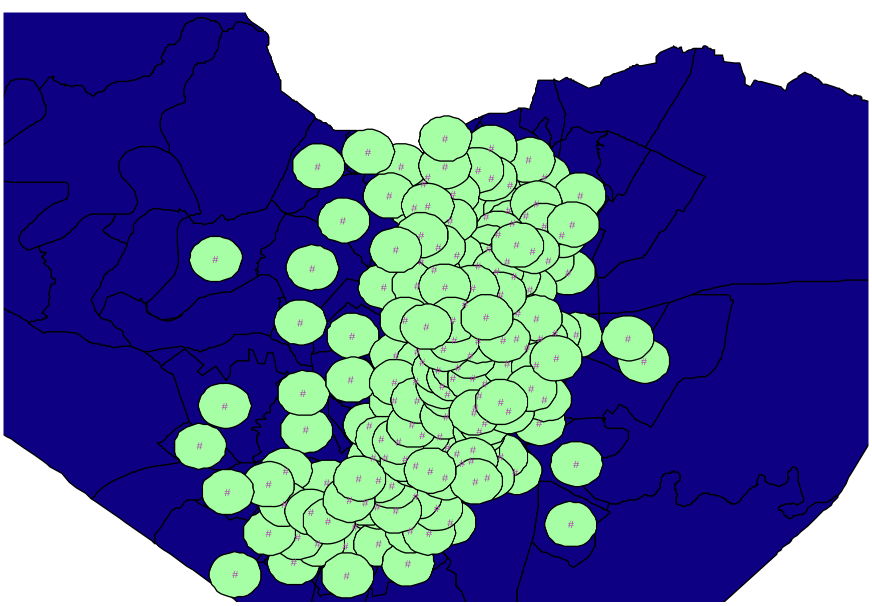

Figure 4: Examples of One-Mile Buffers around Centroids - Austin

Once the one-mile buffers were drawn around each centroid, an extension was used to sum the attribute values (units per square mile) for each centroid that fell within the one-mile buffer of another centroid. These totals were the numerators for each data point. (As is discussed above, the attribute value for the centroid *i* was included in the numerator.) The denominator for each point was the sum of the units per square mile value for each tract in the study area.

Once G_i* values were determined for all centroids in the study area, the mean and standard deviation was calculated. The last step was using ArcView to identify those tracts where the G_i* value was equal to or greater than the mean plus two standard deviations. These tracts are the clusters, or hot spots, of LIHTC units in each city.

Limitations of Study

One difficulty that frequently arises with spatial data is the Modifiable Areal Unit Problem (MAUP). This problem is particularly relevant to social science applications of spatial statistics (Bailey and Gatrell, 1995). The modifiable areal unit problem refers to the fact that sometimes the units into which data are aggregated are arbitrarily drawn. Analyses that have been performed on data that have been aggregated into arbitrary units, or into areal units that could be modified, might yield different results if the data were aggregated into different units. Different results might be reached if the boundaries of the units were shifted (zone changes) and/or if the size of the units were changed (scale changes).

Because this study relies on Census tracts, it likely suffers from the MAUP. Census tract boundaries are arbitrary in the sense that they do not correspond to any real, immutable features. However, to the extent that any given study relies on the use of pre-determined modifiable areal units (either because the data is aggregated by a governmental agency at a certain level or because the results of the study need to be attached to certain areal units to allow comparison to other data), that study will not be able to correct for the MAUP. In many spatial studies in the social sciences, these constraints will be present. In this study, as in many other spatial studies in the social sciences, there is usually little that can be done to solve the problem.[15] Rather, researchers must be aware that the problem exists and that arbitrary areal units do not tell the only possible story in the data.

Another set of issues arises from the nature of the space being studied. One such issue is that of edge effects. Points near the edge of a study area are going to have fewer neighbors and therefore, their values will be lower. In the case of this study, the edge effects are relatively minor for several reasons. Because so many Census tracts within the study areas and immediately surrounding the study areas have zero LIHTC units, the edge effects in most cases are not relevant. Furthermore, during the process of selecting tracts along the city boundaries to be included in the unit of analysis, any tract that overlapped with the city boundary and contained an LIHTC property was considered to be part of the city for this study. Lastly, because tracts at the edges of the study areas tend to be relatively large (especially in southern and western cities), in most cases where an LIHTC property is located in a tract that is outside of but adjacent

[15] One alternative is to conduct the analysis using different modifiable units in cases where the units are nested. For example, in cases where the information is available at the block group level, the analysis can be conducted at the block group and tract level. However, the data must available for the smaller units in order for this to be possible. Furthermore, aggregating information into larger and larger units can undermine the ability of clustering statistics such as G_i* to detect clusters.

to the study area, the centroid of that tract is not within one mile of another centroid and, therefore, would be less likely to result in a significant cluster.

Another limitation of this study is that it does not use a test of significance in defining clusters. As discussed above and in Chapter 4, a cluster, or hot spot, was defined as any tract with a G_i* value of at least two standard deviations above the mean. This has two implications for the results of this study. First, a confidence interval cannot be established for the results; the possibility that any cluster occurred by chance cannot be effectively ruled out. Second, the hot spots in different cities are of varying intensities. As the standard deviations vary from city to city, the thresholds for determining hot spots also varies. However, all hot spots are areas of clustering relative to the development in that city.

Another limitation of this study relates to the nature of the G_i* statistic. As discussed above, the total number of LIHTC low-income units per tract needed to be standardized for the G_i* statistic to work properly. In this case, the actual inputs were the number of units in LIHTC properties set aside for low-income residents per square mile by Census tract. This standardization has implications for cities where the tract sizes vary dramatically, such as cities in the south and west regions of the U.S. For example, most of the Census tracts in Phoenix are of a uniform size. On the outer edges of the city, however, some Census tracts are quite large. (The largest Census tract in the Phoenix study is over 66 square miles.) Where the Census tracts are large, the number of units per square mile is relatively small. This can produce some anomalous results. For example, in Phoenix four of the five hot spots are based on the location of only one LIHTC property. However, the largest LIHTC property in the city is not contained in any hot spot because, while the number of units in the property is high, the number of units per square mile is low. Anomalies such as the large property in Phoenix are best investigated on an individual basis. For example, it is possible that within a very large tract there exits a node of relatively dense development. If that is the case, it may be appropriate for a researcher to use a different area to standardize the number of tracts -for example, the area of the block groups that contain the majority of the population in the tract. However, only by looking at each anomalous case individually can the effect of the standardization of the number of units be determined.

Chapter 5 – Findings

This study uses the G_i* clustering statistic to determine the nature of clustering of LIHTC projects in the 25 largest U.S. cities. Two research questions are investigated:

- what variation among cities in the distribution of LIHTC projects is revealed by local spatial statistics? and
- what are the advantages and disadvantages of conducting research on housing using local spatial statistics over using traditional methods?

Findings related to the first question above, about the program, are presented in this section. A discussion of these findings and the findings related to the methodological question are presented in Chapter 6.

Detection of Hot Spots

The most basic question in any study of clustering is whether hot spots exist in a city and how many exist in each city. The question as to whether a hot spot exists in a certain study area is influenced to a great extent by the threshold that the researcher sets for what determines a cluster. The G_i* statistic does not have a pre-determined threshold to determine hot spots.[16] Ideally, the researcher would use a test of

[16] An example of a statistic that has a pre-determined threshold is the Pearson's Poduct-Moment Correlation Coefficient. This widely used statistic calculates the correlation between two variables that are linearly related. Under this test, the value returned is always between –1 and 1. Any result between –1 and 0 indicates a negative correlation with –1 indicating perfect negative correlation, and any result between 0 and 1 indicates a positive correlation with 1 indicating perfect positive correlation. Because the range of possible values is known, the intensity of the correlation can be judged by comparing the result to the maximum possible value. For example, a result of 0.7 can be easily interpreted because the theoretical maximum is 1.0. Thus, we know that a value of 0.7 indicates a relatively high degree of correlation.

significance to determine which G_i^* values were statistically significant. However, in the case of this study, there are a great many tracts with zero LIHTC units within the search radius of one mile. In an extreme case such as Jacksonville, 115 out of 144 tract centroids (or 79.9 percent) have no LIHTC units within one mile. Thus, the distribution of results is so skewed that no test of significance was found that was robust enough to be used given the inputs and the extreme number of tracts with a zero value based on the G_i^* analysis.

Instead, the threshold used to determine the existence and location of hot spots was related to standard deviations. A hot spot is defined as any area where the G_i^* values are at least two standard deviations above the mean G_i^* value for all Census tracts in that city. It is important to note that standard deviations do not relate to confidence intervals in this case because of the extremely skewed distribution of G_i^* values within each city.

The use of standard deviations is an acceptable substitute for a test of significance. It identifies tracts with G_i^* values that are high relative to the distribution of all G_i^* values in a city. An obvious consequence of using this threshold is that hot spots will likely be identified in every city in the study.[17] Also, defining a hot spot as any area with values at least two standard deviations above the mean results in hot spots of varying intensity among the cities. Because the mean and standard deviation are different in each city, the G_i^* value that is two standard deviations above the mean also varies from city to city. Thus, the hot spots in one city cannot necessarily be directly compared with those in other cities; that is, a hot spot in one city may represent more intense clustering than

[17] It is possible that no hot spots would be found even using this methodology. If all G_i^* values were clustered around the mean, then there might be no tracts with G_i^* values two standard deviations above the mean. This situation did not occur with any city in this study.

in another city. Comparison of hot spots in different cities is possible as long as the mean and standard deviation of each city involved are considered as well.

From a programmatic perspective, however, the use of the threshold of two standard deviations is reasonable. The lack of a confidence interval associated with the standard deviation merely means that it is not possible to rule out the prospect that a hot spot is the result of chance; however, the hot spots *do* exist. The hot spots defined by this method show actual areas where many LIHTC units are located relative to all such units in that city. This information can be used to help program administrators investigate issues such as whether there are reasons that there are so many units in those areas relative to the rest of the city, what those reasons are, what the impact of the location of these hot spots is on the choice of neighborhood for low-income renters, and what the impact of the location of these hot spots is for the neighborhoods in which they are located.

Simply examining a list of tracts that contain a high number of LIHTC units will not provide the same information. For example, a single tract may have a high number of units. However, if these units are part of a single development, the high number of units may not indicate any locational pattern. Conversely, there may be cases where a pattern exists that cannot be detected without spatial analysis. If several projects are located in adjacent Census tracts, this pattern may be not be the result of mere chance. However, this clustering would not be apparent to someone who is looking at a list of tracts with no spatial information.

Number of Hot Spots

As discussed above, every city has a least one hot spot of LIHTC units in this analysis because of the manner in which hot spots are defined. Table 2 shows the distribution of cities by number of hot spots.

Table 2: Number of Cities by Number of Hot Spots

Number of Hot Spots within a City	Number of Cities
1	15
2	4
3	3
4	1
5	2

Even after the threshold of two standard deviations above the mean was set, defining what constituted a hot spot requires some judgment. In most cases, hot spots consist of two or more *adjacent* Census tracts with G_i* values above threshold. For example, the hot spot tracts in Austin and Baltimore (Figures 5 and 6) form clear and distinct hot spots.

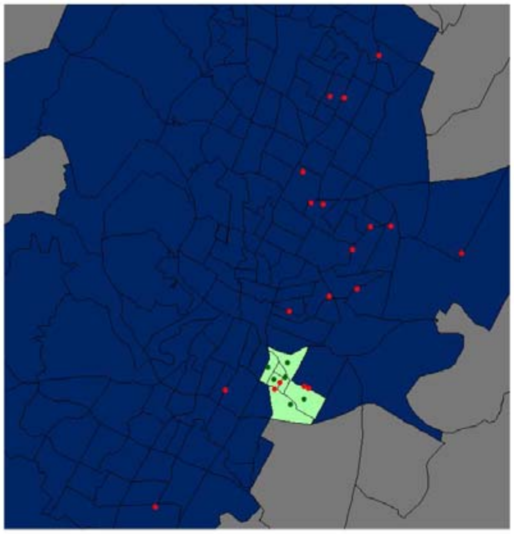

Figure 5: Austin

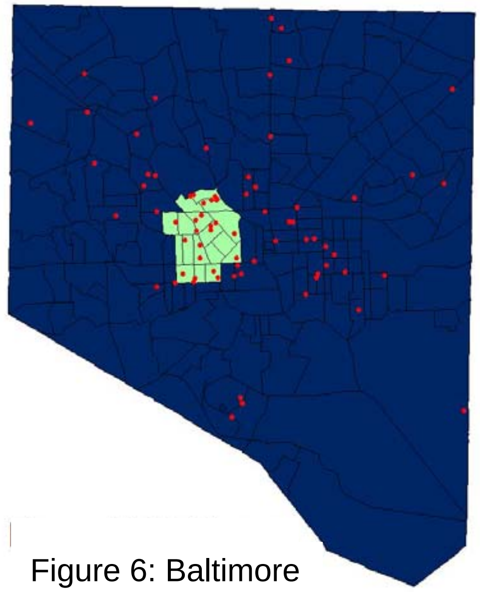

Figure 6: Baltimore

In a few cases, however, it is difficult to determine whether the hot spot tracts constitute one hot spot or two (or perhaps more). For example, in Denver (Figure 7) seven of the hot spot tracts form a clear hot spot. The remaining two tracts are not directly adjacent to this hot spot or even to each other.

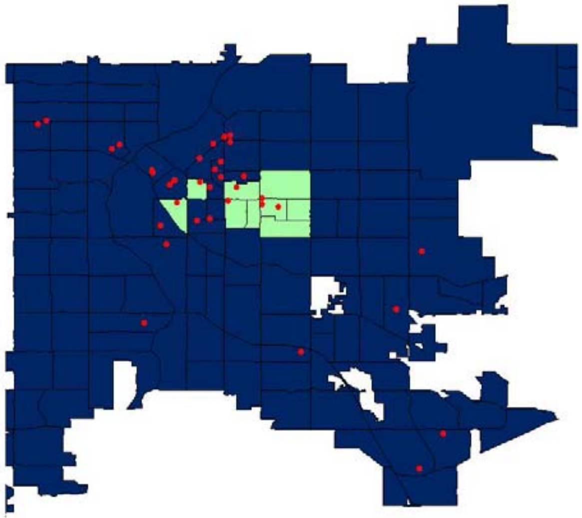

Figure 7: Denver

Because this analysis used a distance of one mile in calculating G_i*, the G_i* value for any centroid is based on the number of units in tracts with centroids within one mile. Thus, the centroid of a tract with no units may have a high G_i* if it is surrounded by tracts with a high number of units. Figure 7 provides an example of this situation. Four of the tracts in the hot spots do not have any units but are located in close proximity to tracts with many units.

A similar pattern of hot spot tracts to that in Denver occurs in Indianapolis (Figure 8). Here, seven hot spot tracts are adjacent to one another. Another seven tracts are in very close proximity to these tracts. They form almost a complete ring of tracts in the center of the city.

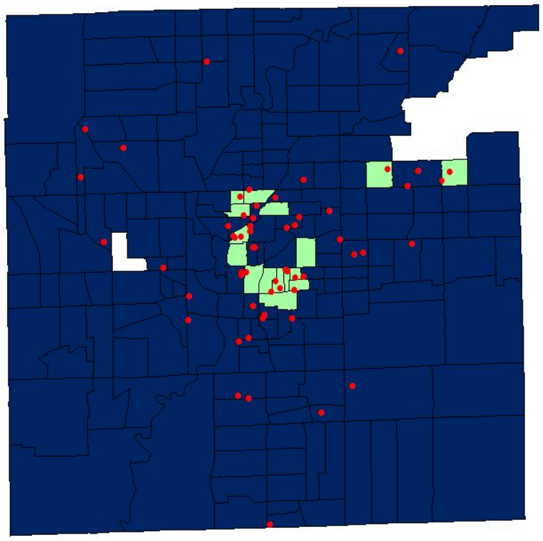

Figure 8: Indianapolis

In both cases, the groups of tracts described here have been classified as single hot spots. These tracts are close enough to one another to be considered single hot spots when they are compared to the study area as a whole. However, these examples emphasize the fact that analyses such as the one used in this study are most powerful when combined with detailed information about the geographies of the areas studied. For example, in the case of Denver or Indianapolis, the built environment of these cities may include barriers (e.g., Interstate highways or large industrial complexes) such that the hot spot tracts in question ought to be considered two hot spots.

The variation in the number of hot spots across cities suggests that forces that influence the location of LIHTC projects in one city may not be present in other cities. For example, the presence of only hot spot in a city may suggest that some aspect of the application procedure is restricting the neighborhoods that developers consider for LIHTC projects. These constraints could be related to the use of market surveys as part of the application process or the incentives provided by the program rules to develop in Difficult Development Areas or Qualified Census tracts. Program administrators in specific areas could use information on the number of hot spots to determine whether investigation into the presence of such constraints is needed and whether new rules should be implemented to address them.

Coverage of Hot Spots - Tracts

The size of the hot spots varies from city to city. One way to measure the size of a hot spot is by the number and percentage of Census tracts included in the hot spot. Because Census tracts boundaries are based more on population size than on physical size, they provide a good way to compare hot spots between densely populated and sparsely populated cities. Table 3 shows this information for all cities in the study.

Table 3: Number and Percent of Tracts in Hot Spots by City

City	Number of Tracts in Hot Spots	Percentage of All City Tracts in Hot Spots*
Austin	6	3.8%
Baltimore	17	8.5
Boston	14	8.9
Chicago	72	8.2
Columbus	13	6.5
Dallas	8	3.0
Denver	9	6.6
Detroit	15	4.7
District of Columbia	9	4.8
El Paso	5	4.5
Houston	11	2.6
Indianapolis	16	7.8
Jacksonville	4	2.8
Los Angeles	39	4.7
Memphis	8	4.6
Milwaukee	14	6.3
Nashville	6	4.3
New York	180	8.1
Philadelphia	26	6.8
Phoenix	20	6.8
San Antonio	13	5.6
San Diego	15	5.6
San Francisco	13	7.4
San Jose	7	3.9
Seattle	9	7.3

*This figure is the percentage of all Census tracts within the study area that are in hot spots. While the study areas closely match the incorporate boundaries of the cities studied, they do not match exactly in all cases.

The numbers of Census tracts that are part of hot spots range from a low of four in Jacksonville to a high of 180 in New York. However, since all Census tracts are approximately the same size with respect to population, Census tracts in more densely populated cities cover less area. Thus, 180 Census tracts in New York City are not equivalent in terms of the area covered to that many Census tracts in another city. A more uniform measure of the relative size of hot spots is the percentage of all Census tracts in a city that are part of a hot spot. Percentages range from a low of 2.6 percent in Houston to a high of 8.9 percent in Boston. Thus, one in every eleven Boston Census tracts is in a hot spot while only one in every forty Census tracts in Houston is.

The number and percentage of all Census tracts in a city that are part of hot spots may have consequences for how much the LIHTC program increases neighborhood choice for low-income persons in a city. To the extent that program administrators want to use the LIHTC program, either by itself or in combination with other low-income housing programs, as a way to increase neighborhood choice for low-income persons and to decrease concentration of poverty, the number and percentage of all Census tracts in hot spots provide a helpful initial way to evaluate the distribution of LIHTC projects in different cities.

Coverage of Hot Spots - Area

This section examines the hot spots in several study cities in terms of the area that they cover. The physical size of a hot spot is likely an important factor in determining the possible impacts of the hot spot on the residents living there. An intense hot spot of LIHTC units that covers a small area may feel very different to residents than a larger hot spot of the same intensity. Residents living in the larger hot spot may feel and may be more isolated than those living in a smaller hot spot.

Researchers have long understood the isolating nature of low-income neighborhoods (Massey and Denton, 1993). During the 1990s, HUD launched three programs designed to help end the isolation of families living in poor areas: the Moving to Opportunity Demonstration, the Jobs Plus Community Revitalization Initiative, and the Bridges to Work demonstration. An analysis of these three programs (Turner and

Rawlings, 2005) makes several recommendations about how to use the lessons from these programs to tackle the problems created by concentrated poverty and isolation. In their recommendations, the authors state at least two goals that relate to addressing isolation. They look at strategies to "[e]ncourage and assist low-income families to move to safe, opportunity-rich neighborhoods" and to "[s]aturate assisted housing developments in high-poverty neighborhoods with quality employment services and supports…" (39). Studies such as this one, which analyze the impacts of "neighborhoods" on residents and make recommendations related to "neighborhoods," are quite common. However, there is no standard definition of what constitutes a neighborhood. The isolation impacts of low-income neighborhoods are likely to vary with "neighborhood" size. Larger "neighborhoods" that are uniformly low-income should have more significant impacts on residents than smaller "neighborhoods." In contrast to studies that focus on neighborhoods, this study focuses on area covered. More research is needed on what constitutes a neighborhood. Such research would allow connections to be drawn between studies of neighborhood effects and spatial studies that define results in terms of areas.

Because this study uses a local spatial statistic in a GIS environment, information about area can be obtained as part of the analysis. Dallas (Figure 9) and the District of Columbia (Figure 10) demonstrate how spatial statistics can help provide a deep understanding of hot spots by providing information about area covered.

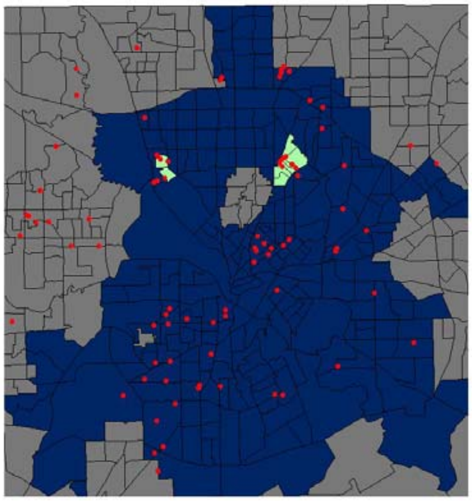

Figure 9: Dallas

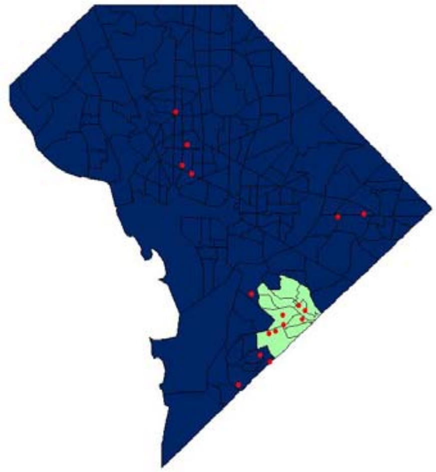

Figure 10: District of Columbia

In terms of number of Census tracts in hot spots, these two cities are similar: Dallas has eight tracts in hot spots and DC has nine. However, the eight tracts in Dallas are divided between two hot spots and they represent a total of 3.0 percent of all tracts in the city. In DC, the nine tracts are in one hot spot and they represent 4.8 percent of all tracts in the city.

Table 4: Hot Spots in Dallas and the District of Columbia

	Number of Tracts in Hot Spots	Number of Hot Spots	Percentage of All Tracts in Hot Spots
Dallas	8	2	3.0
DC	9	1	4.8

Based on these figures, and without looking at a map, one might assume that the hot spots in Dallas are smaller than the hot spot in DC. It seems as though the two Dallas hot spots must be smaller for two reasons. First, the two hot spots in Dallas each must have fewer tracts than the single hot spot in DC since together the Dallas hot spots comprise only eight tracts versus nine in the single hot spot in DC. Second, each of the hot spots must represent a much smaller percentage of all tracts in the city; together they comprise only 3.0 percent of all tracts in the city versus 4.8 percent in DC. Thus, on average, the hot spots in Dallas consist of 4 tracts, or 1.5 percent of all tracts in the city, compared to 9 tracts, or 4.8 percent of all tracts, in DC. However, because the tracts in Dallas are larger than in DC (likely due to less dense development), the Dallas hot spots are not smaller than the DC hot spot. In fact, the larger of the two hot spots in Dallas is larger than the single hot spot in DC in terms of total acres covered (1,528 acres versus 1,369 acres) and in terms of dimension (2.8 miles along the longest diagonal versus 2.2 miles). The smaller hot spot in Dallas measures 468 acres and 1.4 miles along the diagonal.

Two other cities that reveal the complicated nature of clustering are Philadelphia (Figure 11) and Phoenix (Figure 12).

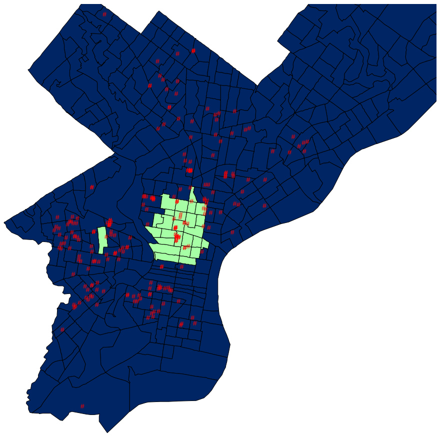

Figure 11: Philadelphia

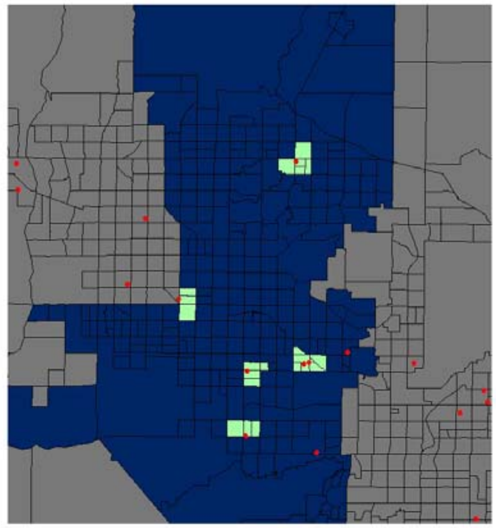

Figure 12: Phoenix

Again, these two cities are similar in terms of number of tracts in hot spots (20 in Phoenix and 26 in Philadelphia) and the percentage of all tracts in hot spots (6.8 percent in Phoenix and 6.8 percent in Philadelphia). In Phoenix, the tracts are divided among five hot spots while in Philadelphia they are grouped together in two hot spots. (However, one of the Philadelphia hot spots consists of only one Census tract.)

Table 5: Hot Spots in Philadelphia and Phoenix

	Number of Tracts in Hot Spots	Number of Hot Spots	Percentage of All Tracts in Hot Spots
Philadelphia	26	2	6.8
Phoenix	20	5	6.8

Based on these results, one might assume that the hot spots in Phoenix are much smaller than the hot spot in Philadelphia because fewer tracts are involved and they are split up into more hot spots. That is, the hot spots in Phoenix comprise an average of 4 tracts each while the hot spots in Philadelphia average 13 tracts each. However, the largest hot spot in Phoenix is 72 percent of the area (1,854 acres versus 2,583 acres) and a full 96 percent of the dimension (2.7 miles along the longest diagonal versus 2.8 miles) of the large hot spot in Philadelphia. The smallest hot spot in Phoenix is 1,134 acres and 2.1 miles, 44 percent of the area and 75 percent of the dimension of the large Philadelphia hot spot. Thus, even though each hot spot in Phoenix is made up of far fewer tracts on average, the hot spots are not significantly smaller in area. Again, this is because the tracts in Phoenix are larger than those in Philadelphia.

It is not surprising that Dallas and Phoenix, two Sun Belt cities, have hot spots that are cover a relatively large area when compared to Washington DC and Philadelphia, two older, Eastern seaboard cities. Cities in South and West tend to have lower densities and, therefore, their Census tracts tend to be larger in area. However, the difference in the underlying geographies of cities and the impacts of that geography on clustering can be lost in traditional clustering analyses. As discussed in detail in Chapter 6, there are multiple aspects to segregation. The G_i* analysis reveals directly information about clustering, one aspect of segregation. However, because the results are presented in a visual form, the analysis also reveals information about concentration, the area covered by the members of a population. The ability to easily visualize and measure area and dimensions is discussed in Chapter 6 as one of the advantages of using a GIS to conduct a clustering analysis.

Means, Standard Deviations, and Highest G_i Values*

In general, the mean and the standard deviation of a population are influenced by extreme values. In this study, every city has a large number of tract centroids with G_i* values equal to zero. This distribution of values works to keep the means for each city fairly low. At the other end of the scale, some cities have a few tracts with very high G_i* values while others have none with extreme values. This distribution leads to a wide range of standard deviations across cities. Despite the fact that it is impossible to know which of the hot spots detected in each city by this analysis are statistically significant, comparing the range of G_i* values relative to the mean and standard deviation in each city allows an "apples to apples" comparison of the range of intensity of clustering in different cities. Table 6 shows the mean, standard deviation, and the range of G_i* values at or above the threshold of two standard deviations above the mean for each city.

Table 6: Mean, Standard Deviation, and Range of G_i^* Values in Hot Spots by City

City	Mean	Standard Deviation	Mean Plus Two Standard Deviations	Range of Observed G_i^* Values at Least Two Standard Deviations above the Mean
Austin	0.02	0.08	0.18	0.31 - 0.43
Baltimore	0.07	0.13	0.33	0.33 – 0.62
Boston	0.12	0.16	0.44	0.45 – 0.52
Chicago	0.02	0.03	0.08	0.08 – 0.19
Columbus	0.02	0.05	0.12	0.12 – 0.24
Dallas	0.02	0.05	0.12	0.12 – 0.35
Denver	0.05	0.10	0.25	0.25 – 0.49
Detroit	0.03	0.05	0.13	0.13 – 0.27
DC	0.06	0.11	0.28	0.37 – 0.48
El Paso	0.03	0.08	0.19	0.28 – 0.39
Houston	0.01	0.03	0.07	0.08 – 0.25
Indianapolis	0.02	0.03	0.08	0.08 – 0.18
Jacksonville	0.01	0.03	0.07	0.13 – 0.19
Los Angeles	0.02	0.05	0.12	0.12 – 0.39
Memphis	0.02	0.04	0.10	0.10 – 0.31
Milwaukee	0.07	0.13	0.33	0.39 – 0.72
Nashville	0.02	0.07	0.16	0.29 – 0.38
New York	0.02	0.03	0.08	0.08 – 0.18
Philadelphia	0.04	0.07	0.18	0.18 – 0.37
Phoenix	0.01	0.04	0.09	0.13 – 0.21
San Antonio	0.01	0.04	0.09	0.10 – 0.29
San Diego	0.02	0.07	0.16	0.16 – 0.33
San Francisco	0.10	0.18	0.46	0.49 – 0.79
San Jose	0.02	0.04	0.10	0.10 – 0.20
Seattle	0.08	0.23	0.54	0.55 – 0.92

The means range from 0.01 to 0.12. Fifteen of the cities have means equal to 0.01 or 0.02. These low values for the means are not surprising given the large number of tract centroids that have zero LIHTC units within one mile.

In five cities, there is wide gap between the tracts below the threshold (i.e., two standard deviations above the mean) and those above. In Austin, El Paso, Jacksonville, Nashville, and Phoenix, all of the G_i^* values that are at least two standard deviations above the mean are actually at least three standard deviations above the mean. That is, there are no tracts with G_i* values that fall between two and three standard deviations above the mean. In these cities, the hot spots identify areas where the clustering of LIHTC units is much more intense than in other parts of the cities. The opposite situation occurs in Boston, where the *highest* G_i* value is only two and a half standard deviations above the mean; that is, all hot spots are between two and two and a half standard deviations above the mean. In fact, the G_i* values for Boston, below and above the threshold, increase gradually. This is one case where the use of a somewhat arbitrary threshold as the definition of a hot spot may draw an artificial distinction between Census tracts, defining one area as a hot spot while another, very similar area is not defined as a hot spot despite very similar G_i* values. In Boston, the factors that influence development make hot spot areas only slightly more attractive than other areas. In Phoenix, on the other hand, the high G_i* values in the hot spots indicate that there are strong pressures or incentives to develop in hot spot area.

The findings presented in this section perhaps make the strongest argument that macro-level analyses, such as those that combine all LIHTC properties in the country or even in all cities into one data set, may obscure important differences in how the program is executed in different places. The range of G_i* values is much larger in some cities than in others. Extreme G_i* values likely indicate the presence of strong pressures, such as those discussed in Chapter 3, on development. These pressures could be related to land values, the existing distribution of low-income persons, or the scoring criteria of the state allocating agency, among others. Whatever the nature of these pressures, it is reasonable to think that they would have an impact on the performance of the LIHTC program in terms of providing neighborhood choice for low-income residents. Furthermore, cities with more extreme G_i* values may have more extreme values in other variables, such as the average rate of poverty in Census tracts with LIHTC properties. These differences may be easily obscured by analyses than aggregate all LIHTC properties together.

Percentage of Units in Hot Spots

Another measure of how much choice in neighborhoods the LIHTC program provides for low-income residents in a city is the percentage of all low-income LIHTC units that are found in hot spots. As discussed in Chapter 3, the LIHTC program is the primary source of affordable housing production today. To the extent that LIHTC units are widely dispersed across a city, this program contributes to locational choice for low-income households, especially since LIHTC rents are based on metropolitan median incomes.[18] The more LIHTC units are clustered together in only a few areas of a city, the less locational choice low-income households have. The results of the hot spot analysis show vast variation across cities. Table 7 shows the results for each city.

[18] The maximum rent that can be charged for an LIHTC unit is equal to 30 percent of the monthly income for a family earning 50 percent (or 60 percent depending on the number of set aside units) of the area median income for a family of similar size. The maximum rent does not vary based on the actual income of the family living in a unit. Thus, the maximum rent for LIHTC units is the same anywhere in a given city.

Table 7: Number and Percentage of All Low-Income LIHTC Units in Hot Spots by City

City	Low-Income LIHTC Units in Hot Spots	All Low-Income LIHTC Units in City	Percentage of LIHTC Units in Hot Spots
Austin	646	2512	25.7%
Baltimore	1298	3176	40.9
Boston	2143	6265	34.2
Chicago	4668	12479	37.4
Columbus	754	4332	17.4
Dallas	2646	13834	19.1
Denver	600	1780	33.7
Detroit	959	3980	24.1
DC	1548	3721	41.6
El Paso	168	1005	16.7
Houston	1539	7299	21.1
Indianapolis	1303	3486	37.4
Jacksonville	339	3666	9.2
Los Angeles	1706	7256	23.5
Memphis	1661	2941	56.5
Milwaukee	314	1525	20.6
Nashville	524	2748	19.1
New York	6374	15174	42.0
Philadelphia	1476	5696	25.9
Phoenix	432	783	55.2
San Antonio	549	1189	46.2
San Diego	482	928	51.9
San Francisco	921	2510	36.7
San Jose	495	3566	13.9
Seattle	2485	4051	61.3

The percentage of low-income LIHTC units that are located in hot spots ranges from a low of 9.2 percent in Jacksonville to a high of 61.3 in Seattle.

Interpreting the results shown in Table 7 in light of other information about the hot spots in each of the cities highlights the extent of the variation between cities in the patterns of LIHTC development. For example, six cities that have more than 20 percent of all low-income LIHTC units in hot spots also have less than five percent of all Census tracts in hot spots: Austin, Detroit, DC, Houston, Los Angeles, and Memphis. The most extreme cities are DC, where 41.6 percent of all set-aside units are located in just 4.8

percent of all tracts, and Memphis, where 56.5 percent of all set-aside units are located in just 4.6 percent of all tracts. Thus, in these cities, approximately half of all low-income LIHTC residents live in less than five percent of the tracts. Conversely, Jacksonville has a very low percentage of tracts in hot spots (2.8) and has only 9.2 percent of all set-aside units in those tracts. While set-aside units are still disproportionately located in hot spots, there are still a relatively high number of LIHTC units available outside of the hot spots.

The findings about the percentage of units in hot spots, like many of the other findings presented in this chapter, suggest avenues for future research. These findings do not reveal anything about why many units in some cities are in hot spots. This clustering could be related to the preferences of developers; that is, many of the proposed projects in these cities could be in these areas, and therefore many of the selected projects are in these areas. On the other hand, this clustering could be related to the scoring process; that is, applications could be submitted for properties throughout the city and some aspect of the process of scoring applications favors developments in these areas. In any case, the wide variation in the percentage of units in hot spots suggests that future research perhaps should include a causal analysis of the pressures on the selection process.

Cities with Hot Spots Driven by Large LIHTC Properties

In three cities, the hot spots identified by the analysis are the result of a few large properties. In Memphis, the average number of set-aside units per property for LIHTC properties in hot spots is 237 compared to 36 for properties outside of hot spots. In

Houston the figures are 294 versus 150, and in San Antonio, the figures are 110 versus 71. Thus, in Memphis the hot spot is created by fewer developments than in Houston and San Antonio. In Memphis and other cities with hot spots driven by large LIHTC properties, there may not be significant pressures or incentives for developers to located developments in the neighborhood where the hot spot is. The location might be due in large part to chance. Nevertheless, in cities with a few large properties, program administrators may want to pay particular attention to how proposed large projects advance the housing goals of the allocating agency. On the other hand, in Houston and San Antonio, the hot spots must have a high number of developments since the average number of units per development is not very different in hot spots and elsewhere. In these cities, it is more likely that there is some factor that has led developers of several properties to locate in the same area. These areas warrant further investigation to see if these factors can be identified.

Cities with High G_i Values and One Hot Spot*

In three cities, only one hot spot exists and the tracts with these single hot spots have high G_i* values. In San Francisco, 78 percent of all LIHTC set-aside units are located within the same hot spot. In Boston, this figure is 76 percent, and in Seattle it is 73 percent. Thus, the LIHTC units in these cities are intensely clustered in just one area. However, the concentration of units is not due to the presence of large properties. In fact, the percentage of *units* within hot spots closely matches the percentage of *properties* within hot spots: 77 percent in San Francisco, 72 percent in Boston, and 76 percent in Seattle. Thus, on average, the properties in the hot spots are roughly the same size as other properties in the city. Again, these results do not tell us anything about why single, intense hot spots are found in some cities. Because the units in these cities are spread proportionally across developments, though, this pattern tells us that there must be some factor attracting developments to the hot spot areas. Further, these location patterns reveal the dramatic differences between how the LIHTC program is administered across cities and how important local spatial statistics are to understanding the administration of the program.

Highly Clustered Cities

Five cities have large natural breaks between the G_i^* values for hot spot tracts and all other tracts. In Austin, El Paso, Jacksonville, Nashville, and Phoenix, all hot spots tracts have G_i^* values of at least three standard deviations above the mean. (See Table 6.) That is, there are no tracts with G_i^* values between two and three standard deviations above the mean. While it cannot be concluded that these hot spots are statistically significant, it is clear that these hot spots are particularly intense compared to hot spots in other cities. These five cities also have relatively few tracts in hot spots. As Table 3 shows, compared to all other cities in the study, these five cities have low percentages of tracts in hot spots. With the exception of Phoenix, these cities are among the seven cities with the lowest percentage of tracts in hot spots. Thus, these cities exhibit extreme clustering and are excellent choices for further analysis.

Index of Clustering

The analysis of the hot spots in the study cities so far has revealed the complex nature of hot spots. One of the most important lessons from the analysis is that the number of hot spots in a city does not paint a complete picture of the pattern of development of LIHTC properties in that city. Some cities have hot spots that are quite large relative to the number of Census tracts in that city and that cover a relatively large area of the city while the hot spots in other cities are not nearly as large in terms of number of tracts and area. Some cities have hot spots with very high G_i* values, indicating intense clustering, while other cities have no areas with very high G_i* values anywhere in the city. Some cities have a relatively high percentage of all LIHTC units in hot spots while a significant proportion of LIHTC units lie outside of hot spots in other cities. Some cities have a few large developments that result in hot spots while others do not have a concentration of large properties.

In order to combine the information provided about each of these individual aspects of the hot spots into a single value, an index was created. The index is based on the results for each city on three factors: the mean G_i* score for Census tracts in that city, the percentage of all Census tracts in that city located in hot spots, and the total number of clusters identified in that city. The cities were ranked from lowest to highest on the basis of the first two factors; lower mean G_i* scores and lower percentages of Census tracts in hot spots indicate that the clustering in a city is less intense. For the third factor, the cities were ranked from highest to lowest on the basis of the number of clusters in the city. In cities with fewer clusters, the factors influencing locational choice focus development in fewer locations throughout the city; therefore, these cities can be thought of as exhibiting greater clustering. Table 8 shows the rankings on each of these factors and the index score for each city.

Table 8: Clustering Index

City	Rank – Mean G_i* Score of Hot Spots	Rank – Percentage of Tracts in Hot Spots	Rank – Number of Clusters	Index
Houston	7	1	5	13
Jacksonville	6	2	5	13
San Jose	4	5	4	13
Dallas	9	3	4	16
Memphis	6	8	3	17
San Antonio	7	11	2	20
Phoenix	5	15	1	21
Detroit	8	9	5	22
New York City	2	19	1	22
Indianapolis	1	18	3	22
Austin	14	4	5	23
Nashville	12	6	5	23
Los Angeles	9	9	5	23
Columbus	6	13	5	24
El Paso	13	7	5	25
San Diego	10	11	4	25
Chicago	3	20	3	26
District of Columbia	15	10	5	30
Philadelphia	11	15	4	30
Milwaukee	16	12	5	33
Denver	14	14	5	33
Seattle	19	16	5	40
San Francisco	18	17	5	40
Baltimore	15	21	5	41
Boston	17	22	5	44

The range of values in the index, 13 to 44, shows the extent of the variation among the study cities in terms of the pattern of development of LIHTC properties. Cities with lower index scores have lower overall levels of clustering when all three measures are considered together. Many of the cities with low index scores are Sun Belt cities. It is possible that these cities have a lower incidence of the causes of spatial interruption. Sun Belt cities are likely to have fewer disamenities, such as brownfields and heavy industrial sites, than Rust Belt cities. They may also have different approaches to land use regulation than other cities – in part because they have had less industrial land uses in their history and in part because they generally experienced growth later than cities along the Eastern seaboard. At the other end of the spectrum, many cities with high index scores have relatively high land values. High land values may restrict the areas of a city that developers are able to locate LIHTC properties in and still make a profit, even with the subsidy of tax credits.

Secondary Analysis

Following the paradigm of exploratory spatial data analysis, additional research questions were developed based on the results of the initial analysis. ESDA is used to identify spatial outliers and clusters and to suggest different spatial regimes. Because the initial analysis revealed the presence of clusters, sometimes intense clusters, this secondary analysis investigates the nature of the clusters more in depth. As discussed throughout this chapter, high G_i^* values likely indicate the presence of pressures or influences that encourage development in certain areas. Questions that should be investigated by future research are whether these pressures are related to developers' preferences or the scoring preferences of the allocating agencies and what the impacts of the resulting hot spots are on the surrounding neighborhoods. An examination of the neighborhoods where hot spots are located may begin to help answer these questions. The presence of intense hot spots in neighborhoods with more favorable demographic and economic profiles, such as lower poverty rates, may be due to the scoring criteria of the allocating agencies. Allocating agencies may award extra points to projects that are located in better neighborhoods. The presence of intense hot spots in neighborhoods with less favorable demographic and economic profiles may be related to developers' preferences. It may be easier to develop an LIHTC project in a neighborhood with a lower-income population because land values are lower or because political pressure to avoid these neighborhoods is lower.

To help reveal more information about the neighborhoods where hot spots are located, two characteristics of the neighborhoods were analyzed: poverty and the presence of other affordable units. First, the poverty rates of the hot spot tracts were considered. Hot spots tracts were categorized as high poverty if the poverty rate was greater than 20 percent. This limit was used because HUD has adopted a threshold of a 20-percent poverty rate to assess the performance of the Section 8 voucher program under the assumption that neighborhoods below this threshold operate as middle-income neighborhoods (Khadduri, 2001). All Census tracts in the five cities with intensely clustered LIHTC properties were coded in ArcView as having a poverty rate equal to or less than 20 percent or greater than 20 percent. Table 9 shows the association between hot spot tracts and high poverty tracts.

Table 9: Association between Hot Spots and High Poverty Tracts

	Total Tracts in Hot Spots	Hot Spot Tracts with Poverty Rates Greater Than 20 Percent
Austin	6	4
El Paso	5	5
Jacksonville	2	2
Nashville	6	5
Phoenix	20	17

A strong association exists between hot spot of LIHTC units and high poverty tracts in all of these cities. The majority of hot spot tracts in cities where LIHTC projects are intensely clustered are high poverty tracts as defined by HUD. In these cities, it seems that strong influences are at play in the decision about where to located LIHTC projects and that these influences tend to push these projects into high poverty areas.

The strong association between hot spots and high poverty tracts is a significant finding. The U.S. Department of Housing and Urban Development seeks to decrease concentration of poverty through some of its programs. The laws and regulations that govern the Section 8 program include specific provisions to reduce concentration of poverty. However, the LIHTC program, the largest federal production program of affordable housing, seems to be building more units in high poverty areas. Because this program falls outside of HUD's jurisdiction, the preferences of developers dictate the location of properties, even if they are in high poverty areas.

Next, the locations of Section 8 voucher holders were compared to the locations of LIHTC hot spots. The locations of Section 8 voucher holders were used as a proxy for the location of affordable units in the study cities. As discussed further in Chapter 6, different housing programs have different thresholds of what constitutes an affordable unit. These varying definitions, combined with the fact that the Census reports rents in wide ranges, make it difficult to measure the number of “affordable” housing units in any given neighborhood or Census tract. However, the presence of many Section 8 voucher holders in a Census tract probably indicates the presence of many units in that tract that rent at the HUD determined Fair Market Rent.

Because the number of Section 8 vouchers in use varies from one city to another, the number of vouchers per tract was coded in terms of standard deviations from the mean number of vouchers per tract for each city to normalize the data. Table 10 shows the results the association between hot spots and Section 8 vouchers.

Table 10: Distribution of Hot Spots and Section 8 Voucher Holders

	Number of Tracts by Standard Deviation from the Mean Number of Section 8 Voucher Holders per City			
	–1 to 0 Standard Deviations	0 to 1 Standard Deviations	1 to 2 Standard Deviations	2 to 3 Standard Deviations
Austin	6			
El Paso	4	1		
Jacksonville	2			
Nashville	4		1	1
Phoenix	18	2		

Based on these results, there does not seem to be a strong association between the neighborhoods where Section 8 voucher holders live and intense hot spots of LIHTC properties.

While these findings cannot be generalized to all urban LIHTC properties, they suggest that the forces driving LIHTC development are complex. Based on the intensity with which LIHTC units in these cities are clustered, some force is working to constrain LIHTC developments in these cities. Poverty rates, and perhaps accompanying low land costs and/or weak political power, may be part of the equation. However, the LIHTC properties seem to be in different areas than properties whose landlords accept

Section 8 vouchers. Further research on these patterns may reveal information not just about the LIHTC program but about differences between different affordable housing programs as well.

Conclusion

One persistent theme emerges in the findings presented in this chapter: there is great variation between cities in terms of how the LIHTC program plays out. The use of the local statistic G_i* reveals much more information about LIHTC developments in the study cities than a global statistic would. A global clustering statistic would only indicate whether clustering was present in each of the cities. Likewise, traditional clustering analysis, which does not include an overtly spatial component, would not reveal the locations of clusters nor would it indicate whether high intensity tracts tended to be located in close proximity to one another.

On the other hand, the G_i* reveals where clustering occurs, how intense it is, and the nature of the individual clusters. Knowing how clustering varies across space in a city and knowing how the hot spots within a city vary from one another provides much more information to program administrators or to researchers looking to develop hypotheses for further investigation. The results of the G_i* analysis make it possible for researchers to identify the tracts where spatial non-stationarity occurs so that they can be investigated further.

Chapter 6 – Discussion and Recommendations

This chapter discusses the implications of the findings presented in Chapter 5. Based on this discussion, several recommendations are presented about approaches that program administrators and local government officials can use to exert more influence over this program that relies so heavily on private actors. Next, findings related to the methodology used in this study are presented. Lastly, this chapter suggests avenues for future research.

Discussion of the Implications of Findings

Perhaps the most important aspect about the LIHTC program from the analysis in this study is that significant variation exists across cities. This study reveals differences in the number of LIHTC units in the study cities that are in hot spots, differences in the number of Census tracts that are in hot spots, and differences in the intensity of clustering of hot spot tracts as measured by G_i*. Also, as is discussed below, the maps of the results show variations of another measure of segregation, centralization (Massey and Denton, 1988), in the study cities.

Aggregating the data on LIHTC properties at the national level will obscure the differences among cities. Even studies that focus only on LIHTC developments in urban areas but that aggregate the data from many cities will miss these differences. As a result, program evaluation that is based on the results of studies at the national level may draw the wrong conclusions about the program. For example, a program evaluation might ask whether the LIHTC program has increased the number of neighborhoods with affordable units. If the program has dramatically increased the number of neighborhoods with affordable units in some cities and has not made much of a difference in other cities, the evaluator, looking at the average results, may conclude that the program has been moderately successful. This conclusion would mask the reality that in many cities the program has not been successful on this account. The results of this study indicate that this problem is not merely theoretical but that there is reason to believe that such distortions may actually be present in national level studies and program evaluations.

The results of this study support a generalized conclusion about which cities exhibit the highest levels of clustering. Sun Belt cities seem to exhibit less clustering of LIHTC properties than older, industrial cities and cities with high land values do. Of the five cities that score lowest on the clustering index (Table 8), four are Sun Belt cities that have experienced rapid suburbanization in the past few decades: Houston, Jacksonville, Dallas, and Memphis. Of the five cities that score highest on the clustering index, three have very high land values: Seattle, San Francisco, and Boston. A fourth, Baltimore, is in a city that was a industrial city in the past. According to Liu's theory of interrupted development, a high number of previous industrial uses in a city may limit the amount of land available for development. Future research is needed to see whether land prices and land use patterns in a metropolitan area have a significant impact on clustering.

The results of the analysis in this study also support the need to identify clusters of LIHTC units and consider them in any future analysis of the locational patterns of this program. There is reason to place special emphasis on clustered units. Researchers from a variety of fields have argued that low-income neighborhoods affect residents' outcomes on a variety of factors, including educational attainment, early career development, and exposure to violence (for example, see Briggs, 1997, and Massey and Denton, 1993). If there is a pattern to the neighborhoods where clusters of LIHTC units are located, then there is likely to be an impact on residents. The forces that lead to clustered units take on special significance if the clusters are located either in neighborhoods with high poverty rates or in those with low poverty rates. The secondary analysis in Chapter 5 shows an association between clusters of LIHTC units and Census tracts with poverty rates greater than 20 percent. Given this pattern, it is even more crucial to understand the pressures and incentives that lead developers to select these tracts for their developments.

Given the impacts of neighborhoods on residents and given that many LIHTC developments are built in clusters, it is important that any analysis of the forces that impact development patterns treat clustered units differently than units that are not in clusters. Oakley (2008) conducts a regression analysis to determine some of the factors that influence the location of LIHTC developments in four cities. It is one of the only such studies that has been conducted on the LIHTC program. It is worth considering here to show clustering studies can be used to improve other analysis of the program.

Oakley concludes her paper with a traditional regression analysis of the location of LIHTC units and another regression that includes a spatial lag variable.[19] She uses Census tracts as her unit of analysis in an attempt to determine which variables predict the presence of LIHTC units. Her dependent variable is the percentage of all private rental units in a Census tract. The independent variables she uses are total population,

[19] A spatial lag variable is a way to include spatial association in a regression.

racial composition (including white, black, Hispanic, and Asian) percentage female-headed households, median household income, percent unemployment, percentage poverty, percentage of residents living in the same house five years ago, percentage vacancy, percentage homeowners. She also includes variables to indicate whether the tract is in the central city, whether it is a Qualified Census Tract, and whether LIHTC units were present prior to 1995. Lastly, she includes a spatial lag term that is the average of the percentage of all units in each neighboring Census tract that are LIHTC units.

In conducting this regression, Oakley chooses a frame that is quite different from that she uses earlier in her paper. Prior to the regression, Oakley undertakes an spatial analysis of the clustering of LIHTC properties in her four study cities. The underlying assumptions of a clustering study are that clustering is an important phenomenon to identify and understand. In fact, her study reveals clustering in each of her four study cities. However, when she performs her regression analyses, she ignores the importance of clusters. She runs regressions that treat all Census tracts the same, without regard for their status in the clustering study. A more useful analysis would be to examine the variables that are associated with the presence of LIHTC units in clustered tracts. If clustering occurs, then there is reason to hypothesize that there are particularly strong pressures on development in certain areas. It is not likely that several developments clustered together through chance. A regression analysis that considers only clustered areas would reveal the pressures that led to development in that area. However, a regression analysis that considers all tracts equally, such as that conducted by Oakley, may return results that dilute the strength of these pressures; that is, because those pressures are likely to be less intense in areas with less clustering, a regression analysis of all tracts together will understate the strength of those pressures in areas of clustering.

A final general implication of this study is that systematic application of these techniques to study other housing programs would be valuable. The intensity of clustering in some cities indicates that there are significant forces and pressures influencing developers' choice of locations. This outcome is to be expected given the LIHTC program's reliance on private developers and market forces. As was discussed in Chapter 3, the reliance on market-driven policies is not exclusive to the LIHTC programs. Many federal housing programs in operation today are similarly reliant on the market. The market pressures that affect the LIHTC program are probably at work in other affordable housing programs. Thus, clustering analyses of these programs is called for.

Policy Recommendations

Roles for the federal government

The LIHTC program is authorized in the U.S. Tax Code and is administered by the Treasury Department. It is not controlled by the Department of Housing and Urban Development. As a consequence, the largest private-development federal housing program receives very little housing policy direction at the federal level. Instead, the responsibility for administering the program is delegated to the state allocating agencies.[20]

While the specific policy decisions are made at the state level, the federal regulations that authorize the program set forth general guidelines that all allocating agencies must follow. All state allocating agencies are required to develop plans that outline the criteria to be used in the selection of projects that will receive tax credits. Also, the IRS specifies seven selection criteria that the allocating agencies must consider: project location, housing needs characteristics, project characteristics, sponsor characteristics, participation of local tax-exempt organizations, tenant populations with special housing needs, and public housing waiting lists. However, the program regulations at the federal level provide much flexibility. While the seven selection criteria are set by the IRS, each allocating agency determines how to define the criteria. For example, allocating agencies must consider housing needs; however, allocating agency have defined housing needs to include a variety of different variables including construction type (new construction or rehabilitation), unit size (by number of bedrooms), and target population (elderly, persons with disabilities, or families) (GAO, 1997). Also, allocating agencies have the flexibility to determine how much to weight each of these criteria. Furthermore, under 17 of the 20 plans reviewed by the GAO in a recent report, allocating agencies could bypass or override the official process outlined in the plan through actions such as giving discretionary awards or giving "designated officials open-ended discretion" (1997, 68).

[20] There are 54 allocating agencies: one for each state, one for the District of Columbia, two suballocating agencies in New York state, and one suballocating agency in Chicago.

The high level of flexibility granted to allocating agencies, combined with the fact that the LIHTC program is not administered by the federal agency in charge of housing, means that the goals of the LIHTC program, as outlined at the federal level, are relative vague. The LIHTC program results in significant flow of federal subsidies, as tax expenditures, across the nation. The Joint Committee on Taxation estimates that the cost of the LIHTC program in tax expenditures in 2007 was $5.1 billion (National Low Income Housing Coalition, 2008). Yet, no federal agency is truly managing this funding stream in terms of outcomes.

HUD plays a small role in monitoring the outcomes of the program. The research division of HUD, the Office of Policy Development and Research (PD&R), contracts with a private firm, Abt Associates Inc., to compile a report on new LIHTC units every year. This report gives information about units placed in service, including general information on location, such as regions of the country where units are located and whether they are located in a central city, suburb, or rural area. However, this information is not used by HUD in any way.

Superficially, the reason that HUD does not use the information in this report in any way is because HUD has no official role in the administration of the LIHTC program. However, creating healthy cities requires multiple agencies working together. HUD administers programs that result in billions of dollars of federal funding to cities. Yet, there is no coordination between those programs and the LIHTC program. HUD does not even provide meaningful information that would allow local and state agencies to look at the interactions of the various programs if they wanted to. The Abt report tracks outcomes at the national level. As the results of this study show, however, national-level results obscure significant variation across different locations.

HUD, as a federal agency with a mission to "increase access to affordable housing free from discrimination," would be the most appropriate agency to take the lead in managing the *outcomes* of the LIHTC program at the federal level. (The Department of the Treasury, the federal agency in charge of taxation issues, should continue to ensure that the strict requirements in the tax code are met by projects that are allocated tax credits.) There are two means through which HUD could encourage the coordination of the LIHTC program and other affordable housing programs. First, it could ensure that local outcomes are reported. The Abt report that is produced every year seems designed to influence policy makers at the federal level. It is useful for demonstrating that the LIHTC program has been successful in producing units throughout the country and that the program results in a good return on federal dollars invested. More localized data could be used by policy makers at the local level to monitor the outcomes of the program in their cities and states Second, HUD could require coordination with other federal housing programs. One of the broadest tools that HUD has for requiring local jurisdictions to coordinate affordable housing programs and to consider housing needs is the Consolidated Plan. Cities, metropolitan counties, and states that receive funding under the HOME Investment Partnerships program or the Community Development Block Grant must complete a Consolidated Plan. Jurisdictions are required to list the amount of tax credits awarded to projects within the jurisdiction; however, there is no requirement that local governments act on this information. HUD could certainly place restrictions on the programs it administers with respect to location patterns of all affordable housing in an area. Further, HUD could implement regulations for its program that might encourage a change in the scoring preferences for the LIHTC program since HUD has no authority to require such changes.

Despite the fact that HUD has increasing access to affordable housing as part of its mission, engagement at this level by HUD is not likely. In the 22 years since the LIHTC program was created, HUD has shown no inclination to become involved in monitoring the outcomes of the program. Thus, given that the program is structured so that the allocating agencies have much control over the implementation, changes to the process of allocating tax credits might best be made at the state and local level.

Roles for allocating agencies

Allocating agencies have the most direct means of implementing change in the LIHTC program. Allocating agencies have wide flexibility in establishing the scoring procedures for applications for LIHTC projects. As discussed above, allocating agencies must consider certain factors, including the locations of proposed projects and the housing needs of the communities of proposed projects. However, most agencies consider these factors only to a limited degree. (See Appendix B for a summary of the scoring preferences related to location for the allocating agencies for the study cities.)

If agencies want to exert more control over the housing created by the LIHTC program, they could create scoring procedures that would encourage or require the use of analyses that take into account clustering of LIHTC units and deconcentration goals. One consideration that allocating agencies could add to their scoring procedures is the presence of other LIHTC properties in the vicinity of a proposed project. The results presented in Chapter 5 show that substantial clustering exists in some cities when several years' worth of LIHTC properties are considered. Furthermore, residents and local officials in some areas have recently begun to complain about perceived clustering of LIHTC properties in their areas (*Houston Chronicle*, 2004; Ramshaw, 2004). By requiring applicants to submit information about previous year's allocations, allocating agencies could improve the program's ability to serve different sections of metropolitan areas.

Allocating agencies could also provide guidance to potential applicants on other types of analyses that they might want to undertake as part of their applications. This guidance could be developed with the allocating agency's broader goals and mission in mind. For example, an agency that is committed to deconcentration could suggest possible sources of information and types of analysis related to the locations of low-income persons and existing units of affordable housing. The agency could take these analyses into account under existing scoring procedures or it could create a new scoring system to encourage applicants to undertake such analysis.

Roles for local governments

Local governments – city and county governments - may be the best place to improve this program that is authorized at the federal level and allocated at the state level. No federal agency is a clear choice as a place to implement reforms or improvements; the Treasury Department is not in the housing business and HUD has no authority over the program. At the same time, state allocating agencies must create allocation plans to allocate tax credits in urban, suburban, and rural areas of their states. Accordingly, their plans are likely to be somewhat vague in order to make them applicable to a variety of environments. Local governments, on the other hand, are in the best position to understand the micro-level needs in their areas. Furthermore, because tax credits are allocated at the state level, it is reasonable to think that local governments have the potential to influence the allocation process.

One of the most expeditious ways for local governments to influence the allocation process would be for them to undertake spatial analysis of existing low-income housing, in general, and subsidized housing, in particular, in the area. Because of their knowledge of local conditions, local governments could include an assortment of variables that are relevant to decisions about where to locate affordable housing. The most basic analysis would include information about the distribution of the existing housing stock and population. Beyond that, local governments could analyze how transit lines (existing and planned) and employment centers relate to the stock of affordable housing. They could also incorporate information from community master plans, such projected trends in land use and development, into their analysis.

Local governments could use the results of this analysis in a variety of ways. First, they could make it available to applicants for tax credits to be used as part of the market studies that many states require as part of applications for tax credits. Since state allocating agencies are required to consider the appropriateness of each proposed development to local conditions, this information could help strengthen applications. Only those applicants who are proposing developments in areas that are in need of subsidized housing according to the local government's analysis would be interested in including the results of the analysis in their applications. Thus, the local government would be providing information that would strengthen only those applications for developments in the areas that it has identified as having the greatest need. Another alternative would be for local governments to use the results of their analysis as a guide in giving letters of support to proposed developments. Some allocating agencies give preference to tax-credit applications that have letters from local officials (GAO, 58). Local officials could give letters only to applications for developments in areas of need based on the local government's analysis or they could give stronger letters of support to such developments.

Local governments can further strengthen the influence they have over the locations of LIHTC properties by petitioning the allocating agencies for a formal change in the scoring procedures. For example, local governments could ask that additional points be awarded to applications for developments that are located in areas of need as defined by certain spatial criteria. The criteria for additional points would need to be determined in conjunction with the allocating agency so that scoring criteria are appropriate for all cities in a state. Including the state agency would also help safeguard against local officials using this approach to funnel LIHTC properties into areas with little political power.

Methodological Discussion

As the discussion above shows, this study reveals new information about the LIHTC program. The results show that LIHTC properties have a tendency to cluster and that this clustering is extreme in some cities. Just as importantly, though, this study shows benefits to using local spatial statistics to examine the patterns of affordable housing development. The LIHTC progam's reliance on the private market means that the execution of the program is exposed the same pressures and forces that impact unsubsidized development. Other affordable housing programs that involve the private market may likewise be affected. Local spatial statistics provide a good methodology to investigate whether clustering occurs in other affordable housing programs. Below, the disadvantages and advantages of using local spatial statistics in a GIS environment are discussed.

Disadvantages of Using Spatial Methods in a GIS Environment

Georeferenced housing data are not readily available

All housing researchers face certain limitations in getting access to detailed, timely data. Census data, while providing a wealth of information, are not timely.[21] The Census is conducted only once every ten years, and there is a considerable lag between the collection and the release of the data. Thus, Census data can be 12 or 13 years old before a new set is available. Another source of housing data, the American Housing Survey, is conducted every two years, but the geographic coverage is intermittent. Only 47 metropolitan areas are covered by the AHS, and each area is surveyed only once every six years.

Furthermore, neither the Census nor the American Housing Survey collects data on whether housing units are subsidized. For researchers of subsidized housing, data on subsidized housing units and the families that live in them often must be collected from

[21] In January 2005, the Census Bureau began collecting information using a new survey, the American Community Survey. The ACS will collect information from a rolling, random sample of households throughout the country on a monthly basis and will replace the Census long form. The first data sets became available during the summer of 2006 although data at the Census tract level will not be available for another three to five years beyond that time. Once the ACS is fully implemented, it will greatly improve the ability of researchers to obtain timely data about communities.

the agencies that administer affordable housing programs. However, there are many programs and many agencies involved in government-subsidized housing. At the federal level alone, there are several major housing programs in operation, including public housing, Housing Choice Vouchers (also called Section 8 Vouchers), the HOME Investment Partnerships Program, the Low-Income Housing Tax Credit, and privately-owned subsidized housing such as Section 202 and Section 236 housing. Each of these programs targets different populations and has different income limits.

Further complicating matters is the fact that many different agencies are involved in the administration of these programs. Public housing and Housing Choice Vouchers are administered by public housing authorities. The HOME program is administered by cities and counties. Many states also administer Housing Choice Vouchers and all states administer their own HOME programs.[22] As this report has discussed, the LIHTC program is administered by the U.S. Treasury Department and the tax credits are allocated by state allocating agencies, which sometimes are different from the agencies that administer vouchers and HOME at the state level.

While collecting accurate, up-to-date housing data is challenging for all housing researchers, collecting housing data with geographic information suitable for georeferencing is even more difficult. Again, because of the variety of affordable housing programs and oversight agencies, the challenges surrounding the collection of georeferenced data vary from program to program. For example, confidentiality is perhaps the biggest issue on data about Section 8 Voucher holders. The identities of recipients of these vouchers are protected by law. Thus, housing authorities and other

[22] In most cases, the State administers these programs in areas that are not served by another agency, often rural areas.

agencies that administer vouchers cannot reveal the addresses where vouchers holders live. Furthermore, because the agencies that administer the voucher program rarely conduct their own analyses of the spatial distribution of voucher holders in their communities, the agencies do not have the addresses of voucher holders aggregated at a level that would fulfill the confidentiality requirements while allowing researchers to conduct a spatial analysis (e.g., by Census tracts). While the Section 8 voucher program is the only major housing program that has stringent confidentiality issues, it is a significant constraint given that approximately two million vouchers are currently in use.

Another example of the difficulties of collecting housing data is provided by the HOME[23] program. The HOME program is administered by cities, counties, and states, called participating jurisdictions (PJs). A researcher wanting to analyze the locations of HOME-subsidized properties in an area would have to contact each PJ individually. In some large cities, more than a half dozen PJs serve the area because some large suburban cities are PJs. Furthermore, because each PJ uses a HUD-created software system to store information about the projects they have funded, information on property locations is not stored in a way that makes it easy to export the data into a GIS. A researcher would have to take the information from a PJ, most likely in the form of print-outs, and enter it into a GIS to obtain basic information such as Census tracts.

These examples reveal the complex nature of conducting spatial analysis of affordable housing. Researching just one program can be time-consuming and difficult.

[23] The HOME program is a relatively small affordable housing program in terms of federal appropriations when compared to other programs: $19.6 billion dollars was appropriated to the program from 1992 to 2004. However, the program leverages $3.2 dollars in other funds for every dollar of HOME program funds. Thus, it has the impact of a much larger program.

A truly comprehensive analysis of subsidized housing in an area would examine all subsidized units in the area, not just those financed by a single program. However, a researcher who wants to study subsidized housing would find it a Herculean task to attempt to study even just the major federal programs all at once.

While there is no short-term solution to these challenges, one possible solution would be for housing researchers to study all programs that target a certain population (rather than attempt to study all programs together). For example, a researcher could focus on those programs that target extremely low-income families or the elderly. By combining those programs that target a particular population, a more comprehensive picture of how people in that population are served can be gained.

Housing data are frequently difficult to use with spatial statistics

Even when a researcher is able to collect data with geographic information, housing data are frequently a poor fit for spatial statistics. The primary reason for this poor fit relates to the number of data points in a given study area. Because of the difficulties in collecting data on several affordable housing programs (see above), studies of subsidized housing frequently focus on an individual program. The number of units in a city, county, or MSA subsidized by a single housing program can be very low in some cases. For example, only 20 LIHTC projects were placed in service in Jacksonville in the 1990s despite the fact that the LIHTC program is the largest private-development affordable housing program at the federal level. It can be difficult to identify patterns when very few data points exist and confidence levels on findings might be low. One possible way to address this challenge would be to analyze data from several programs. However, as discussed above, this approach presents its own problems.

Advantages to Using Spatial Methods in a GIS Environment

GIS analysis can reveal multiple facets of segregation

Massey and Denton have identified five different aspects of segregation: evenness, exposure, concentration, centralization, and clustering (1988). Evenness measures the extent to which members of one population are over-represented or under-represented in some areas. Exposure measures the extent to which members of one population have the opportunity to interact with members of other populations in their own neighborhoods. (Exposure differs from evenness because the relative size of the groups being studied matters.) Concentration measures the amount of space occupied by the areas where members of one population can be found. Centralization measures the proximity of areas inhabited by members of one group to the center of a city. Clustering measures how close together enclaves of one population are to one another.

Traditionally, segregation measures have focused on only one of these aspects at a time. Furthermore, traditional measures of segregation have been aspatial and global (Reardon and O'Sullivan, 2004; Feitosa, et al., 2004). Aspatial measures take into account the composition of each individual neighborhood but not the proximity of neighborhoods to one another.[24] Global measures assume that the aspect of

[24] This problem is frequently referred to as the 'checkerboard problem' (Reardon and O'Sullivan, 2004). To understand the problem, imagine a checkerboard consisting of white and black squares. A traditional measure of segregation that focuses on the composition of individual neighborhoods would not capture differences such as whether the black and white squares are evenly distributed or whether they are highly clustered together. Alternately, a clustering measure would not capture differences in the compositions of neighborhoods.

segregation being measured is uniform throughout the area and, therefore, can obscure the presence of pockets of variation.

One specific advantage of conducting a clustering analysis using G_i^* in a GIS environment is that more than one aspect of segregation can be detected. The G_i^* statistic reveals the extent to which groupings of LIHTC units are located near other groupings of LIHTC units. However, because the results are presented visually, features such as evenness, concentration, and centralization can be revealed. Even without conducting a quantitative analysis, it may be possible to see that in some cities, LIHTC units are not distributed evenly around the city. All hot spots may be located in one quadrant of the city in one city and scattered throughout all areas of another city. Figures 13 and 14, maps of Houston and Phoenix, provide examples of variations in evenness.

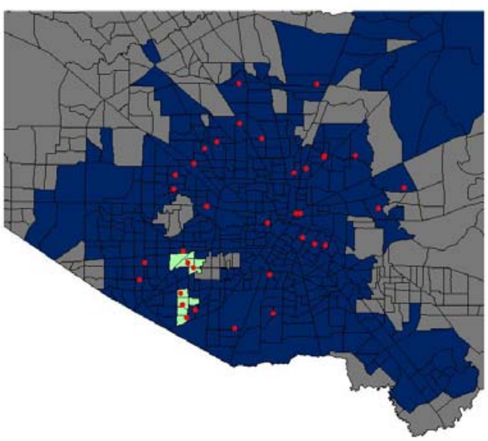

Figure 13: Houston

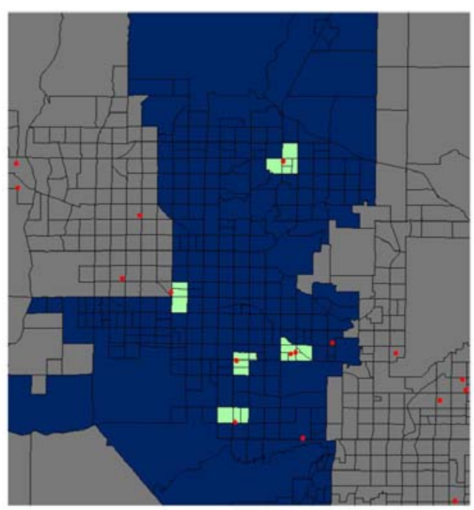

Figure 14: Phoenix

Levels of concentration can also be detected visually. The hot spots in one city may all be made up of relatively small Census tracts while the hot spots in another city may cover much larger areas. For example, the hot spot in Figure 15, the map of Jacksonville, covers a relatively small area of land.

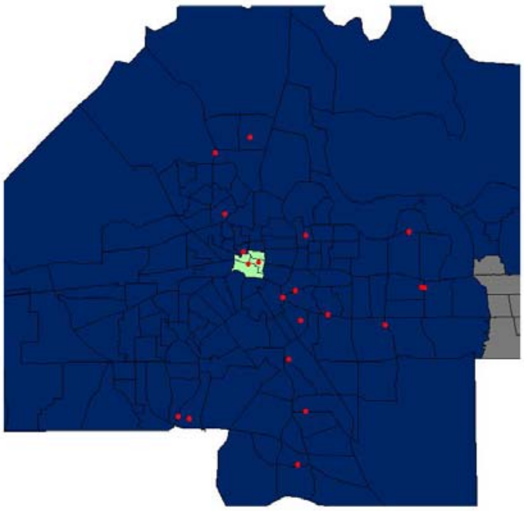

Figure 15: Jacksonville

Lastly, centralization is easily detected visually. In cases where all hot spots are located very close to the center of the city, a map of hot spots reveals this readily. For examples of variations in centralization, see Figures 15 and 16, the maps of Washington DC and Jacksonville.

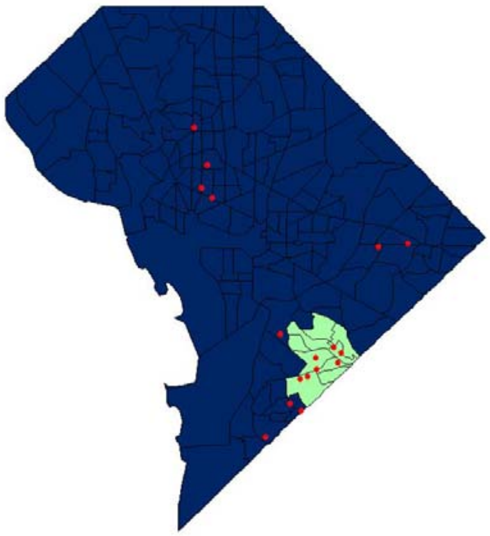

Figure 16: District of Columbia

Despite the fact that the G_i* analysis measures only clustering directly, it provides much more indirect information about the other measures of segregation than an aspatial analysis would. The variations in the different aspects of segregation that are revealed by the maps in this study are good starting points for further investigation. The maps, with their visual presentation of results, make it easy to identify those aspects of segregation that seem to have the widest variation and to select other measures of segregation that could be most fruitful to use in further research.

Future Research

As discussed in Chapter 3, exploratory spatial data analysis produces results that can be used for confirmatory analysis. In this case, the study has identified those LIHTC developments in the study cities that are part of a hot spot and those that are not.

Traditional statistical analysis could be used to learn more about the areas that tend to attract a disproportionate number of LIHTC projects. As is discussed above, an analysis of the variables that predict the presence of LIHTC units in hot spots could reveal information about what factors lead to clustering. Because of the variation across cities, such an analysis might best be conducted on individual cities.

Another potential avenue for future research would be to use spatial methods to examine clustering of subsidized rental housing of all types together. This study looked at the locations of LIHTC units placed in service during the 1990s and for some cities the locations of Section 8 voucher holders in 1998. To these data would need to be added all other LIHTC units, Section 8 project-based units, public housing, and HOME program units. Also, units constructed under the Section 202/811 programs, which serve elderly persons and persons with disabilities, might be useful to include. Such projects frequently face slightly less resistance from existing residents and may be located in different areas than other subsidized housing.[25] In areas with extensive local housing programs, units subsidized by the state or local government would also need to be included.

As discussed above, some of these data would be difficult to obtain. Furthermore, combining these data together might be difficult since they are available for different points in time. For example, information on Section 8 voucher holders at the Census tract level is available only through *A Picture of Subsidized Housing*, which captures a

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[25] One of the recent lawsuits concerning the LIHTC program claims that elderly LIHTC projects elderly in New Jersey are disproportionately located in suburban areas while family LIHTC projects are disproportionately located in urban areas, a claim that the New Jersey Housing and Mortgage Finanace Agency does not dispute (Zimmerman, 2004). Since both the LIHTC programs and Section 202/811 programs are private development programs, there is reason to believe that similar patterns might be found in the Section 202/811 projects.

single point in time. On the other hand, data is available for some programs that span the entire history of the program. A study that looks at all types of subsidized housing together would probably have to be undertaken for an individual city rather than for several cities.

Spatial methods could also be used to study the quality of neighborhoods where clusters of subsidized housing are found on a city-by-city basis. Most previous studies of the characteristics of neighborhoods where affordable housing is located have used aspatial measures. These analyses suffer the same drawbacks as the traditional measures of segregation discussed above. Using spatial methods can provide a richer understanding. For example, two cities may have the same number and percentage of Census tracts occupying the same amount of land in the city with high poverty rates. However, if all of high poverty tracts in one city are grouped together in one large cluster while the high poverty tracts are widely dispersed in small clusters in the other city, the people living in those tracts will likely experience different effects. Combining the results of a spatial analysis of neighborhood characteristics with the locations of affordable housing units can provide much more useful information about the experiences of residents of subsidized housing in a given city.

Conclusion

Following the paradigm of exploratory spatial data analysis, this study looked for patterns in the distribution of LIHTC units throughout the study cities. The analysis revealed important findings for both practitioners and researchers. Practitioners should be mindful of the wide variation among cities. One-size-fits-all policies are likely to have vastly different consequences for this program given this variation. State and local officials are in the best position to closely analyze the patterns in the LIHTC program in their areas and formulate specific goals. A spatial analysis of the program in their states and cities can greatly improve their ability to create policies to achieve these goals. Researchers should consider the deep understanding that spatial analysis can provide as well as the ability of local spatial statistics to reveal differences between areas. This study has provided suggested directions for future research and the further use of exploratory spatial data analysis with housing data will likely reveal more directions for research.

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Appendix A – Maps of Study Cities

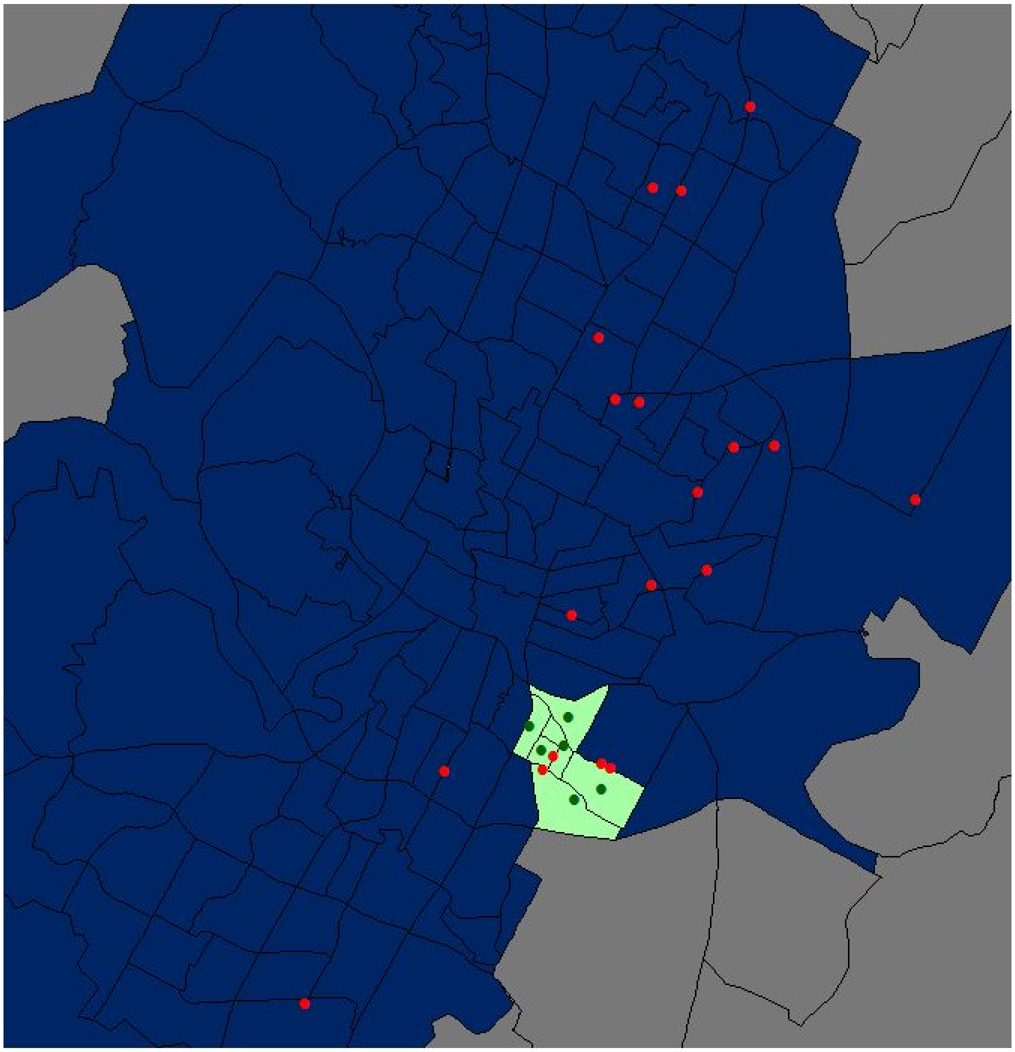
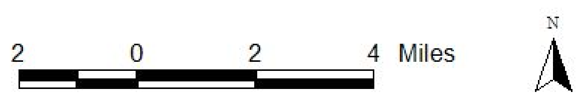


Figure 1: Austin



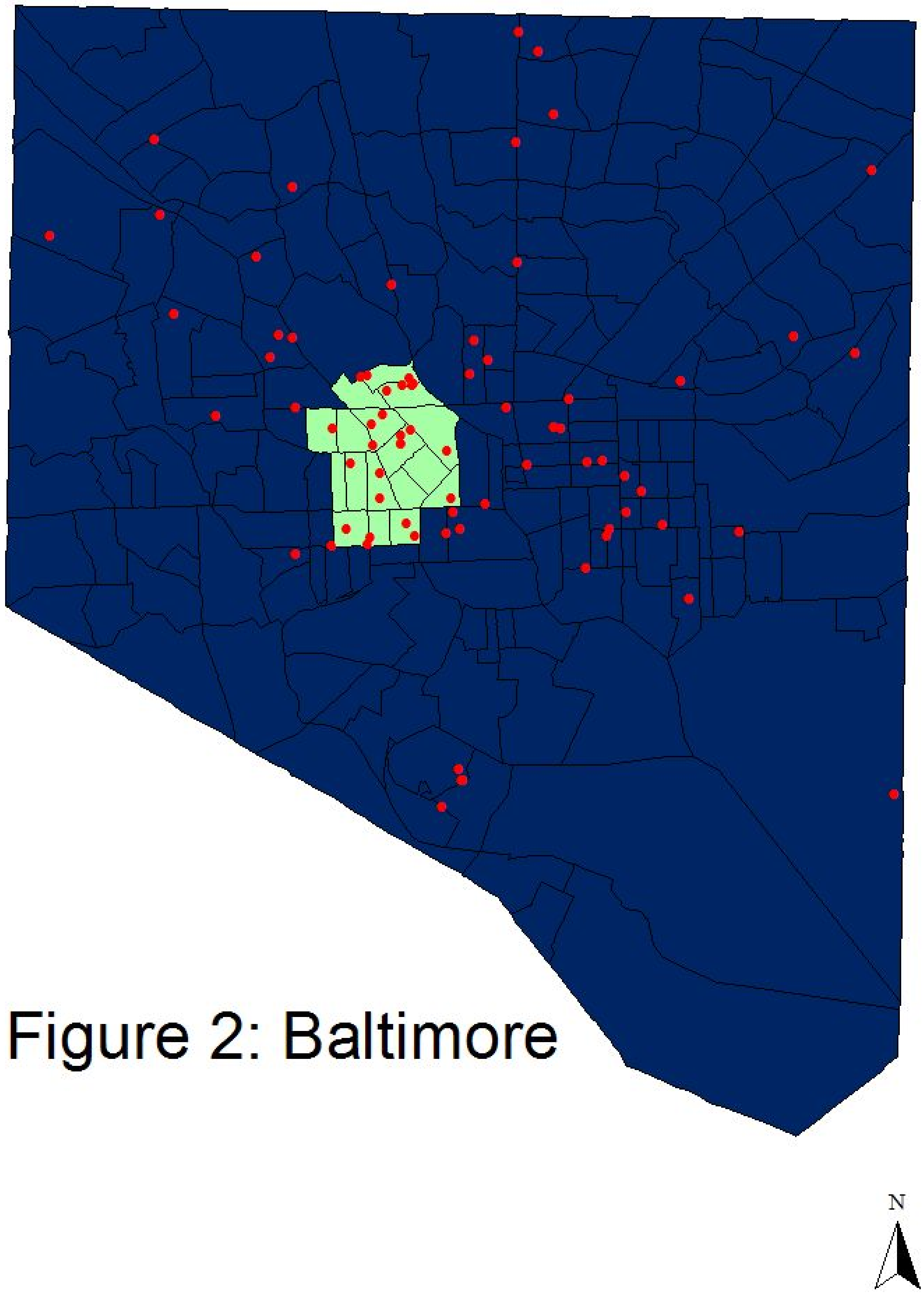


Figure 2: Baltimore

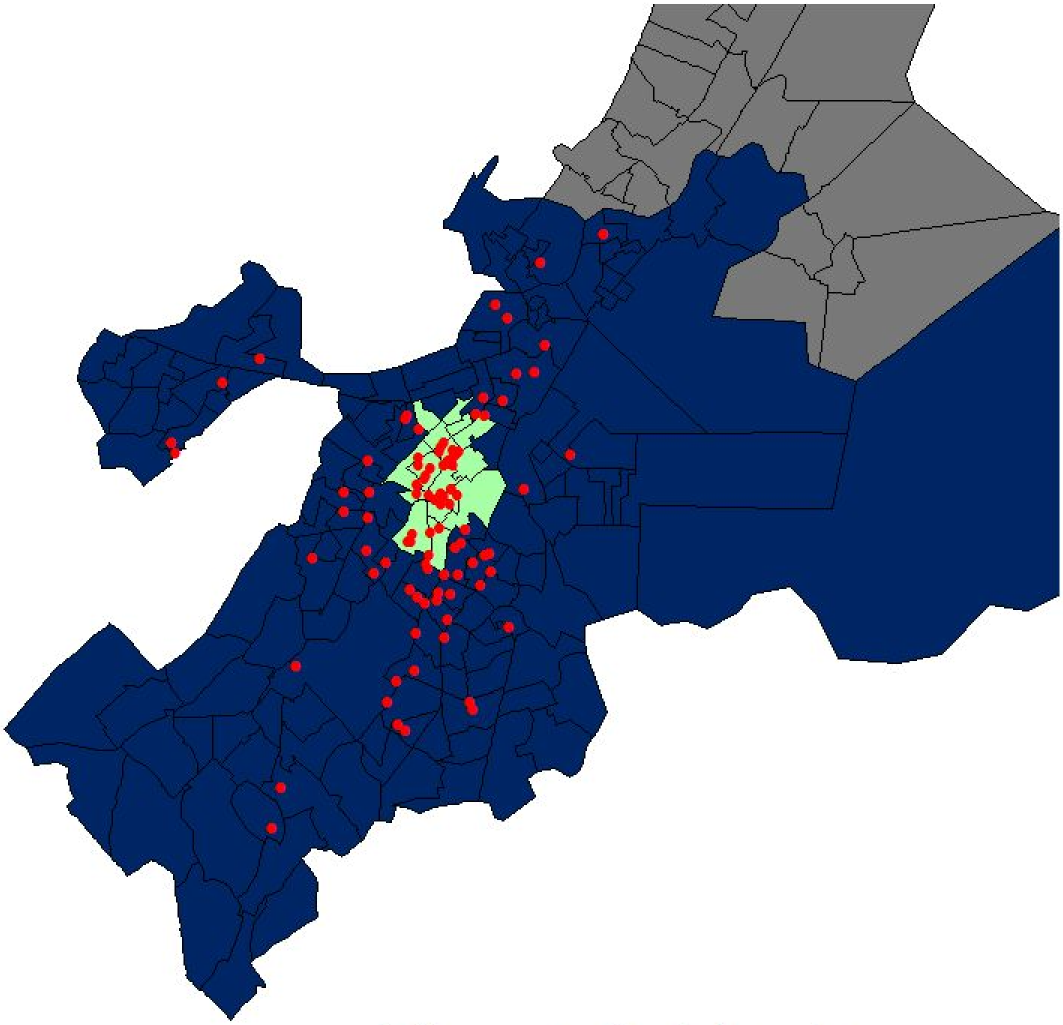
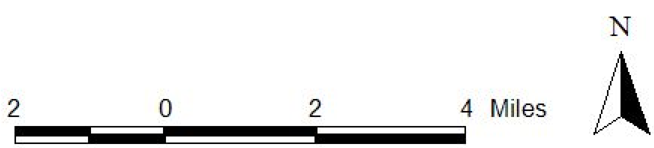


Figure 3: Boston



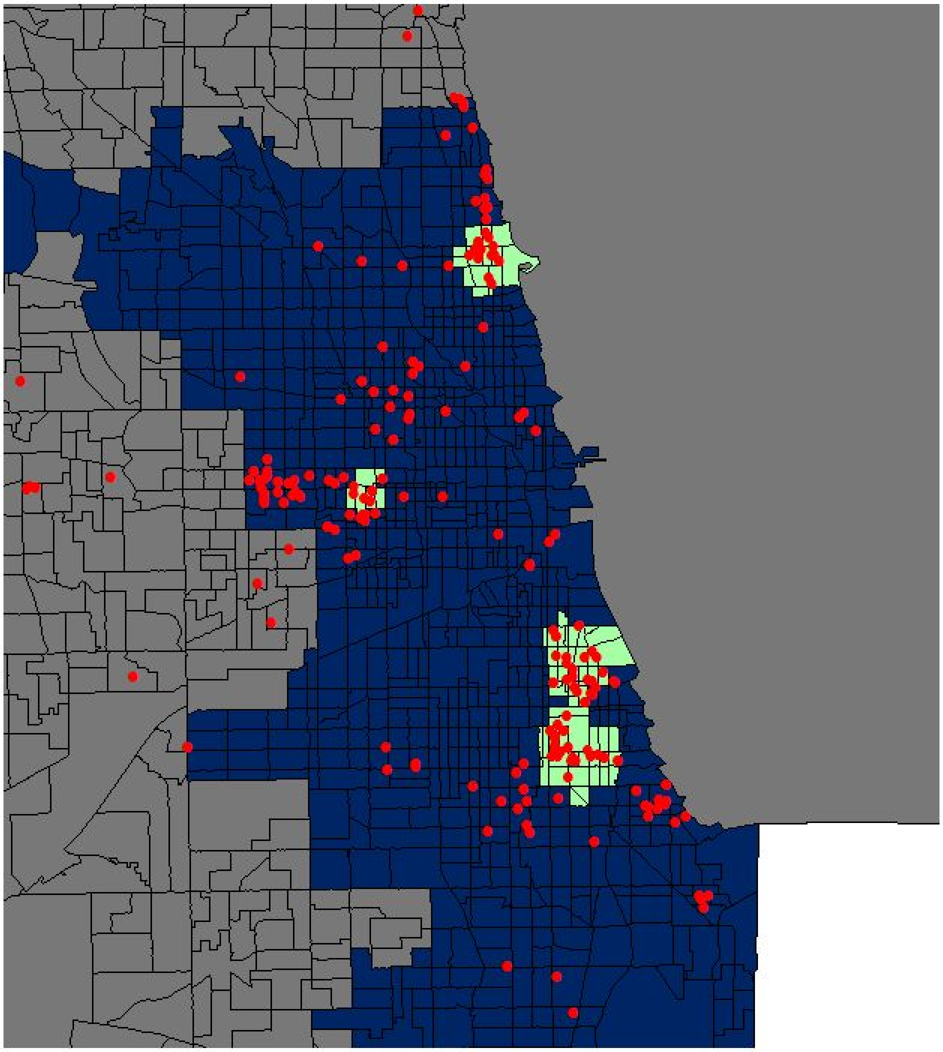


Figure 4: Chicago

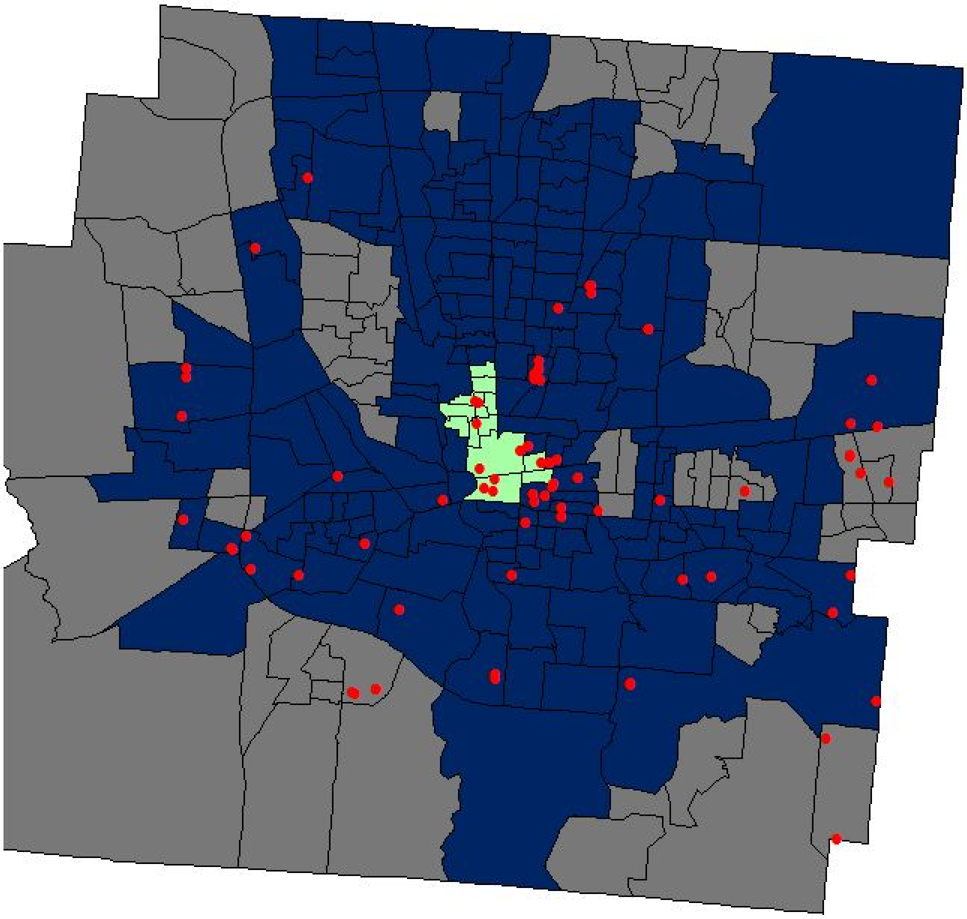


Figure 5: Columbus, Ohio

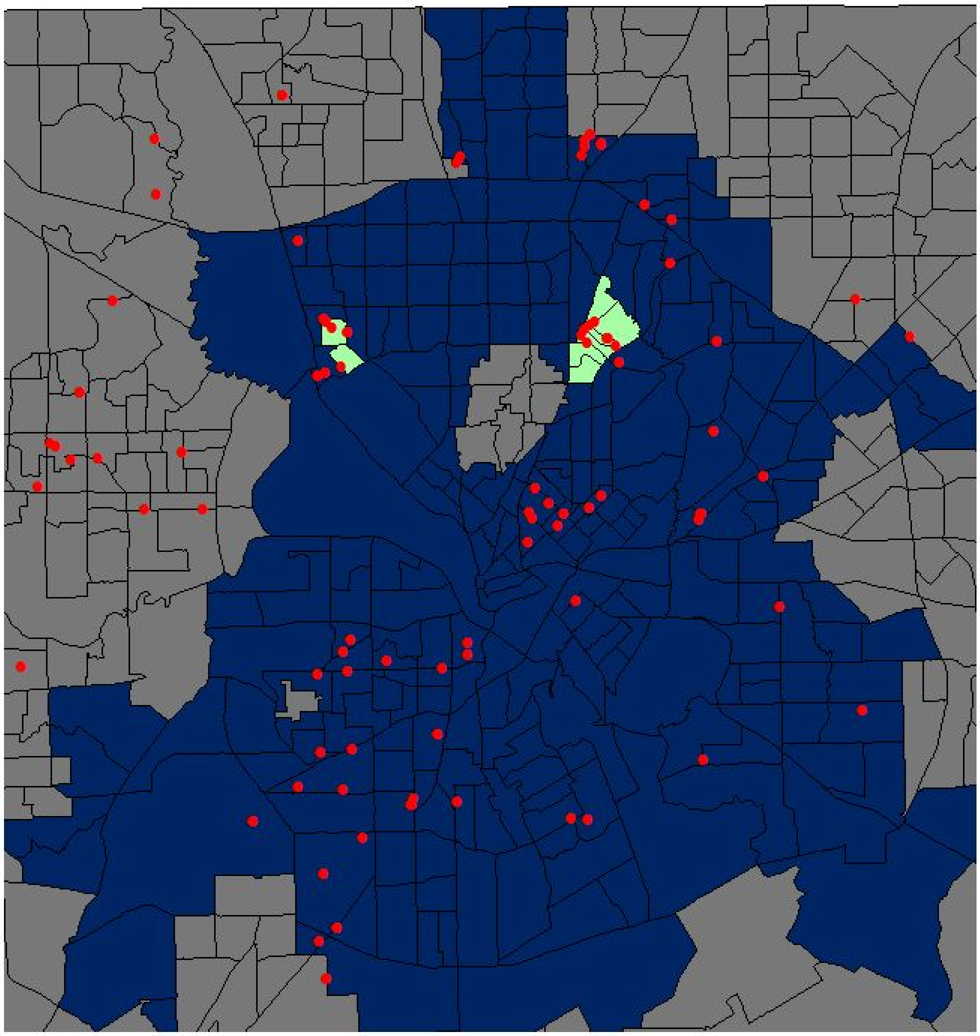


Figure 6: Dallas

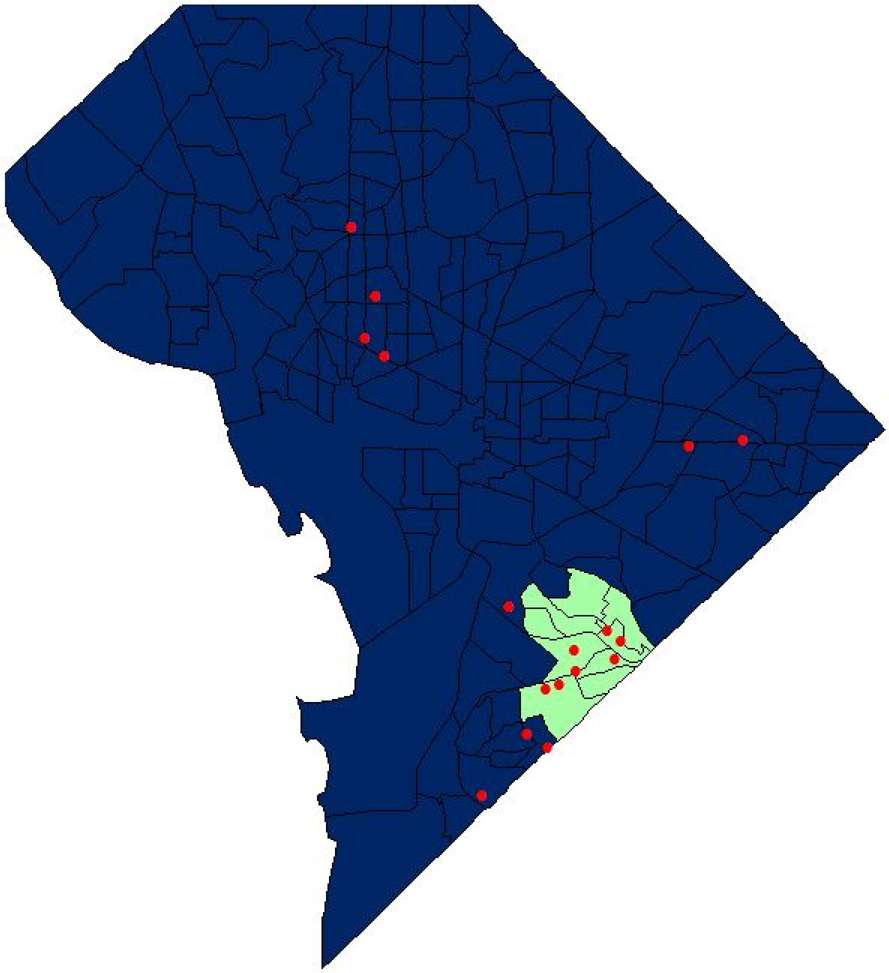
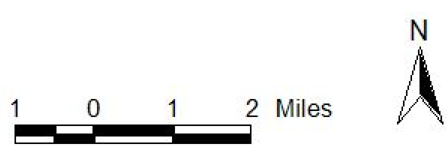


Figure 7: District of Columbia



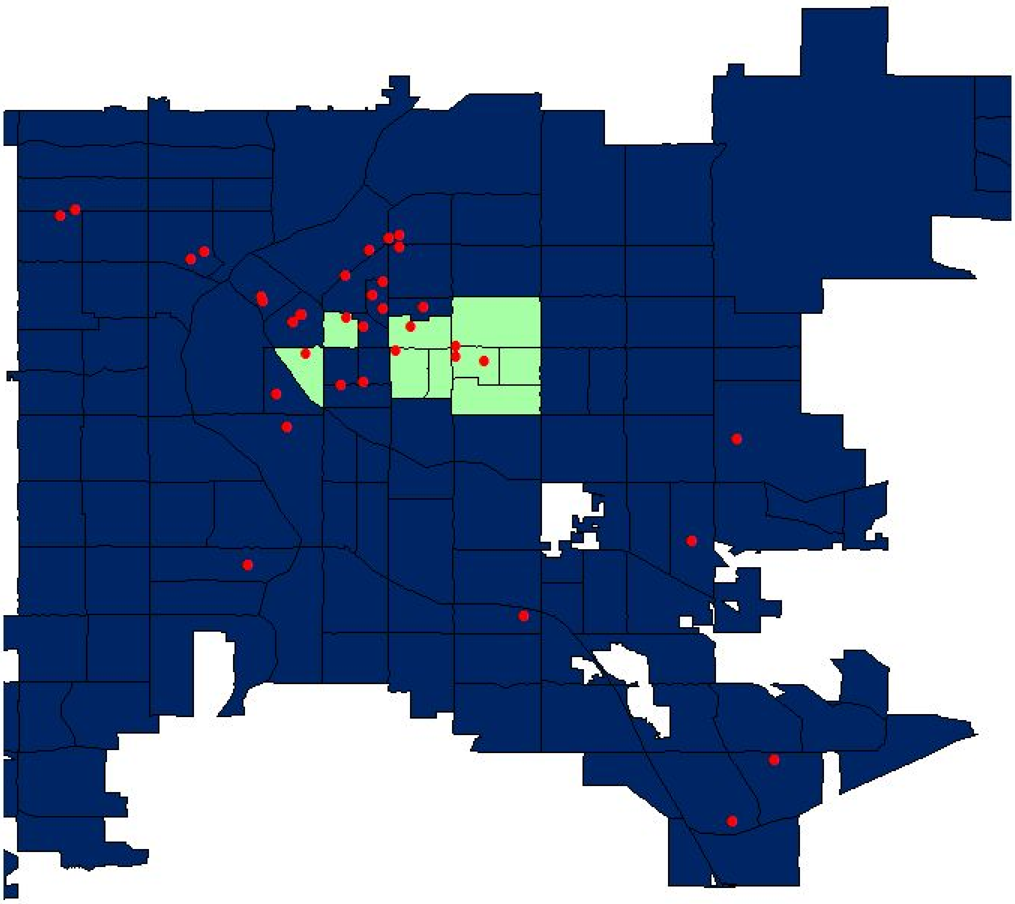
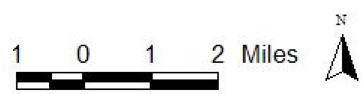
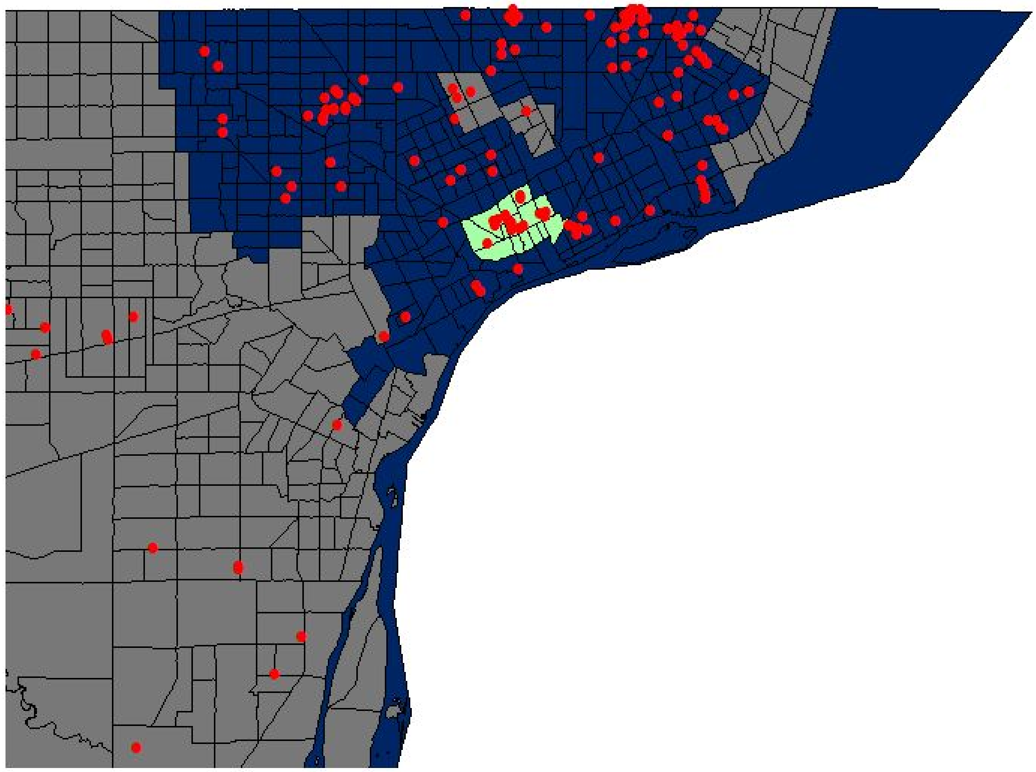


Figure 8: Denver





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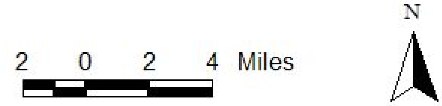

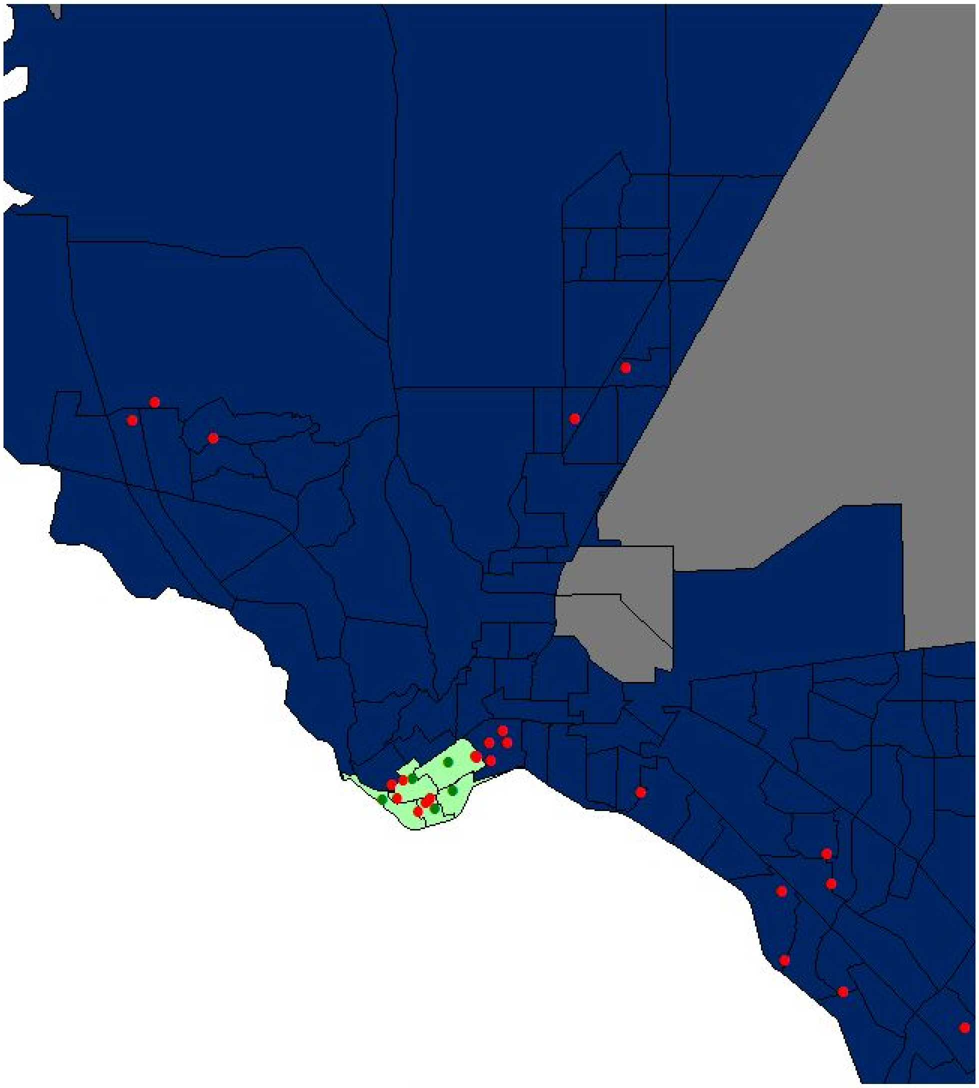

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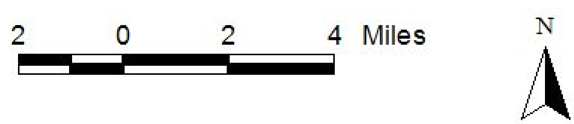


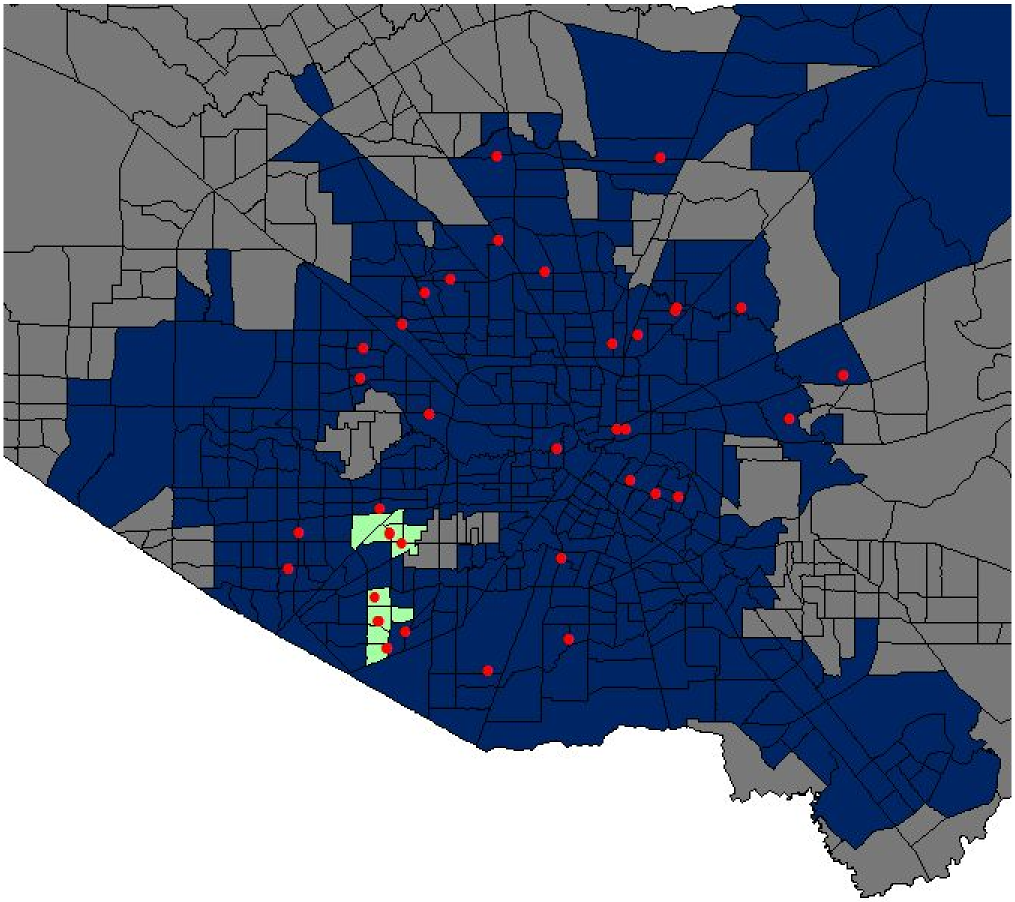
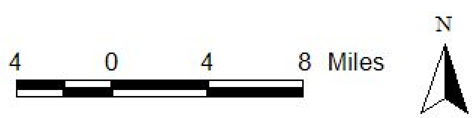


Figure 11: Houston



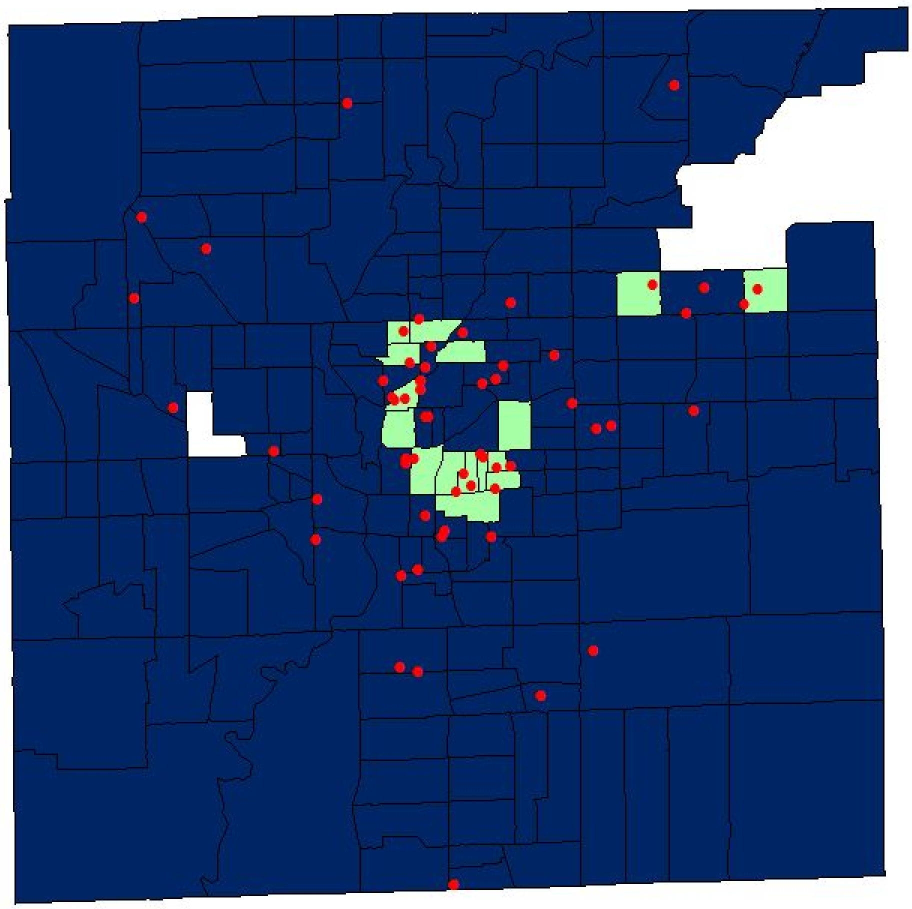
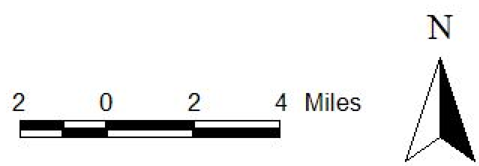


Figure 12: Indianapolis



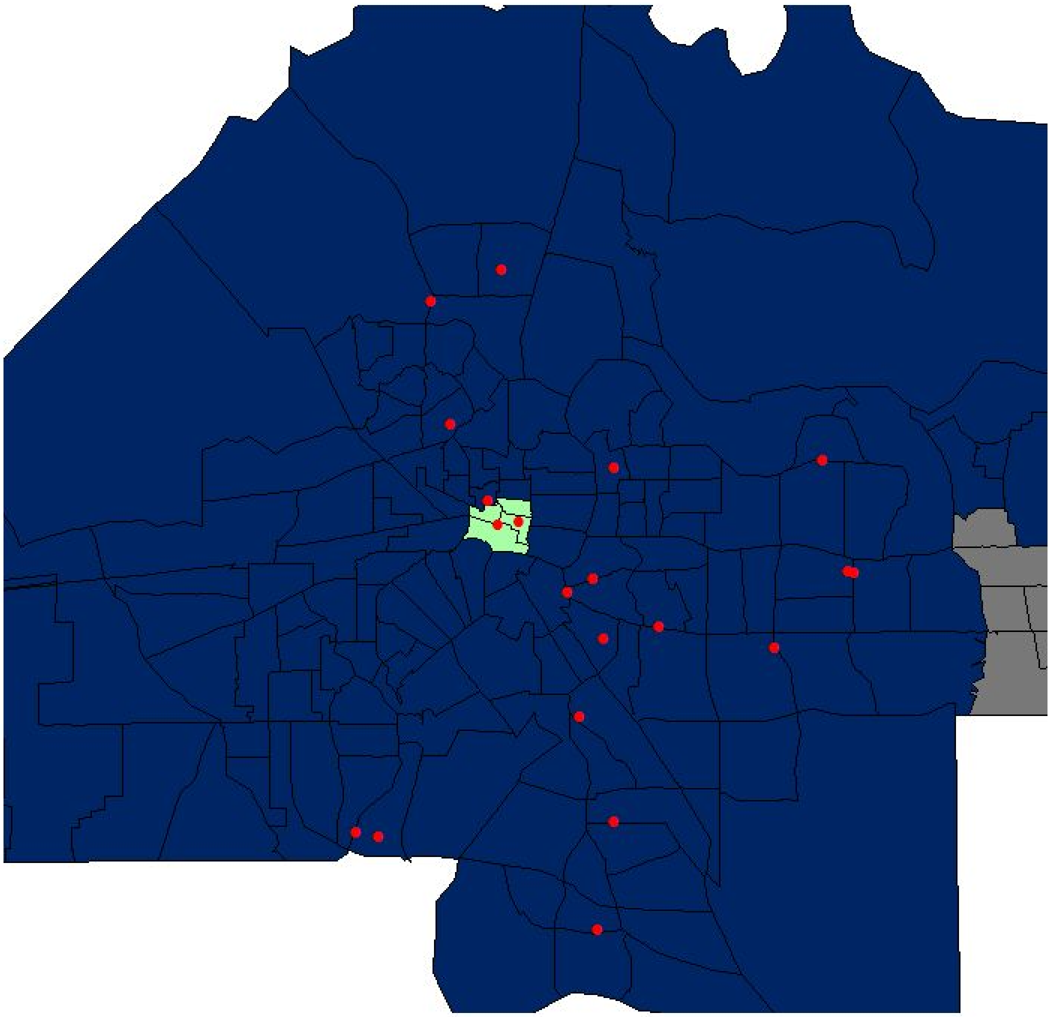


Figure 13: Jacksonville

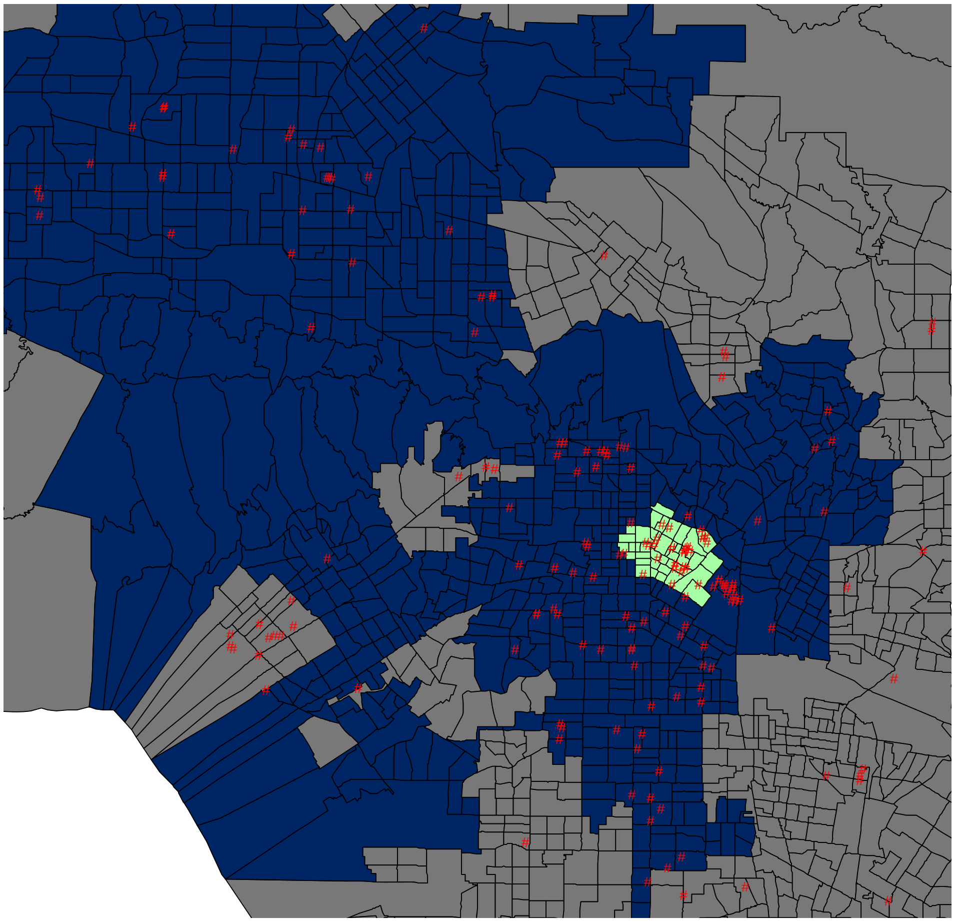
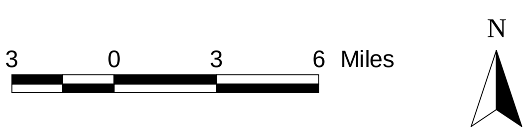


Figure 14: Los Angeles



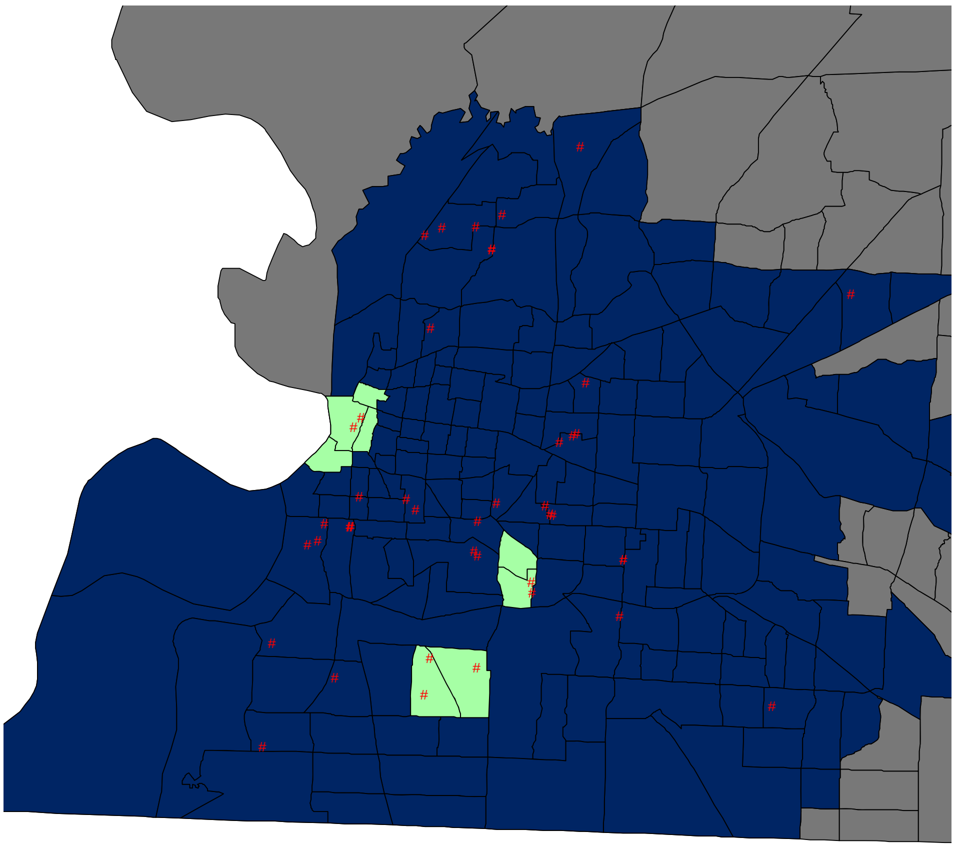
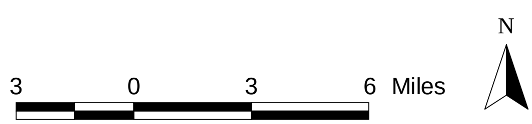


Figure 15: Memphis



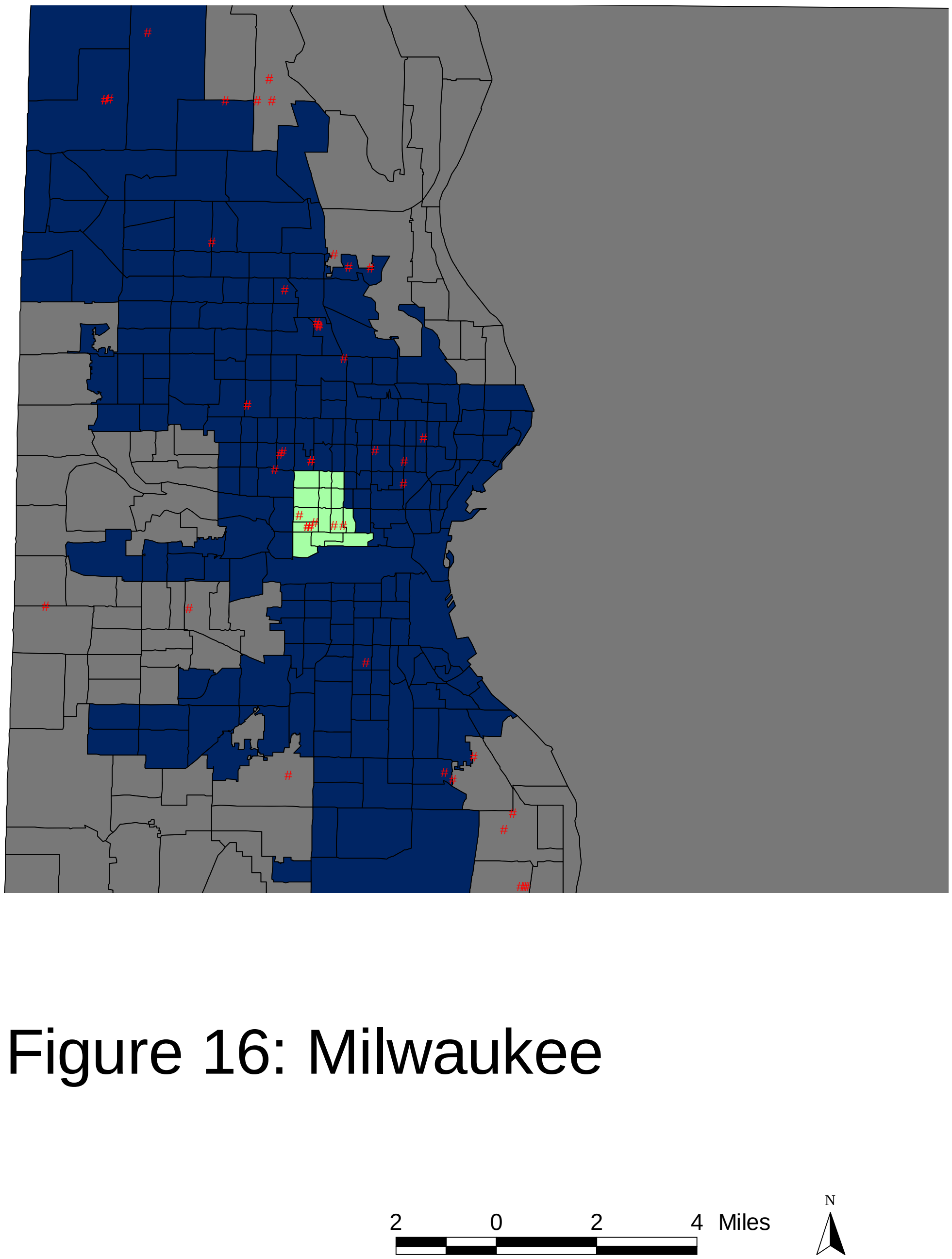


Figure 16: Milwaukee

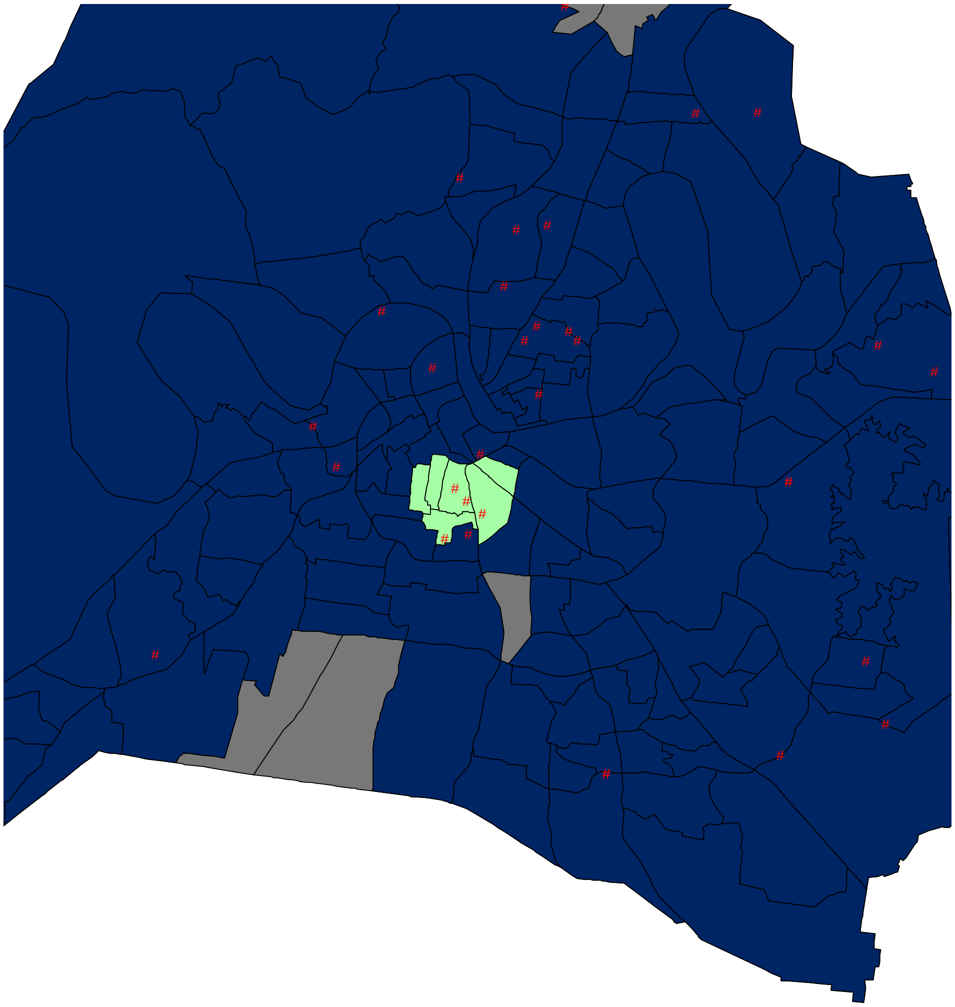


Figure 17: Nashville

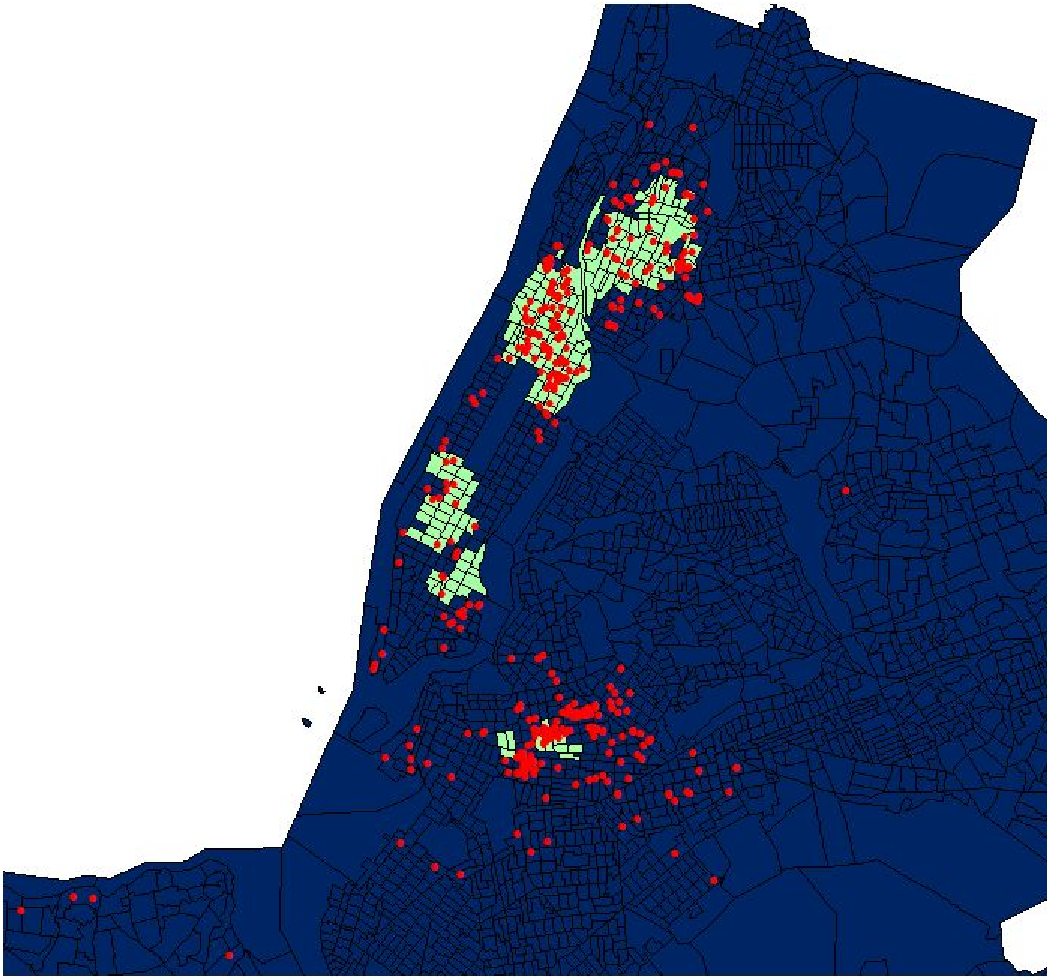
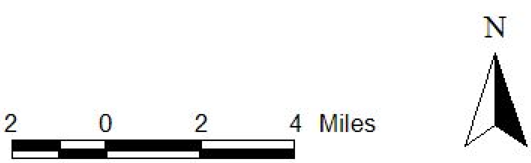


Figure 18: New York City



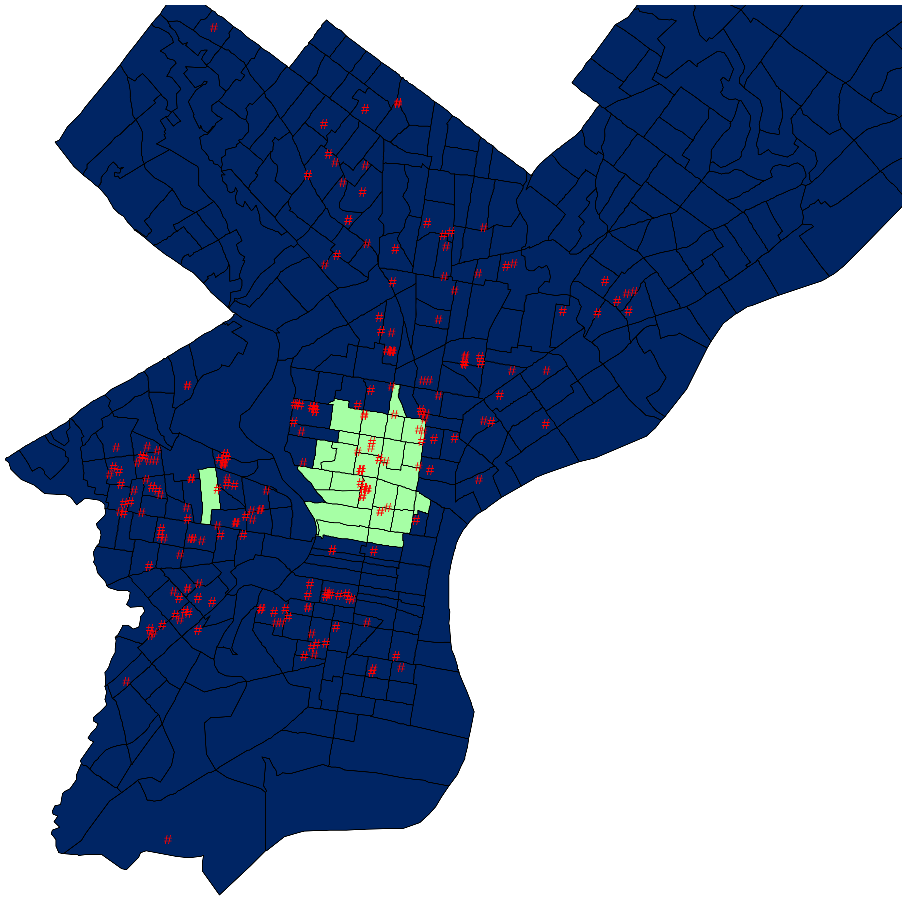
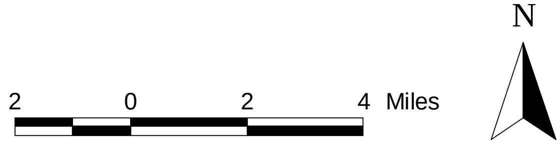


Figure 19: Philadelphia



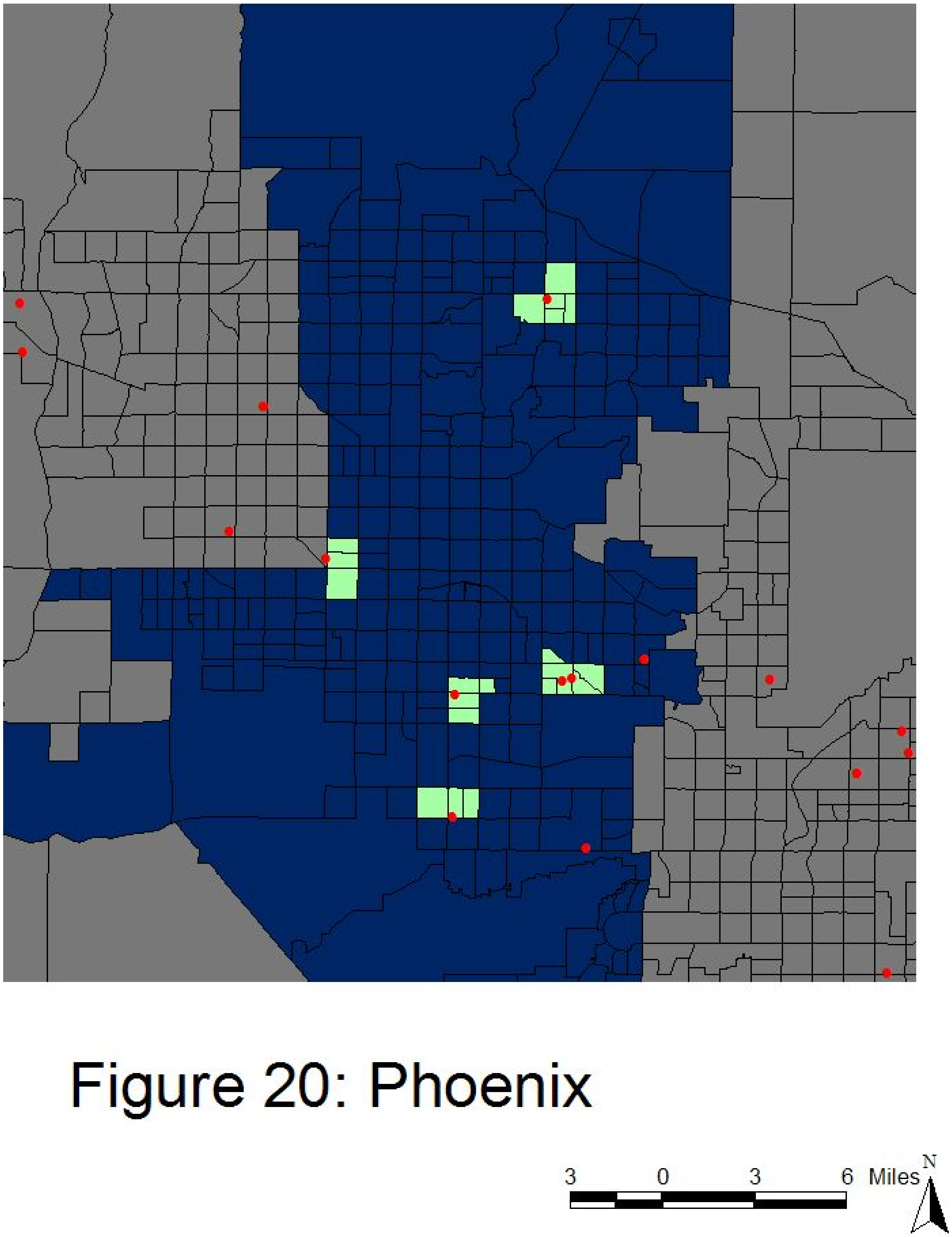


Figure 20: Phoenix

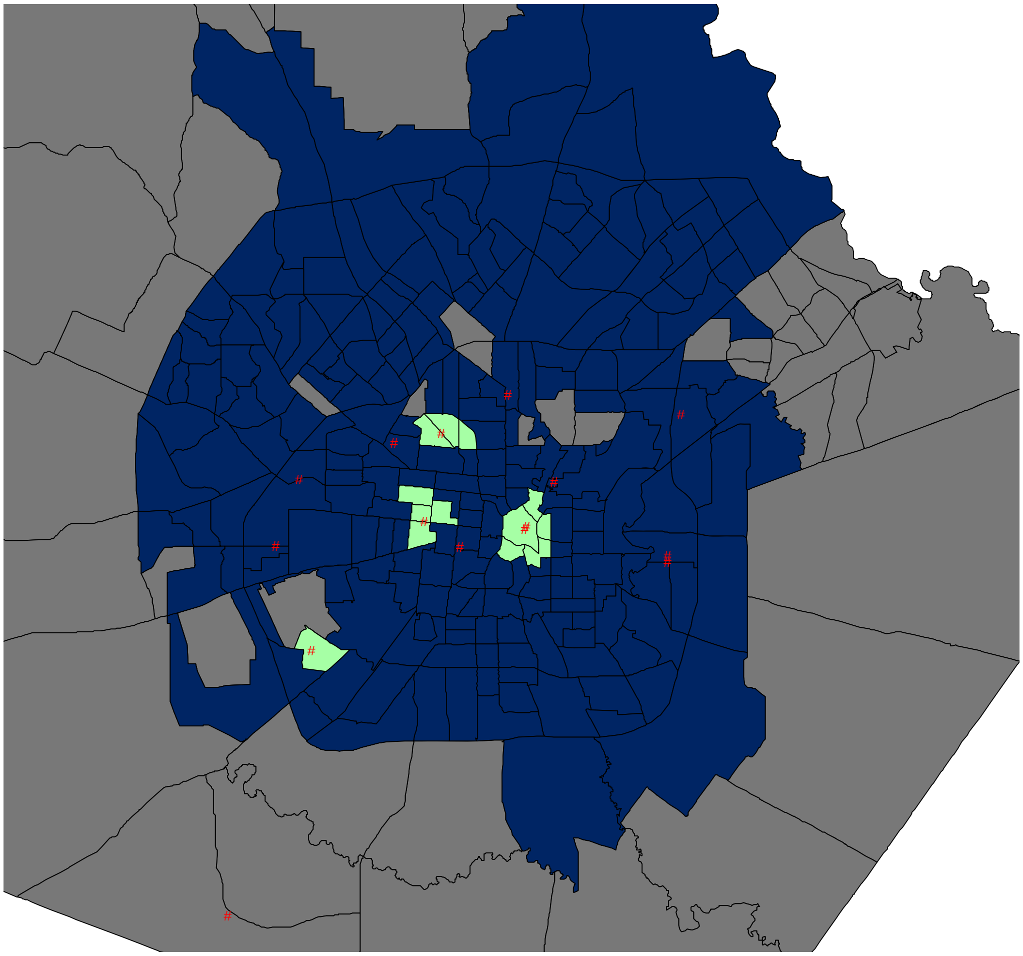
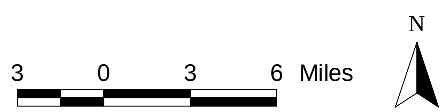


Figure 21: San Antonio



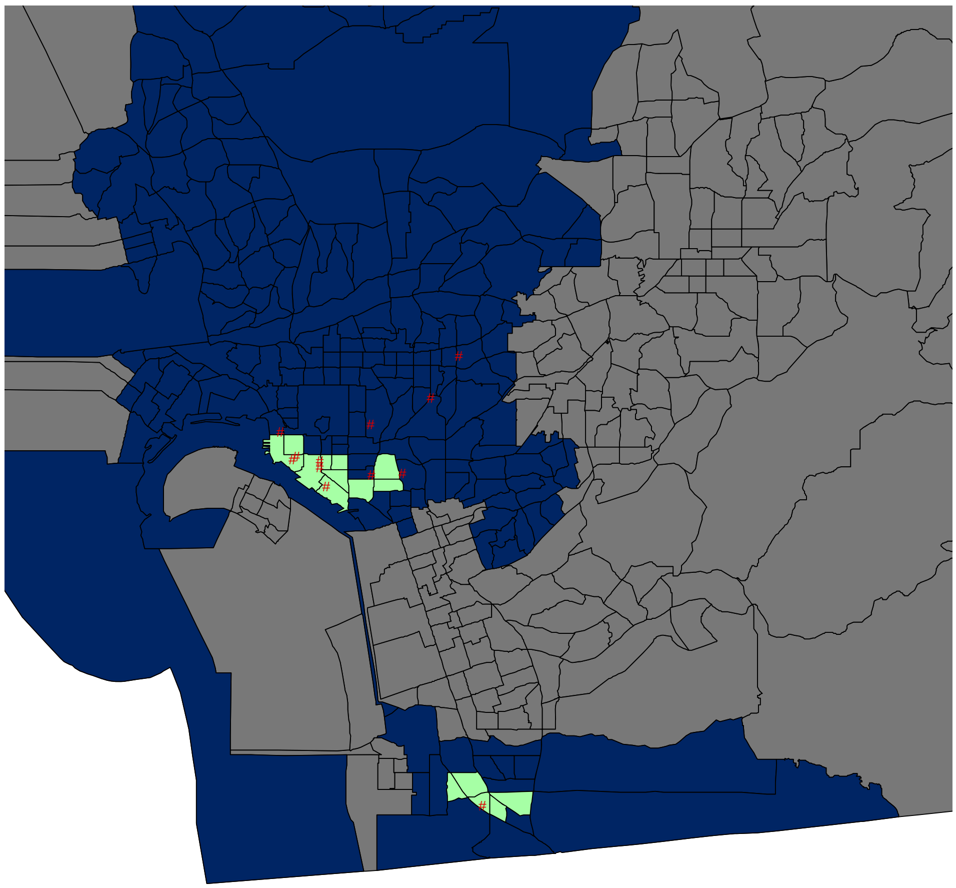
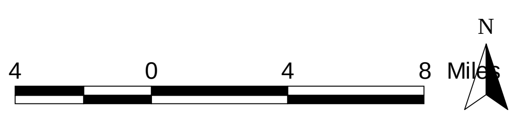


Figure 22: San Diego



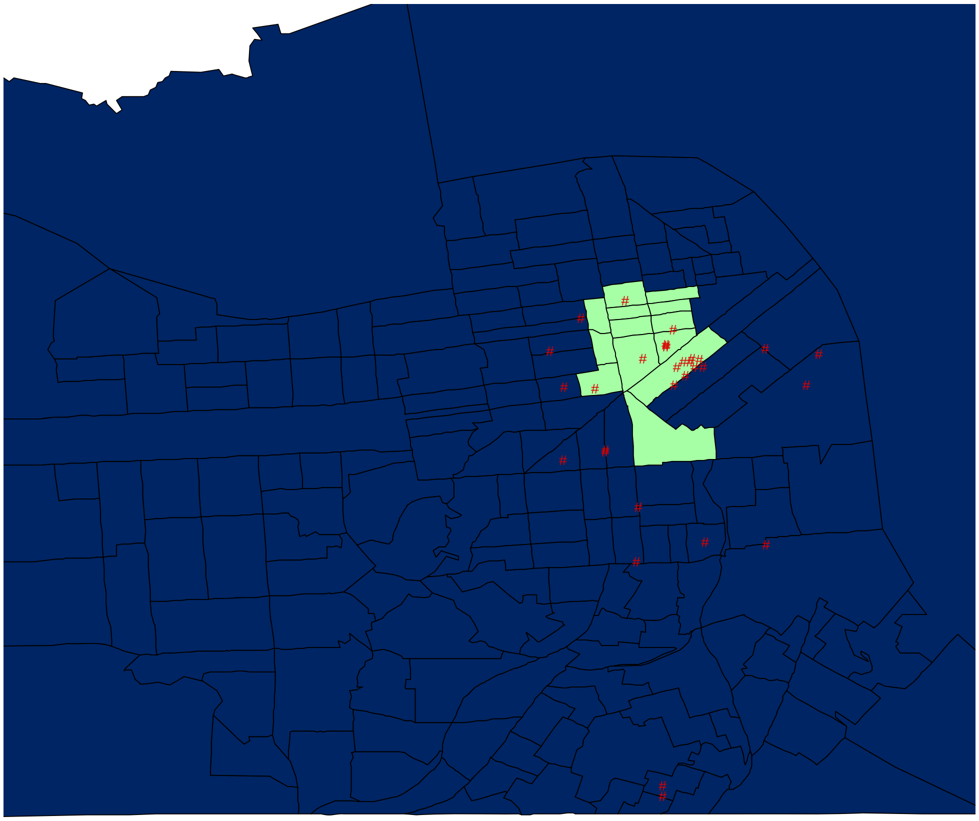


Figure 23: San Francisco

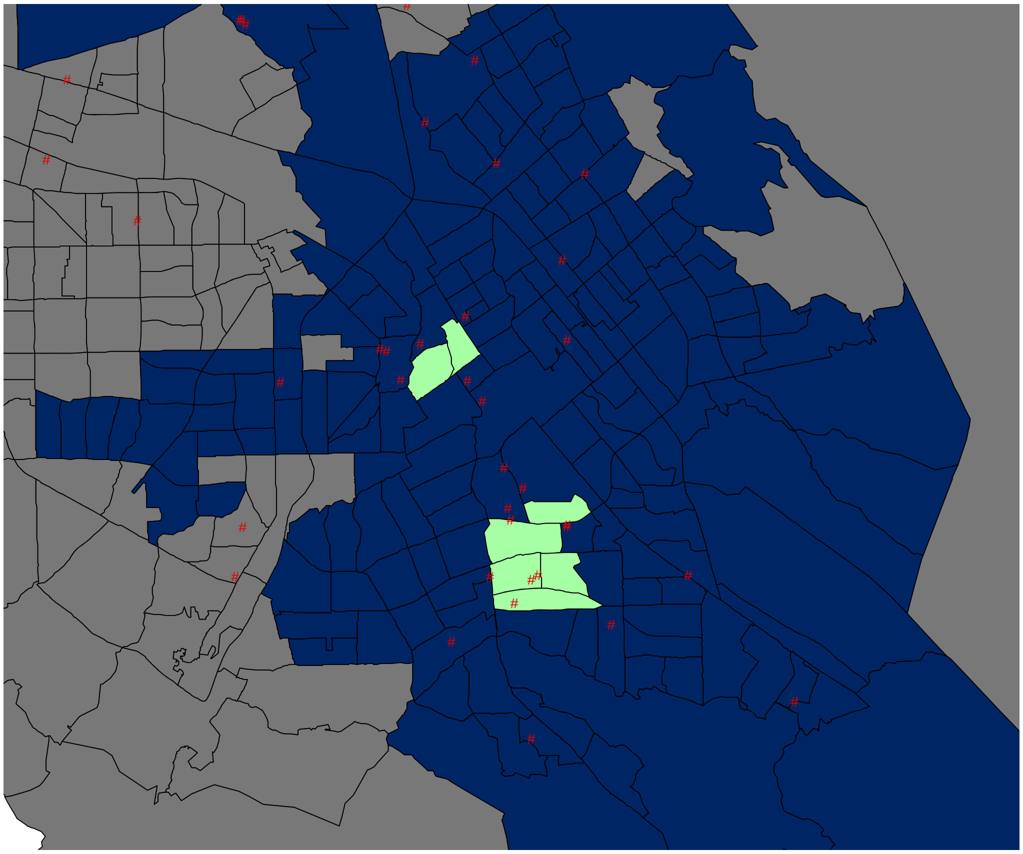
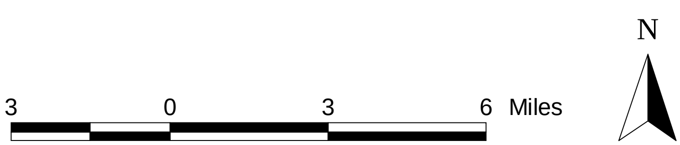


Figure 24: San Jose



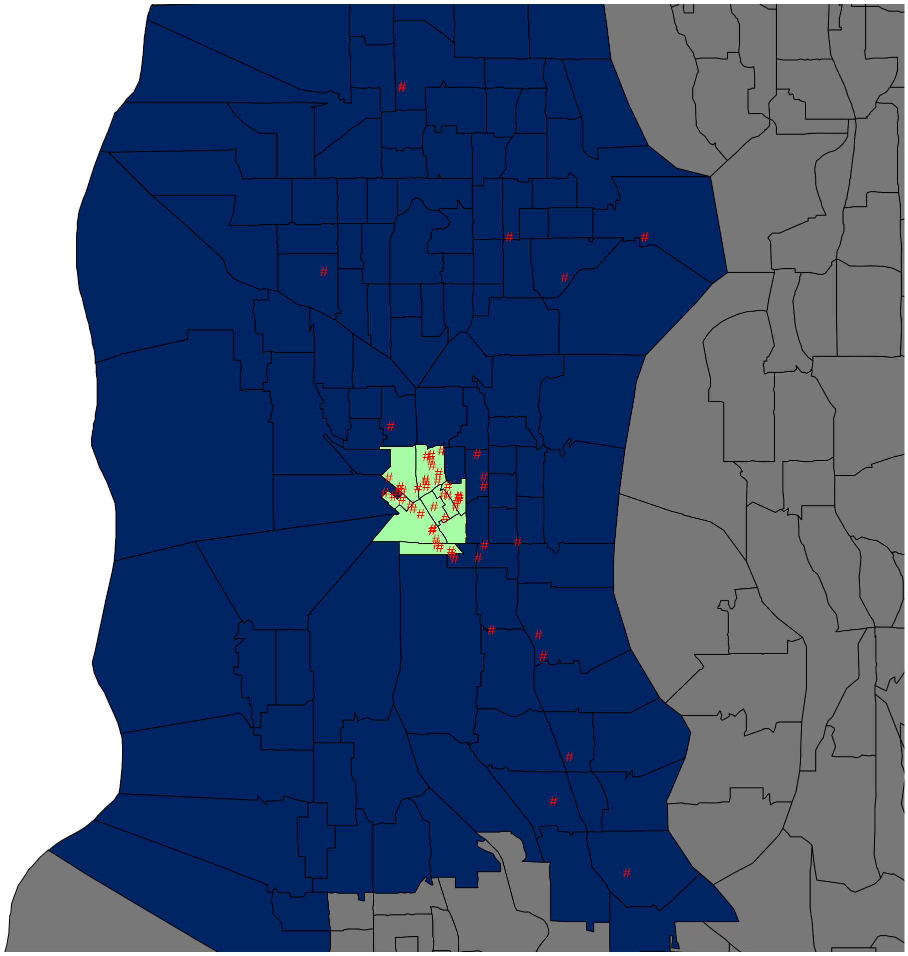
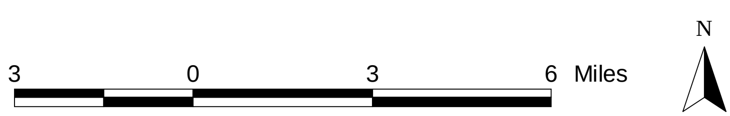


Figure 25: Seattle



Appendix B – Qualified Allocation Plans

Each state must prepare an allocation plan that outlines how Low Income Housing Tax Credits will be allocated. These plans identify states' priority housing needs and define the criteria that will be used in scoring proposals for tax credits. States are given much flexibility in establishing these criteria.

Below is a summary of the criteria in the plans for the states where the study cities are located. Specifically, the criteria that deal with the location of projects are summarized. The information below includes only criteria that would preference one location over another within that same city; criteria that would preference one city over another are not included because this study focuses on the distribution of LIHTC projects within the study cities.

Low Income Housing Tax Credit – 2006 Qualified Allocation Plan – State of Arizona

- Points are awarded for projects that are part of a community revitalization effort.
- Projects in Qualified Census Tracts or Difficult Development Areas receive points.
- Additional points will be awarded for successful documentation that all zoning is in place for the project site.

California Tax Credit Allocation Committee 2006 Competitive Application for Low-Income Housing Tax Credits

- Points are awarded for projects located near a wide variety of amenities, including transit, parks, libraries, grocery stores, schools, and medical clinics.
- Developments located in neighborhood revitalization areas receive points.

- Developments can qualify for points if they contribute to the development of balanced communities.

Low Income Housing Tax Credit – Allocation Plan 2006 – Colorado Housing and Finance Authority

- Points may be earned for projects located in communities that have identified housing as a priority.

Multifamily Housing Application Guidelines – D.C. Housing Finance Agency – Draft Rev. 7/03

- Points are awarded for projects located in Qualified Census Tracts or strategic investment areas.

- Points are awarded for projects located in sub-markets with relatively low amounts of affordable housing, that are gentrifying, or that have been underserved by the Agency in the last five years.

2006 Qualified Allocation Plan – Housing Credit Program – Florida Housing Finance Corporation

- Projects in "qualified Urban In-Fill areas will be targeted."

Low Income Housing Tax Credit Qualified Allocation Plan – State of Illinois – Draft – Calendar Years 2006 & 2007

- The plan allows the allocation agency to "take into account awards of Tax Credits to other Projects during the current year and any prior year."

- The agency may deny tax credits to any projects that would negatively affect the surrounding neighborhood or other affordable housing in the area.

- Points are awarded for projects located near employers that have documented difficulty in attracting quality workforce due to the lack of affordable housing in the area.

- Points are awarded for projects that are part of a larger revitalization plan.

- Projects located near the following amenities are awarded additional points: transit, recreational facilities, retail or medical facilities, schools, and other desirable amenities.

2006 Qualified Allocation Plan ("Allocation Plan") for the State of Indiana

- Points may be awarded for projects located near the following amenities: retail and service establishments, schools, transportation, parks, recreational facilities, medical facilities, libraries, and major public/private employers.

- Projects in Qualified Census Tracts or Difficult Development Areas receive additional points.

- Projects that support community revitalization will receive points.

Low Income Housing Tax Credit Program – Draft 2007 Qualified Allocation Plan – Commonwealth of Massachusetts

- Additional points are awarded for inclusion in a comprehensive neighborhood revitalization effort.

Maryland Department of Housing and Community Development – Multifamily Rental Financing Program Guide – Attachment to the 2007 Qualified Allocation Plan

- Points are awarded to projects located in Qualified Census Tracts and Difficult Development Areas or that are part of a revitalization plan.

Low Income Housing Tax Credit Program – Qualified Allocation Plan 2005 – 2006 – Michigan State Housing Development Authority

- A score is generated by the Authority's website for individual Census tracts. No information is provided in the QAP about how this score is calculated.

- Projects that are part of a community revitalization plan or are located in any of a series of targeted zones (e.g., Empowerment Zones) receive points.

- Points are awarded to projects that are part of a walkable community, defined as close proximity to transit, commercial services, parks, and bike lanes among others.

New York State Housing Finance Agency Low Income Housing Tax Credit Qualified Allocation Plan (2001)

- Points are awarded for projects that contribute to the geographic dispersion of low income housing.

2006 Housing Credit Program Qualified Allocation Plan – Draft #1 – Ohio Housing Finance Agency

- Points are awarded for projects located in Qualified Census Tracts or that contribute to a community revitalization plan.

Pennsylvania Housing Finance Agency (2007 Application) – Tax Credit and PennHOMES Selection Criteria

- Application must include information on the impact of the development on existing affordable housing, subsidized housing, and LIHTC developments. Adverse impact may lead to rejection of the application.

Tennessee Housing Development Agency Low-Income Housing Tax Credit 2006 Qualified Allocation Plan

- Projects that are located in Qualified Census Tracts or that are a part of a community revitalization plan receive points.

2006 Housing Tax Credit Program – Qualified Allocation Plan and Rules with Amendments – Texas Department of Housing and Community Development

- Projects that are part of a community revitalization plan may receive additional points.

- Points may be awarded for projects located in a wide variety of geographical locations, including a Qualified Census Tract, Difficult Development Area, Empowerment Zone, and a census tract with a higher median family income than the county in which it is located.

- Points are awarded to projects that are located in Census tracts with no other tax credit developments.

- Points are awarded for proximity to a wide variety of amenities, including retail stores, grocery stores, banks, restaurants, recreational facilities, schools, and parks.

- Points are deducted for proximity to a variety of negative amenities, including junkyards, railroad tracks, and heavy industrial uses.

Washington State Housing Finance Commission – Low-Income Housing Tax Credit Program – 2007 Application

- Points are awarded to projects located in Qualified Census Tracts, Difficult Development Areas, and areas targeted by the local government for affordable housing. Additional points are awarded for projects that are located in a QCT and that contribute to a community revitalization plan.

Low Income Housing Tax Credit 2007-2008 Qualified Allocation Plan for the State of Wisconsin

- Developments are located within a Qualified Census Tract and that contribute to a community revitalization plan receive points.

- Developments in infill locations or that have linkages to public transportation receive points.

Vita

Tara O'Neill was born in Omaha, Nebraska, and grew up in Dallas, Texas. She received her Bachelor's Degree in Economics and English from Trinity University in San Antonio. She also received a Master's of Science in Community and Regional Planning from the University of Texas at Austin.