ABSTRACT

Title of dissertation:	DO NEIGHBORHOOD HOUSING MARKET TYPOLOGIES MATTER? MEASURING THE IMPACT OF THE HOME PARTNERSHIP INVESTMENT PROGRAM IN BALTIMORE, MARYLAND Lynette Katrina Boswell, Doctor of Philosophy, 2011
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Since the late 1990s, neighborhood housing market typologies (NHMTs) have become a popular policy tool used by cities to evaluate neighborhood housing markets. NHMTs support place-based interventions, and are used to guide municipal investments as cities target resources based on neighborhood conditions. The assumption is that the effectiveness of local investment strategies to trigger neighborhood change is linked to existing neighborhood conditions. However, this assumption has not been tested explicitly in terms of neighborhood housing markets. This study examines the following key question: does the impact of public investments on nearby home sale prices vary across neighborhood housing markets?

This dissertation consists of three related essays examining the utility of NHMTs in Baltimore, Maryland. Essay one examines the theoretical foundation of and

development of NHMTs. Essay two focuses on the HOME Partnership Investment Program (HOME Program) and examines whether the impacts of this program on surrounding sale prices vary across neighborhoods housing markets. Essay three discusses the implications of encouraging cities to target investments in proximity to neighborhood amenities, such as parks and transit nodes, and uses spatial econometrics to determine if and how amenities in different housing markets impact surrounding home sale prices.

This study finds that NHMTs do matter to assess the impact of housing program investments and urban amenities on nearby sale prices of homes located in different housing markets. In this analysis, neighborhood housing market types are identified using a cluster statistical methodology based on a combination of indicators, including property values, neighborhood-wide property conditions, and socioeconomic characteristics of households. To examine public investments and urban amenities, separate hedonic price functions are estimated for each market type. Results of these analyses suggest that HOME Program investments and urban amenities affect surrounding home prices, and when estimated from separate price functions, the results show significant differences across market types.

DO NEIGHBORHOOD HOUSING MARKET TYPOLOGIES MATTER? MEASURING THE IMPACT OF THE HOME PARTNERSHIP PROGRAM IN BALTIMORE, MARYLAND

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DEDICATION

To all those in Flint, Michigan, who inspired me to begin this research.

~

And to my love, Michael, who pushed and supported me to get it *done, done*.

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A REVIEW OF LITERATURE

Introduction

Dramatic shifts in global and domestic economies in the last decade have subjected many U.S. cities to significant population losses, elevated crime and poverty rates, weakened housing markets, and increased property vacancy rates. For cities like Baltimore, Maryland, such challenges are not new and have earlier beginnings. Like most post-industrial rustbelt cities, Baltimore has undergone a cumulative cycle of disinvestment that began in the early 1970s with substantial population losses triggered by declines in the manufacturing industry and suburbanization. To counteract this disinvestment, the city has employed numerous revitalization strategies. While some neighborhoods have rebounded due to these efforts, others have continued to decline. More recent developments in subprime lending, mortgage foreclosures and losses in national and regional labor markets have acerbated problems in already distressed neighborhoods and presented new challenges in those that were once considered stable.

Addressing the effects of 40 years of prolonged economic distress has not been an easy task. In the past ten years, instead of employing reactionary economic recovery tactics in response to city-wide setbacks, Baltimore has embraced more sustainable and comprehensive strategies that are both *place-based* and *market-oriented*. With an increasing poor population, a declining tax base, and a landscape dominated with vacant and abandoned properties, the city has begun to use targeted, place-based approaches to tackle neighborhood challenges and to maximize locational strengths as a means of lessening the adverse effects of persistent weaknesses in its rapidly changing neighborhood housing markets. In response to limited federal and state dollars, the city began a market, place-based approach which called for new analytical tools to target investments and resources in neighborhoods with functioning housing markets or in areas perceived to be in the initial stages of disinvestment. This new direction also changed the focus on neighborhoods with existing community assets and urban amenities (e.g., parks, transit, and commercial services). The new attempt is not to ignore the more distressed neighborhoods, but to develop policies that cater to the unique market conditions of the neighborhood and link the appropriate strategies to address challenging conditions.

Since 2002, the City of Baltimore has used a *neighborhood housing market typology (NHMT)* as a policy tool to help guide reinvestment efforts. As a tool, the typology is used to evaluate neighborhood housing conditions. In general, NHMTs support place-based interventions and are designed to guide municipal investments according to current neighborhood conditions. Methods used to develop typologies allow cities to classify neighborhoods into distinct categories based on a quantitative analysis of neighborhood housing and socioeconomic characteristics. Data used in this analysis vary based on practices employed in sample cities, as some cities rely on general social and economic indicators to develop typologies, while others focus solely on housing-related neighborhood characteristics. In general, typologies are often used to tailor neighborhood reinvestment efforts to best address the needs of a given area. They are also used by policy makers and practitioners to track neighborhood performance, forecast neighborhood change, or to support a comparative analysis of select neighborhoods. Based on detailed and thorough analyses, housing market typologies provide a tool for cities to understand neighborhood market conditions and, more importantly, help guide investment decisions.

Influenced by place-based policies and the desire to stabilize neighborhoods in decline, cities employ typologies to identify the unique qualities of neighborhoods before deciding where and how to invest resources. The general assumption is that the effectiveness of local investment strategies and the ability of a given investment program to trigger neighborhood change are linked to existing neighborhood conditions. This assumption has not been tested explicitly across market conditions in a single city.

As researchers continue to build upon the knowledge of housing markets and other factors associated with neighborhood change, it is important to question how the effects of reinvestment strategies vary across housing markets. The current literature suggests that the impact of local investments, particularly those focused on housing, is influenced by both the characteristics of the neighborhood and the scale of the investment (Ding, Simons, and Baku, 2000; Ellen et al., 2001; Galster, Tatian, and Accordino, 2006). As one might expect, these analyses indicate that the effects of neighborhood investments are influenced by local conditions and characteristics, such as household income and race, as well as the magnitude of the investment to address these conditions.

Accordingly, policymakers and practitioners are often encouraged to target investments based on the socioeconomic conditions or the racial and ethnic composition of neighborhoods. This approach, however, fails to acknowledge the complex and dynamic nature of neighborhoods. The focus on socioeconomic conditions of the residents, such as income, does not account for the critical relationship that exists between neighborhood housing markets and neighborhood wellbeing. Galster defines these markets as “a bundle of spatially based attributes associated with clusters of residences” (in Sullivan and Gibbs (eds.), 2003, p. 154). Certainly, one can define housing submarkets within the context of the socioeconomic characteristics of the residents, as well as the neighborhood's physical features. While income may be determinates of a household's ability to invest in and maintain their property, other factors, such as private sector investment, foreclosure rates, and the percentage of rental properties in a neighborhood, may also impact local housing market dynamics. These factors differ significantly in separate market types.

Additionally, since the late 1990s, literature has emerged related to valuing environmental quality. This literature attempts to estimate the impact of amenities on surrounding property values and capture the spatial effects of housing markets (Kelejian and Prucha, 1998; Boyle and Kiel, 2001;Wu et al., 2004;Brasington and Hite, 2005;). The spatial element of housing is based on the fact that housing values and even household behavior is associated with the location of the housing, or more specifically, the quality of the neighborhood. Scholars continue to improve statistical hedonic price function models used to decompose housing markets based on property characteristics, the socioeconomic conditions of households and other neighborhood characteristics (Can, 1990 and 1992; Anselin, 1988 and 1998; Kelejian and Prucha, 1998; Ding, Simons, and Baku, 2000; Fik, Ling, and Mulligan, 2003). These models provide the implicit value households hold for various characteristics of houses or the quality of neighborhoods where the housing units are located. These studies use variations of spatial hedonic models to determine the effects of environmental quality based on surrounding housing conditions and homebuyer behaviors. This literature adds to the understanding of housing markets and how the adjacent homes influence housing prices. However, price values regressed on individual houses present gaps in the literature, as Day (2003) suggests that housing structures, values, and neighborhood quality differ across submarkets.

Until scholars understand how differing housing market conditions influence the impact of neighborhood investment, local policymakers may not have a clear understanding of how best to develop and use investment strategies. NHMTs can presumably provide cities a context and the tools necessary for understanding how neighborhood conditions can mitigate the impact of targeted investment by the locality. Further, by explicitly recognizing the importance of housing markets, NHMTs provide a more comprehensive context for exploring the relationship between housing markets and investment, or the impact of urban amenities on surrounding home sale prices. Unfortunately, only Day's (2003) work documents this relationship through an analysis of the effects of urban amenities. This study will determine if and how the uniqueness of neighborhood attributes contribute to the effects of housing investments and neighborhood amenity investments in Baltimore. The Baltimore case study will provide insights on how variations across neighborhoods can affect the impact of locally targeted investment as measured by housing market conditions and socioeconomic characteristics.

In three related essays, this study will examine neighborhood housing market typologies and their usefulness to guide citywide reinvestment strategies. The first essay will provide an understanding of NHMTs, their development, and how cities use typologies. This paper will evaluate the typology as a tool to construct neighborhood markets.

The second essay will examine NHMTs within the context of a specific reinvestment program. Specifically, this study will evaluate the impact of the HOME

Investment Partnership Program (HOME Program) on neighborhoods in Baltimore. The HOME Program is administered by the U.S. Department of Housing and Urban Development (HUD). It is one of the largest federal block grant programs and is intended to help state and local governments carry out housing redevelopment projects, typically to provide affordable housing for low-income residents. Using a traditional hedonic model, this essay will estimate the effects of HOME Program investments on surrounding property values across different market types from 1994 to 2003.

The third essay will address the impact of investments, controlling for urban amenities, on surrounding home sales from a spatial perspective. It explicitly recognizes that a primary neighborhood characteristic is its location and proximity to other neighborhoods. In this light, the spatial lag and the first stage of a two-stage hedonic regression model is used in this study to provide a spatial analytic approach to assess the impact of investments, as mitigated by neighborhood typologies.

1.1. U.S. Place-based Policies and Development

Neighborhood Housing Market Typologies focus on place. Place-based policies (PBPs) in the United States have long been used to address inner-city poverty. They were first introduced during the Great Depression to help replace the dilapidated housing stock for the poor. Since that time, these policies have evolved, as well as our understanding of neighborhood change, its causes, and strategies to respond. Early people-based policies relied on socioeconomic indicators to identify residential neighborhoods dealing with high levels of distress. It was thought that financially stable and affluent households sought neighborhoods commensurate with their status, while lower income households remained in older, poorer neighborhoods due to their financial immobility. At the time, public investments were made in the form of public assistance directed to low-income households to ensure better quality living conditions, in the form of people-based policies.

In the 1950s, people-based policies were refocused and policymakers began to target the physical infrastructure and dilapidated housing stock in an effort to recapture the jobs and wealth leaving inner-city neighborhoods. As such, attention shifted from people-based policies that assisted poor households, to place-based policies that dedicated financial resources to urban renewal projects, for example, that encouraged the development of private sector retail, office, and entertainment venues in downtown central business districts.

By the 1990s, PBPs were revised once again, this time merging the earlier focus on the individual with the private sector focus, such as target reinvestment zones that addressed distressed households but were truly aimed at improving a neighborhood's physical infrastructure. Today, many PBPs support the strategic geographic targeting of public investments into neighborhoods based on social, economic, and housing characteristics (Thomson, 2008). Some scholars assert that such efforts will have a greater community impact through better coordinated and leveraged local resources and assets (Mallach, 2006 and Thomson, 2008). In contrast to previous people-based investments, which sought to identify and target the most distressed areas based on individual needs, new strategies use data-driven methods to target areas based on market conditions.

PBP investments consist of both housing and economic development programs administered at the federal, state, and local levels. To help identify neighborhoods appropriate for PBP investments, urban neighborhoods are analyzed using prescriptive policy tools. Increasingly, NHMTs are used as a policy tool to understand neighborhood market conditions and subsequently guide reinvestment strategies. NHMTs rely on statistical methods, such as cluster and z-score analyses, to classify neighborhoods into distinct categories. Profiles of neighborhoods developed from these analyses are used to target areas for investment.

Despite their widespread acceptance and use by local governments, there has been little systematic investigation of whether the indicators used to classify neighborhoods portray accurate representations of neighborhood conditions. More significantly, there is a dearth of evidence in the current literature which leads scholars to question which factors, such as housing and socioeconomic characteristics, should be included in the development of NHMTs. To this end, this study will begin with a review of federally targeted PBP investments and their effects on neighborhoods. In turn, we will focus on the use of NHMTs and their ability to aid neighborhood revitalization efforts in Baltimore. Lastly, the review will discuss the implementation of the HOME Program in Baltimore.

For the past two decades, the ability of PBPs to improve conditions in distressed communities has been subject to debate (Bolton, 1992; Gyourko, 1998; Kraybill et al., 2003; Bradford, 2005; and Crane, 2008). Central to this debate is whether it is more effective to provide assistance directly to the people experiencing social and economic distress or to support them indirectly through neighborhood-focused programs. In other words, the debate is between people-based and PBPs.

People-based policies—or personal assistance policies (PAPs)—target low-income individuals who generally have poor social support networks and reside in substandard housing (Gyourko, 1998; Gillen, 2004). Federal PAPs fund social development resources, such as job training, affordable housing finance, financial education, and health services. In contrast, PBPs address the broad spatial needs of neighborhoods, communities, and regions.

Federal PBPs evolved from the understanding that PAPs fail to adequately address the socioeconomic challenges of communities and the realization that poverty is multidimensional (Crane et al., 2008, and Bradford, 2005). PAPs targeted the symptoms of poverty without addressing the underlying causes (Bradford, 2005). In contrast, PBPs are believed to strengthen the foundation of communities and to improve quality of life for all (Graham et al., 1999; Bradford 2004 and 2005; and Spencer, 2004). These policies provided the supportive infrastructure to allow those in need to improve their quality of life.

The notion of PBPs signifies that place matters and that the spatial elements of a community are determinants in the successes and failures of a community's residents. This perspective assumes that poverty is a product of neighborhood neglect—not the cause of any one person or group of people (Mason, 1999; and Butler, 1991). For example, PBPs may use investments to facilitate economic development by encouraging businesses to locate (or remain) in distressed neighborhoods. Financial incentives, tax abatement, and similar offerings are made available to the private sector with the expectation that commercial investments in these areas will create employment opportunities for residents (Ladd, 2004).

Today, there are a number of hybrid programs supported by a combination of place- and people-based program areas. These hybrid PBP/PAPs speak to both place and people (Ladd, 2004). Hybrid PBP/PAPs attempt to create a link between economic development and personal wellbeing. The economic development component focuses on the revitalization of commercial centers, mixed-use facilities, and incentives to promote private sector redevelopment (Ladd 2004). At the same time, the personal well-being component addresses individual concerns with such efforts as job training programs, affordable housing redevelopment, crime prevention efforts, and other neighborhood services. Collectively, hybrid PBP/PAPs work to revive both the commercial and residential viability of distressed neighborhoods.

1.2. Brief History of Place Based Policies and Policy Tools

Over the last 80 years, there has been an evolution in the way policymakers understand neighborhood change, its causes, and the ability of PBP programs to revitalize inner-city neighborhoods. In general, PBPs seek to "channel resources to places where they will have the greatest impact per dollar invested and/or serve the greatest need" (Mallach 2006, p. 634).

Place-based policies (1930s-1960s)

PBPs were first introduced with the Housing Act of 1937 and the mandate by Congress to provide suitable housing for all citizens (Hoffman, 2000). This Act led to federally built public housing developments spanning entire city blocks for low-income families. By the 1940s, there was increasing opposition to the notion of the federal government building housing for the poor. Policymakers felt that the federal government should not be building scatter-site housing in non-distressed neighborhoods. Instead, they believed their role was to address the quality of poor urban neighborhoods so low-income households could remain in their neighborhoods (Hoffman, 2000). This notion led to a shift in federal policy from narrowly focused PAPs to wider-reaching PBPs, and new legislation passed under the Housing Act of 1949.

The Housing Act of 1949 and the federal programs that soon followed presented a heavy reliance on 1930s-era neighborhood change theories developed by the Chicago School theorists Ernest Burgess (1925) and Homer Hoyt (1933) (Schwirian, 1983). Their theories of neighborhood change viewed neighborhoods as undergoing an ecological cycle, from growth to decline. Most significant was the view that decline was inevitable and a natural part of neighborhood evolution (theories further discussed in the next section).

Housing Acts of 1949 and 1954: Urban Renewal

The Housing Act of 1949 was the basis for the urban renewal programs of the 1950s (Keating, 1999). Such programs were designed to improve poor urban neighborhoods, characterized by substandard housing and blighted areas (Garvin, 1996). Urban renewal funds were used for either property acquisition and rehabilitation or demolition and new construction. As a PBP in its purest form, urban renewal led to the dramatic redevelopment of neighborhoods through "large-scale slum clearances, high-rise towers for new [market-rate] housing, and downtown redevelopment" (Fishman, 2000, p. 203).

However, it is important to note that the urban renewal plans and the identification of slum or substantially disinvested neighborhoods were primarily based on subjective criteria without the formal assistance of data or statistical analyses (Goetze and

Colton, 1980). Substandard housing was demolished based on the perceptions by local government that poor neighborhoods needed a new or rehabilitated housing stock to facilitate social and economic advancement. To complement the urban renewal focus, there was also an increased emphasis on retail redevelopment and public infrastructure improvement in the central business district (Hays, 1985). In this case, the goal was to halt the outmigration of both middle class residents and commercial businesses from the downtown areas.

In the late 1950s, urban renewal plans drew significant criticism for their physical disruption and destruction of racial and ethnic neighborhoods. Urban renewal remained the principle federal response to city decline, but these strategies were ineffective against the social unrest and racial riots that would soon consume urban America in the 1960s. The unrest came as a result of prolonged disinvestment and hyper segregation (Massey and Denton, 1993). In partial response, policymakers began to target distressed areas through three major programmatic efforts, including the (1) Model Cities, (2) Urban Renewal, and (3) Empowerment Zone and Enterprise Community programs. Economic development and housing programs were also drawn from to assist with the renewal of neighborhoods, including housing related programs and the Community Development Block Grant program (CDBG).

Model Cities Program (1966)

Model Cities was a spatially targeted PBP program, as well as a hybrid PBP/PAP. Sponsored by HUD, the Model Cities program was an ambitious initiative to "integrate physical redevelopment with social, economic, and political actions" (Garvin, 1996, p. 219). This federal program was established in 1966 and provided funding through categorical grants. Categorical grants aided communities to access funding for specific activities without placing restrictions on how cities allocate resources community wide (Keating and Krumholz, 1999). Discretion was given to cities to decide how the funds would be used, and not the federal or state government. Presumably, cities better understood their neighborhood needs (Keating ed., 1996). As such, local governments would target specific neighborhoods, or “model neighborhoods” for categorical funding (Garvin, 1996, and Keating and Smith, 1996). Notably, explicit in the Model Cities agenda was the maintenance of neighborhood integrity. Unlike the Urban Renewal practices, Model Cities would not displace poor households or disrupt poor neighborhoods. Unfortunately, the Model Cities Program did not address the shortcomings of past renewal policies in that it did not provide or require cities to develop policy tools to target funding or identify areas with the greatest need for funding. Funds were dispersed with little regard for need or potential return on investment (Scott, 1969). However, not all cities loosely scattered their resources.

The City of New York’s Model Cities Program directed funding to neighborhoods using city maps to identify areas with high rates of vacant buildings, fires, and crime. Targeted areas received funding for both social services including early childcare centers, after-school tutoring programs, and property development including industrial development, rental property redevelopment, and the construction of public housing (Garvin, 1996).

The Model Cities Program ended in 1974 for lack of Congressional support amidst questions of the program’s overall effectiveness. In its place, the federal policymakers established the CDBG Program, which today is one of the largest federally funded urban revitalization programs.

Community Development Block Grant (1974)

Though the Model Cities Program was short lived, it represented the start of many similar federal reinvestment zone programs that spatially targeted federal resources for the purpose of economic revitalization. The first such initiative was the CDBG Program, established in 1974 as a hybrid PBP/PAP. CDBG is not a categorical grant program but represents several categorical grants folded into a single block grant. As such, funding is not restricted to specific activities. Cities have greater flexibility in how funds are spent, from infrastructure developments to employment training (Abravanel et al., 2010).[1] Cities are able to use funds for social services, housing rehabilitation, and economic development activities. The flexibility of the CDBG Program gives cities the ability to develop their own investment strategies according to the issues facing their community (Goetze, 1980; and Gleiber and Steger, 1983).

As described by Gleiber and Steger (1983, 46-47), the legislative objectives of the CDBG Program include the following:

> The elimination of slums and blight, elimination of conditions detrimental to public health, safety, and welfare, maintenance and improvement of the nation's housing stock, expansion and improvement of community services, improved utilization of community land and resources, integration of income groups and the

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[1] Under the a categorical program, HUD approved proposed projects that the city desired to undertake based on categorical requirements of the program. The federal government only paid for 80 percent of the cost of planning, administration, and nonfederal share. With the block grant program, however, funds were equally distributed to cities, which were given 100 percent of the cost of housing rehabilitation, public infrastructure improvement, economic development and other place-based activities (Garvin, 1996).

promotion of neighborhood diversity, and restoration and preservation of properties of historic, architectural and aesthetic significance.

CDBG funds are allocated annually to states using a funding formula based on population, poverty rates, age of housing stock, and other needs factors (Galster, Temkin, and Walker, 2004; and Keating and Krumholz, 1999). Cities that meet the funding formula threshold are known as entitlement communities. Cities that do not meet the threshold are also eligible for funds, but they must submit a successful grant application and qualify according to a statutory dual formula.[2] Under the Reagan Administration, CDBG-eligible cities were required to use a Neighborhood Classification System (NCS) to target neighborhoods for funding and to guide city investment decisions.

The NCS was used by cities during the initial administration of the CDBG program to identify and rank neighborhoods according to their levels of distress based on income and housing conditions. This classification system helped cities define the geographic boundaries of areas with similar characteristics, known as Neighborhood Strategy Areas (NSAs).[3] NSAs with poor socioeconomic and housing conditions were classified as distressed; those with positive socioeconomic and housing conditions were classified as stable; and neighborhoods that were neither distressed nor stable were classified as transitional (Goetze, 1980). Neighborhood classifications were used to identify distressed areas for cities to target CDBG funding.

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[2] HUD determines the amount given to an entitlement community based on a statutory dual formula. Formula A and Formula B are used to allocate funds based on several objective measures of community needs, including the extent of poverty, population, housing overcrowding, age of housing and population growth lag in relationship to other metropolitan areas (U.S. Housing and Urban Development (2010) retrieved from: http://www.hud.gov/offices/cpd/communitydevelopment/programs/entitlement/)

[3] NSAs are supported by the Census Bureau with cities and neighborhood groups as mutual and exclusive planning areas or districts. Boundaries are census blocks which are modified to express perceived neighborhood boundaries. NSAs may include two or more census block or tracks based on cities discretion.

Despite being a federal program, there was no single prescribed NCS formula. As such, statistical methods and data analyses to determine NSAs varied from city to city depending on the intended use of CDBG funding. Over time, some cities continued to use NSAs to guide investments, but many others abandoned the practice, citing them as impractical and sometimes detrimental to residents living in neighborhoods classified as distressed by such spatial policy tools (Goetze, 1980). Critics of classification systems feared that labeling neighborhoods as distressed would result in a self-fulfilling prophecy and encourage disinvestment by businesses and financial institutions as well as outmigration by residents, ensuring the demise of the area. As a result, some cities chose to adopt informal PBP tools to guide CDBG investments. Some went so far as to create allocation taskforces to distribute funds.

Enterprise Community (EC) and Empowerment Zone (EZ) programs (late 1980s)

The Enterprise Community (EC) and Empowerment Zone (EZ) programs are hybrid PBP/PAPs, but unlike the CDBG program and its predecessors, these programs are targeted at zones within selected cities for economic improvement. Promulgated in the late 1980s and early 1990s and administered by HUD, each program targeted a specific area for tax incentives to encourage job creation and economic development.

The EC Program directed funding based on an areas low economic performance as measured by wage rates, business starts, and capital investments (Sohn and Knaap, 2005). Funding was limited to infrastructure projects in order to encourage businesses to move to the area, thereby increasing job opportunities. Similar to the EC economic performance indicators, EZ allocations were based on levels of distress, but it was a much more comprehensive program.

Designated EZs were generally large, centrally located areas that qualify for tax incentives and a number of other federal, state, and local grants. EZs focused on infrastructure development projects, increasing employment opportunities, as well as beautification initiatives. EZs were designed to attract new businesses to draw new commercial investments and provide job opportunities for inner-city residents.

The EZ and EC programs encouraged complementary PAP and PBP approaches to revitalize distressed areas. They were among the first federally funded programs to geographically target distress areas, not just distressed cities. Both programs were designed to attract, concentrate, and coordinate a broad range of public and private resources to revitalize distressed neighborhoods and support community-based partnerships.

The evaluations of the effectiveness of such programs have presented different results. Evidence had shown improvements in employment figures, such as the number of jobs created in both EZ and EC areas. In addition, others have found a reduction in poverty within the program zones and positive spillover effects in adjacent neighborhoods (Oakley and Tsao, 2007). Nevertheless, questions arose as to the programs' ability to attract businesses and provide employment for isolated inner-city residents. Research suggests that the programs had been minimally beneficial in reducing poverty and creating positive spillover into adjacent neighborhoods (Papke, 1994; Boarnet and Bogard, 1996; Gillen and Newman, 1998; Barnnet, 2001; and Oakley and Tsao, 2007). In Katz's (2010) evaluation of EZs and ECs, he asserts the following:

> Both types of zones attracted much less industry than anticipated and many of the new jobs went to employees who lived outside the districts. Local politics

> undermined the districts, inhibiting their ability to mount effective programs and catching them up in patronage and corruption. (p. 15)

Finally, other studies have found that the programs' net impacts are minimal due to the large scale of the targeted areas and the overwhelming negative physical conditions and poor socioeconomic characteristics of designated zones (Galster et al., 2004).

Housing Subsidy Programs (1980)

Federal housing production programs have complemented federal attempts to subsidize redevelopment efforts such as model cities, urban renewal, and CDBG grants. Such housing programs have sought to increase the supply of affordable housing through tax incentives to building developers or to provide monetary support through vouchers for disadvantage households. Over time, there have been six primary housing production programs to provide affordable and quality housing in distressed communities, including Section 8 New Construction/Substantial Rehabilitation, HOPE VI, the Low Income Housing Tax Credit (LIHTC), and the HOME Program.

Under the Section 8, market rents are subsidized by the federal government. Residents pay approximately 30 percent of their income as their share of the market rent while the federal government pays the excess value. HOPE VI is a PBP that replaces public housing projects with new construction or substantial rehabilitation. As a result, large public housing sites are replaced with lower density housing that provides both subsidized and market rate units to encourage a mixture of household income groups. The HOME Program (to be discussed in more detail in Section 1.5) started in 1992 as a housing block grant administered to municipalities, counties, and states to assist extremely low-income residents. The LIHTC was created in 1986 to provide tax credits to private investors in return for equity investments in privately owned rental housing developments. The application of tax credits results in lower cost housing with the savings manifested in more affordable rents.

While these programs are not geared towards targeted zones, they are considered place-based initiatives based on the intent of the programs to improve the quality of housing conditions. In some cases, programs are designed to revitalize distressed neighborhoods. However, scholars question the extent to which programs are successful to revitalize versus stabilize neighborhoods (Khadduri, Burnett and Rhodda, 2003). Similar to CDBG and business reinvestment zones, these programs produced mixed results (to be discussed in the next section).

Comprehensive Market Driven Place-based Strategies (2000)

An overview of place-based policies from the 1950s to 2000 show that efforts employed to revitalize communities focused on concentrating resources in specific neighborhoods based on arbitrarily defined criteria of distress. Neighborhoods demonstrating dire socioeconomic needs were targeted, while the geographic scale of the targeted areas where the poor resided varied with the program.

By 2000, cities began to think differently about place-based strategies and how resources should be targeted. Attention now turned from addressing the needs of the individual household to a more comprehensive approach, where the focus was to improve neighborhood market conditions through coordination and collaboration. For cities struggling with a shrinking tax base and fewer federal and private resources, target areas became smaller and resources were more spatially concentrated. More significantly, program targeting was to be data driven, allowing resources to be channeled into areas with demonstrated neighborhood assets and anchors.

In 2000, policymakers began to make funding decisions based on local market conditions. More significantly, in contrast to a myopic focus on distressed areas, strategic, geographic targeting occurred on non-distressed neighborhood blocks. The underlying message was that different places had different challenges and required customized tools to address those issues. Further, cities were encouraged to target areas that contained assets, including anchor institutions (e.g., universities) or other inherent community assets (e.g., proximity to transit) that could be leveraged for improvement. In this re-conception of PBP efforts, socioeconomic conditions were not the sole determining factor for place selection. Now, the market was the key determinant. Neighborhoods were selected for investment based on the vitality of the local housing markets as well as available neighborhood assets, and the capacity to leverage them. In this light, cities were to employ proactive strategies that relied on a market driven analysis to identify areas most in need, and best able to take advantage of a new influx of resources. Since the late 1990s, the application of PBP tools relies on thorough statistical analyses of neighborhood housing markets, spatial analytic techniques, and geographic information systems technology. These tools encourage cities to make market-conscious decisions based on measurable and presumably objective neighborhood indicators.

The City of Richmond, Virginia, is a specific example of a community that used data driven policies to redirect federal and citywide funding. In 1999, Richmond initiated the Neighborhoods in Bloom (NIB) housing program. This program relies on a data driven assessment of community conditions complemented with an intensive public participatory process. This approach led to the classification of neighborhoods based on existing conditions and their future potential. To this end, characteristics such as the condition of the structures, crime, and safety, and the socioeconomic characteristics of the residents were part of a neighborhood assessment. In addition, the city evaluated neighborhoods' potential to improve based on a neighborhood-wide engagement in revitalization efforts, by assessing active community groups, neighborhood redevelopment plans, Community Development Corporation (CDC) involvement, reinvestment zones, as well as neighborhood market factors. These criteria are the basis for neighborhood rankings using these criteria. NIB funding is targeted at the block level of selected neighborhoods.

The NIB initiative targeted 80 percent of the city's CDBG, HOME, and Local Housing Initiative Corporation (LISC) funds to six of 49 neighborhoods with low- to moderate-income households. In addition, the city complemented this monetary effort with social service support, including more aggressive housing code enforcement and police presence, in addition to housing investment resources. Over a five-year period, property values and homeownership rates increased in the targeted areas (Mallach, 2006). Galster, Tatian, and Accordino's (2006) analysis of Richmond's NIB presents positive findings for this spatially targeted housing effort. Using an adjusted interrupted time series methodology, the study revealed that homes in targeted areas had a greater appreciation in market values than comparable homes in similarly distressed neighborhoods, controlling for structural elements and neighborhood conditions.

1.3. Impacts of Investment and Place-Based Programs

In review of revitalization efforts and the impacts of place-based programs , there is conflicting evidence whether community development initiatives and housing production subsidies improve the quality of distressed neighborhoods (Galster, 2003; Khadduri, Burnett, and Rhodda, 2003; and Abravanel, Pindus, and Theodus, 2010). This may be due to the fact that such programs as those listed above all tend to target the most distressed neighborhoods and that the level of support is not sufficient to overcome the scale of neighborhood problems. This is evident in studies that evaluate the impacts of these housing investments on neighborhoods and focus on the relationship between the housing investment and the change in sales value of nearby properties. Taking into account such factors as the neighborhood socioeconomic characteristics, the scale of the investment and the distance between the investment and the sale property, the findings from these studies are mixed.

Impacts of subsidized investments on surrounding property values

Lyons and Loveridge (1993) analyzed the impact of subsidized housing units in Ramsey County, Minnesota on surrounding non-subsidized residential units. The analysis finds that scale and magnitude of housing subsidies have a significant impact on surrounding housing values. In their analysis, the authors evaluated public housing, Section 8 and 221, and other subsidized housing programs. In addition, the study find that a greater number of subsidized development units were associated with a negative impact on property values. However, Lyons and Loveridge pointed out that surrounding housing values significantly appreciated near smaller densities of public housing and Section 221 units. Ellen et al. (2001) came to different conclusions in their analysis of New York Nehemiah Program and the Partnership New Homes program which subsidized the construction of affordable owner-occupied homes in distressed neighborhoods from 1980 to 1999. The study used a difference-in-difference approach to evaluate the impact of subsidized investments on surrounding sales. Ellen et al. analysis find that larger projects based on the number of units all have significant impacts on property values.

Galster, Santiago, and Tatian (2001) conducted a study of subsidized housing projects on single-family homes in Denver during the 1990s and found that a greater number of subsidized housing units positively influenced sale price if they were within a certain distance of a property. These findings were similar to Ding, Simons, and Baku et al. (2000) study of targeted, subsidized new construction and rehabilitation projects on surrounding home sale prices in Cleveland, Ohio. The authors conclude that small-scale investments, as opposed to large-scale investments, have little impact on property values and that their impact diminishes the further the investment is from the property. Galster, Tatian, and Accordino (2006) measure scale in terms of dollars invested in their analysis of subsidized new construction and rehabilitation projects for the Neighborhood in Bloom Richmond Virginia program in 2000. Galster et al. conclude that in a given block within the target areas when city investment exceeded $20,100, the average home sales price in the block increased by over 50 percent (assuming that higher dollar investments equate to a greater number of rehabbed or newly constructed housing units).

Ding Simons, and Baku (2000) further suggest that the effects of investments on property values are based on proximity. The authors conclude that residential investment in new construction and rehabilitation has positive impacts on surrounding property values located within a 150-foot radius of the investment site. Other scholars claim effects of subsidized housing investments on surrounding house sale prices could be observed at 500 to 1,000 foot radius of the property (Ellen et al., 2003; Johnson and Bednarz, 2002).

Consequentially, not all research concludes that housing investments have significant impacts. Based on analysis of public housing sites that ranged from 4 to 48 units, Briggs, Darden, and Aidala (1999) find that there is little evidence that the size of the development significantly influences sales prices. This conclusion is echoed by Lee, Culhane, and Wachter (1999) analysis of Section 8 certificates and vouchers impacts on property sales from 1989 through 1991. The authors find that the size of the investment is insignificant, but point out that proximity or distance between investment and neighboring properties might affect the relationship between housing investments and property values.

In terms of neighborhood characteristics, studies suggest that neighborhood conditions matter and influence investment impacts (Green, Malpezzi, and Seah, 2002; Lee, Culhane and Wachter, 1999; Cummings et al., 2002). Green, Malpezzi, and Seah (2002) analyze the effects of LIHTC on surrounding property values in the metropolitan Milwaukee, Wisconsin area from 1991-2000 and find that the impact of public investments depends on the socioeconomic status of the residents. The authors find that areas with a high percentage of low-income households, high poverty rates, and a high percentage of African American households present negative effects on property values in spite of investments. In contrast, the authors find that areas with more affluent characteristics result in either positive or neutral effects. In their analysis of Philadelphia neighborhoods, Lee, Culhane and Wachter (1999) find that subsidized units had negative effects on property values.

Cummings et al.'s (2002) evaluation of the Nehemiah Housing Program in New York, New York, found a relationship between the housing investment and nearby property values, despite the large scale of the project. Similarly, Briggs, Darden and Aidala (1999) found no price effect resulting from small-scale subsidized housing development. In contrast to these findings, Ding, Simons, and Baku's (2002) study presents evidence that new construction and rehabilitation have a significant and positive impact on sales prices in low-income areas, as well as predominately non-minority neighborhoods. Galster, Tatian, and Accordino (2006) also find positive impacts in distressed neighborhoods, but conclude that investments must be large-scale and concentrated for a measurable impact.

In summary, empirical studies present mixed findings related to the evaluation of the impacts of housing subsidy programs on surrounding property values. Most conclude that scale, distance from the investment, and neighborhood characteristics are important factors that influence investment impacts. Scholars claim investments present only modest impacts because they are unable to address the multi-layered socio-economic factors effecting distressed neighborhoods. (Galster, 2002). In review of PBP initiatives, the impacts of investments in distressed neighborhoods are minimal based on the conditions of the neighborhoods. While studies have tested the impacts of investments in distressed neighborhoods, not all new construction and rehabilitation investments are located in the most distressed neighborhoods. Criteria for subsidized housing programs make allowance for investments to be located in non-distressed areas as demonstrated in the HOME Program. Only one study addresses the impacts of investments accounting for different neighborhood characteristics. Ding, Simons, and Baku's (2000) study in Cleveland, Ohio, examine impacts across income and race differences among neighborhoods and sheds new light on housing subsidy programs' varying effects based on neighborhood conditions. However, neighborhood housing markets are composed of other factors, such as housing type, the qua lity of the housing stock, and neighborhood characteristics (e.g., percent of vacant properties) that may produce different findings.

Spatial models to evaluate impacts of urban amenities

There is a significant body of literature that examines the demand or impacts of neighborhood amenities and dis-amenities on property values. Amenities and dis-amenities include proximity measures to parks (Wachtner and Gillen, 2006), transportation networks (Abelson, 1979; and Wu, Adams and Plantinga, 2004), commercial development (Ding and Knaap, 2002), as well as other socioeconomic factors in neighborhoods (Galster, et al., 2004; Lynch and Rasmussen, 2001; and Jud and Watts, 1981). These empirical studies demonstrate that amenities may positively or negatively affect residential home sale prices. There is limited research on the role that such characteristics play in affecting the influence of subsidized housing investment on surrounding home sale prices. Galster et al.'s (2004) analysis of CDBG spending in 17 cities between 1994 and 1996 find a relationship between CDBG spending and neighborhood quality improvements, but the analysis does not account for all factors that affect the impacts of community development investment on neighborhood outcomes. Galster et al. concluded that their study fails to address other community development or neighborhood assets that influence investment impacts.

The literature related to valuing environmental quality has expanded in the past ten years as scholars attempt to improve their analyses with spatial multivariate analyses to improve the estimation of the impact of amenities on surrounding sales values. Past analyses which use hedonic regressions and difference-in-difference variations of hedonic models commonly used in studies are comprehensive in scope, but further exploration is needed to analyze spatial dependency in data output to explain the spatial effects of amenities. The purpose of evaluating spatial effects is to account for neighborhood quality and other factors that may affect the sales price of homes. Empirical studies that use hedonic models have applied various methods to capture non-fixed spatial variables and neighborhood effects through the phenomenon of spatial drift of coefficients (Can 1990 and 1992; and Ding, Simons, Baku, 2000). Spatial drift of coefficients attempts to capture neighborhood effects by using interaction terms, a concept built upon by the interaction of Cartesian coordinates with housing attributes to generate unique location values (Fik, Ling, and Mulligan, 2003; and Carruthers, Clark, and Renner, 2009). However, the traditional ordinary least squares regression model may be insufficient to capture spatial dependence in housing markets through spatial interaction and diffusion effects, hierarchies of place, and spatial spillover (Anselin, 2007).

Numerous studies in the last ten years have begun to employ geographically-weighted regression (GWR) and other spatial regression models to analyze spatial impacts (Boyle and Kiel, 2001; Brasington, 2003; D. M. Brasington, 2005; D. M. Brasington, 2000; Chattopadhyay, 1999; Hite, Chern and Randall, 2001; and Leggett and Bockstael, 2000). These models have been developed to model spatial drifts in linear model coefficients through spatial hedonic regression models. The ability of these models to capture housing markets' spatial dependence are generally found in studies valuing the quality of the environment, which apply GWR models to estimate the marginal implicit price and a series of implicit demand functions to describe the relationship between the price of distance from environmental amenities and dis-amenities (Carruthers, Clark, and

Renner 2009; and Cho et al., 2006). When comparing the classic hedonic regression model with spatial models, studies have shown improvement in the predictability of the model and in the way it addresses highly correlated variables due to spatial dependence. In general, GWR models provide implications regarding indicators to include in the development of neighborhood housing market typologies because they are not constrained by rigid boundaries. These findings may inform policymakers on the spatial impact of investments.

Summary

Table 1 provides an overview of PBP and strategies implemented since the Model Cities Program in 1966. The Table summarizes neighborhood revitalization strategies based on the policy, the target population within a geographic area, the scale of the geographic area, the intent of the policy or strategy, and, more importantly, the programs' impact on the neighborhood or geographic area. Though all programs have similar goals—revitalizing urban neighborhoods—the differences are the scale of the intervention and the character of the neighborhoods targeted. Citywide strategies employed higher dollar amounts to address neighborhood challenges but presented limited impacts of investments because of the scattered site nature of the investments. Neighborhood-targeted strategies, such as EZ/EC zones, concentrate in a few neighborhoods, but still present few positive findings. Block-level targeting, such as Richmond, Virginia, presented significant findings with fewer dollars targeted into a few neighborhoods within the city.

Table 1: Overview of Place-Based Polices

Strategy	Name	Sponsor	Years	Goal	Policy Tool/Mechanism to Target Funding	Neighborhood Type	Funding	Impacts
City-Wide Strategy	Urban Renewal Program (Housing Acts 1949 and 1954	Federal Government	1949-1963	Slum Clearance	Urban Renewal Plans	Distressed urban areas and downtowns	12.7 billion in nearly 1,000 cities	With over 2,535 Urban Renewal plans few cities demonstrated impacts
	Model City	HUD	1966-1974	Revitalize distressed neighborhoods through housing and economic development	Urban Renewal Plans	Distressed urban areas (multiple neighborhoods)	$38 million in 1969 and $53 million in 1970	Impacts are minor due to short duration of program and limited funding (Keating, 1999; Keating, 2006)
	CDBG	HUD	1975 - Present	Community- or neighborhood-wide revitalization efforts based on City discretion to address housing and economic development initiatives	Neighborhood/ Consolidation plans (Neighborhood Statistical Areas/Neighborhood Classification Systems)	Distressed or moderately distressed areas, or based on local jurisdiction discretion (city-wide or multiple neighborhoods)	Funding in 2002 averaged $2.9 million per eligible city or county and $25 million per state	Impacts at city-wide level is difficult to measure, neighborhood level impact is more measureable and occurs when funds and investments are targeted at the block level (Galster, 2002; Galster, 2006)
	HOME	HUD	1990- Present	Revitalize distressed neighborhoods through housing investments in new construction and rehabilitation	Neighborhood/ Consolidation plans (Neighborhood Statistical Areas/Neighborhood Classification Systems)	Distressed or moderatly distressed urban areas	HUD allocates approximately $2 billion among the states and hundreds of localities nationwide.	Empirical studies have not specifically measured impacts of these funds, however studies have included funds as part of larger city investment strategy (Fitzgerald and Leigh, 2002)
Target-Neighborhood Strategy	EZ/EC	HUD	1994-2009	Revitalize distressed neighborhood through job creation, economic development and tax incentives to attract businesses	Designated Urban Reinvestment Zones	Distressed urban areas (multiple neighborhoods)	$100 million in Empowerment Zones (EZ), and an additional $350 million in Enterprise Zones (EC) through federal grants and tax incentives (Davis and Brocht, 2002)	Empirical studies (Oakley and Tsao, 2007; and 2006) have demonstrated programmatic spillover effects to impact employment and poverty rates in neighborhood zones and adjacent zones.
	HOPE VI	HUD	1993 - present	Revitalize distressed public housing and surrounding neigborhoods	NA	Distressed urban areas (single neighborhoods)	1992-2002: 193 grants, $5 billion (~$26 million per site) over a 5-10 years	Positive impacts on surrounding property values, and ability to attract city services and business, impacts are based on surrounding neighborhood conditions and concentration of investments (Ellen, 2006; Popkin, 2004; Zielenbach, 2003; and Salaama, 1999)
Block-level Neighborhood Strategy	HNI/NIB	City-specific public/private partnerhsip	1998- Present (Virginia), 2000- Present (Baltimore)	Stabilize neighborhoods through housing-based strategies which focus on residents and leadership capabity	Neighborhood Plans (Neighborhood Housing Market Typologies)	Weak but still functioning urban neighborhoods	Baltimore: $3 million from HUD, and $10 million from other non-federal sources; Virginia: 10,787,096 from HUD and 3,136,148 from other federal and local sources	Baltimore: Qualitative impacts tracked by not robustly measured (HNI Real Estate Transaction, 2006); Virginia: Positive impacts when public investments are greater than $20,000 at block level, and investments are concentrated (Galster, 2006)

Source: Table adapted from "Review of Revitalization Initiatives" (Abt Associates, 2004) with additional sources from Keating, 1999.

Based on Richmond's success, other cities, such as Baltimore, Maryland, are increasingly employing similar data driven, place-based strategies to revitalize their distressed neighborhoods. The Richmond experience is indicative of the trend toward more data-driven place-based strategies and the increasing reliance on NHMTs. Numerous cities have employed NHMTs in response to the CDBG allocation criteria, but more recently have become increasingly popular tools as cities seek more systematic ways to distribute increasingly limited resources due to increasing foreclosures.

1.4. WHAT ARE NHMTs?

NHMTs provide a systematic and structural classification of variables into a simplistic typology to better understand similarities or dissimilarities of groups under analysis. Categories or clusters are developed to simplify complex phenomena. Fields ranging from the social sciences to biology have used typologies to classify data and explain patterns developed from the data. Neighborhood-level typologies differ in that they provide a simple representation of a spatial distribution of demographic and compositional characteristics of residents and housing (Hunter, 1979). The ranking and ordering of the neighborhood may be based on various indicators including race, socioeconomic status, familial composition, the condition of the housing stock, and a number of other variables that reflect the quality or condition of the neighborhood (Schwirian, 1983). The variables used in typologies are for analytical purposes to understand citywide conditions.

In 1955, Shevky and Bell presented early analyses for the ranking and ordering of socioeconomic characteristics of residents by census tracts to understand neighborhood composition. They categorized neighborhoods into social areas through a social-area factorial ecology to understand social rank, urbanization, and segregation. This work was complemented by Berry's (1967) analysis of neighborhoods using factors such as socioeconomic status, race, and lifestyles of urban residents. This analysis relied on a varying spatial distribution of individual variables to identify specified characteristics of U.S. metropolitan areas. Numerous studies followed, analyzing change and patterns at the neighborhood level to explore racial stability and diversity as causes of neighborhood change (Downs, 1981; Hunter, 1979; Schwab and Marsh, 1980; and Schwirian, 1983).

For fields like public health, sociology, and geography, a neighborhood is "a social unit of social organizations… that is larger than a household and smaller than a city" (Hunter, 1979, p. 5). Census geographic boundaries and a statistical cluster methodology are used in these fields to classify neighborhoods according to racial and ethnic variables. The results can explain how neighborhoods evolve over time or how neighborhood indicators positively or negatively affect residents. NHMTs differ from these classification methods in that these typologies focus on housing stock quality and locational attributes, giving minimal consideration for residents' socioeconomic status. The purpose of NHMTs is to identify housing submarkets and to develop solutions to improve market conditions. The developments of typologies are influenced by urban housing theories and models.

Typologies: Theoretical Foundation

Before discussing the actual development of an NHMT and exploring the use of typologies, this section will begin with an overview of selected theoretical constructs that are the foundation of typologies and their development. It begins by posing salient questions related to the literature on typologies or classification systems: What is a neighborhood, what are the geographic boundaries that define neighborhoods, what factors impact neighborhood conditions, and more importantly, what indicators make neighborhoods comparable? These questions infer that neighborhoods are defined by spatial units, and represent a grouping of similar characteristics within a geographic boundary.

A neighborhood can be defined as a “spatial, statistical aggregation of individual characteristics” (Hunter, 1979, p. 6). Galster (1999) provides more contextual details to this definition. He suggests that neighborhoods are a “bundle of spatially based attributes associated with clusters of residences” (p. 155). Galster’s definition implies that neighborhoods are heterogeneous of each other but contain homogenous characteristics to represent distinguishable units. This multi-dimensionality of neighborhoods and their composition is explored in the literature related to neighborhood change and housing markets, which include neighborhood stage theories, classification systems, and the development of housing submarkets (Downs, 1981; Hunter, 1979; and Goetze and Colton, 1980). These theories and models help researchers better understand and operationalize neighborhood markets to determine why neighborhoods change and identify mechanisms that can alter the course of negative change.

Neighborhood Stage/Lifecycle Model

The earliest attempt to create descriptive typologies of urban areas was first introduced by urban sociologists, such as Park and Burgess in 1921 and Hoover and Vernon in 1930. Scholars like Park and Burgess classified neighborhoods into types to understand neighborhood change. Park (1921) defines neighborhoods as “different natural areas that experienced a set of sequential stages of change” (in Hunter, 1979, p.

15). He suggests that change was a natural process based on social and economic factors affecting neighborhoods; therefore, residents lack control to alter the direction of neighborhood change. These natural processes of change were termed as neighborhood stages. Burgess uses an ecological theory of neighborhood change to classify his stage model in the context of invasion-succession models. Neighborhood stages were based on land uses that surrounded the central business district and neighborhoods based on city development. Growth, expansion, decline, and rebirth are categories that define neighborhoods based on the movement groups and their socioeconomic status. Burgess suggests that this process was inevitable and natural. His model was followed by Hoyt's (1933) and Ratcliff's (1949) economic theory and filtering model. Hoyt suggests that neighborhood change is based on household investment decisions including property maintenance, and new construction that attracted demand to other parts of the city. According to this model, change can be measured by to the key factors of population and housing conditions.

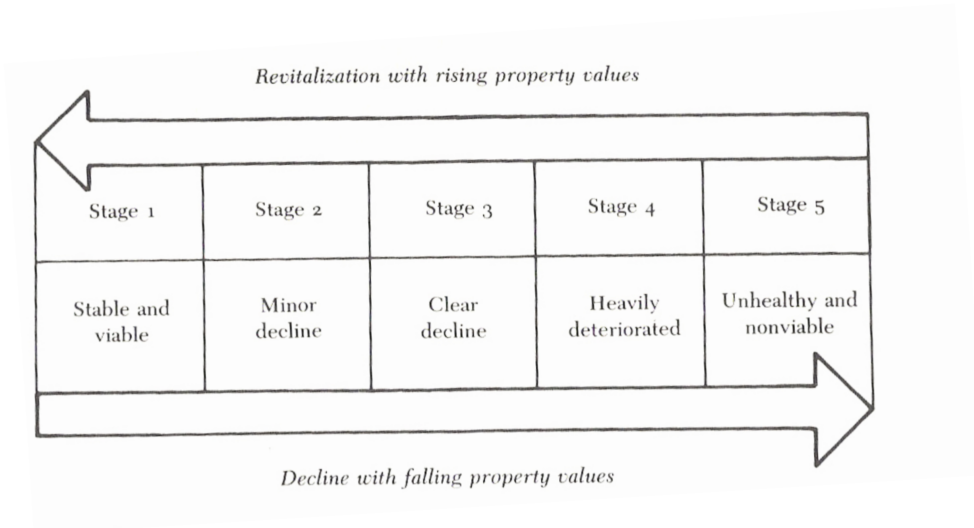
In 1967, Hoover and Vernon built upon Park and Burgess's work in studies that examined social, economic, and housing dynamics of urban neighborhoods. They suggest that neighborhoods experience drastic changes over time that caused them to shift from one condition to another based on changes in the quality of housing conditions. Within this stage model, Hoover and Vernon conclude that neighborhoods change at different rates in three directions: (1) improved or upgraded; (2) remain the same; and (3) decline to the subsequent stage. This analysis helped them to define five neighborhood stages and to present the beginning of neighborhood typologies.

Hoover and Vernon's stage model was further developed by scholars in the 1970s and 1980s in an attempt to build upon the literature of neighborhood change (Downs, 1981; and Hunter, 1979). Downs refined the stages and provided definitions (Downs, 1981, p. 63-64):

- Stage 1: Stable and viable. Relatively new and thriving or relatively old and stable neighborhoods with rising property values with desirable amenities and housing stock that continue to attract residents to maintain them.
- Stage 2: Minor decline. Older areas where structural maintenance is beginning to decline. Minor physical deficiencies are visible and density is higher in area. Property values are stable or increasing slightly. Public services and social status is below Stage 1.
- Stage 3: Clear decline. Rental properties are increasing or dominant in the housing market. Minor physical deficiencies are visible and overall confidence in the neighborhood is weak with increasing abandoned housing. Social status is lower than Stages 1 and 2 because lower income groups dominate the housing market.
- Stage 4: Heavily deteriorated. Housing is very deteriorated and dilapidated, and most structures are in need of repair. Profitability of rental units is poor and housing is only being marketed to lower income groups. Abandonment is prolific in the neighborhood and a pessimistic view of the future of the neighborhood.
- Stage 5: Unhealthy and nonviable. Neighborhoods are at the terminal point with massive disinvestment and abandonment. Residents represent the lowest social status in the city and region. Area is not considered marketable with increasing crime and depleting public services.

Downs (1981) refers to neighborhood stages as lifecycles and suggests that neighborhoods are in fact influenced by outside factors and susceptible to experience decline if intervention methods are not used to slow or stop the process of neighborhood disinvestment. Lifecycle theories placed neighborhoods into stages of change that included stable, transitional,

Figure 1: The Neighborhood Change Continuum



Source: James Mitchell, The Dynamics of Neighborhood Change, prepared for the Department of Housing and Urban Development, Office of Policy Development and Research, HUD-PDR-108 (HUD, 1975) p. 9

decline, and in some cases, renewal. These stages are based on several indicators, including population, socioeconomic status of residents, and housing conditions.

Downs's (1981) analytical categories identify the status of neighborhoods and the reinvestment strategy associated with each neighborhood stage. Above, Figure 1 presents Downs's model of neighborhood change. Downs's link between neighborhood conditions and intervention strategies are to improve at-risk neighborhoods or to stabilize those experiencing impending or natural decline (Hunter, 1979). For example, neighborhoods showing heavy decline with high population loss, decline in housing values, or changes in residents' socioeconomic status called for drastic interventions, such as massive demolition and redevelopment. Downs argues that these conditions of the neighborhood influence its capacity to improve. He notes that the effectiveness of policies relies heavily on a neighborhood's current stage at the time a given policy is applied. The late 1980s and early 1990s brought about other conceptions of neighborhood change, many of which implied that policies must be customized to fit the specific conditions of a neighborhood (Goetze and Colton, 1980; and Mallach, 2006).

Neighborhood Classification Systems/Models

In the early 1980s, Goetze and Colton (1980) explored neighborhood dynamics through classification systems within the context of supply and demand theory to bring housing markets into equilibrium. They posit that monitoring the interface between buyers and sellers is the best proxy to explain neighborhood change and identify neighborhood categories. In their analysis, neighborhood market types are based on the identification of neighborhood factors that lead to an excessive supply of housing, an excessive demand for housing, or equilibrium between supply and demand. They analyzed quantitative indicators, such as property values, residents' socioeconomic status and investment decisions, property conversions, property tenure, and conditions to identify market types. Based on these indicators, neighborhoods can be classified as rising (demonstrating gentrification), stable (demonstrating an ideal neighborhood situation), or declining (demonstrating heavy disinvestment).

Similar to Downs, Goetze and Colton's indicators are dependent on causes or factors that result in too few buyers or high rates of demand. Their market types are linked to corrective remedies to bring neighborhoods into equilibrium. Examples of their prescribed remedies include assisting disadvantaged populations, increasing code enforcement efforts, and boosting neighborhood confidence through aggressive marketing strategies. While Downs suggests that scaled government intervention impacts neighborhood conditions, Goetze and Colton assert that as neighborhoods change, natural forces may not exist to counteract changes. Therefore, government intervention may in fact make the situation worse. According to Goetze and Colton (1980), intervention methods should incentivize private sector investment and participation in neighborhood improvements.

Housing Market Segmentation

Neighborhood stage models and classification systems were developed to better understand the causes of neighborhood change. These models and systems focus on both socioeconomic and housing structural characteristics to explore the composition and status of neighborhoods. NHMTs used today are designed to address housing structural and physical conditions, in the essence of the term and in an attempt to capture the submarket of neighborhoods. An emphasis on housing markets—and not just neighborhood stages—introduces a more sophisticated approach toward defining neighborhood markets, known as market segmentation.

Market segmentation theorists hypothesize that housing characteristics are spatially-based and result from submarkets of clustered housing and locational qualities, thus separating the housing market into groupings of similar housing units (Maclennan and Tu, 1996; Borassa et al., 1999; Bourassa, Hoesli, and Peng; 2003; and Bates, 2006). The identification of market segmentation has been under considerable scrutiny as scholars attempt to sort out how to define neighborhood housing markets. Some scholars define markets by the physical characteristics of housing units (Maclennan and Tu, 1996), while others assert that the definition of markets should include homebuyer characteristics or socioeconomic variables, such as income levels, employment status and occupation, and household composition.

Are housing markets a bundle of structural and physical conditions of dwelling units or influenced by spatial factors? Scholarly research examining this question suggests that the quality or structural characteristics of housing present differences in home prices and consumer tastes (Grigsby, 1975; and Galster, 1996). These scholars assert that housing structures—which include varying physical characteristics like material, size, type, amenities, and age of the housing stock—are key factors that create submarkets and distinguish areas from each other to provide better representation of neighborhood conditions. Goodman (1979) and Straszheim (1975) both identify housing attributes and home prices as factors that determine homogenous housing markets. They claim that neighborhood submarkets are mainly determined by spatial differences in housing structural characteristics and amenities. However, not all scholars agree.

Dissenting scholars claim that racial and socioeconomic compositions determine different submarket variations according to household income, race, and occupational composition across market types (Galster, 1979; Palm, 1978; Gabriel, 1984; and Day, 2003). Bourassa et al. (2001) also report that socioeconomic factors, physical conditions of nearby housing, and access to central business district are defining factors that lead to housing submarkets and are determinants of housing quality. This may be evidence that housing consumption is based on residents' income constraints, the price of housing, and taste, along with other variables (McClure, 2005; and Galster, 1998). Additional empirical studies present evidence that race and ethnicity may also influence housing submarkets, as racial and ethnic minorities may be restricted in certain submarkets (Kain and Quigley, 1975; and Yinger, 1998). Bourassa et al. (2001) conclude that the defining factors separating housing markets into submarkets are those related to the physical conditions and socioeconomic status of neighborhoods. Further, Bourassa, Hoesli, and Peng (2001) report that neighborhood socioeconomic status is more important in identifying submarkets than individual property characteristics.

Some scholars believe that housing markets are spatial submarkets, stratified not only by the socioeconomic characteristics of residents, but by housing values influenced by locational factors. Goodman and Thibodeau (1998) report that the heterogeneity of housing encompasses both spatial attributes and neighborhood structural characteristics used to explain the multi-dimensional complexity of housing as a commodity. Other scholars have built upon these findings and suggest that housing values are influenced by locational attributes and the physical conditions of neighborhoods, such as surrounding vacant properties or proximity to neighborhood amenities, like urban parks. Bourassa et al. (2001) note that locational factors affect submarkets. Schnare and Struyk's (1976) analysis relies on such locational indicators as distance to the central business district (CBD) to define submarkets. Goodman (1981) also claims that locational attributes define separate submarkets, like the CBD. These locations capture the physical conditions of properties, as the case in cities where high value property is located near the CBD. Galster (2003) asserts that spatially based attributes do not necessarily infer geography, but that some physical elements, including views, are not easily duplicated and result in the formation of a housing market.

Presently, typologies rely on a diverse number of socioeconomic, housing, and locational variables. Exactly which variables are used in a given typology depends upon the specific methodology and purpose of the analysis.

History of Neighborhood NHMTs

In the 1980s, HUD's CDBG Program and other categorical grant programs began to mandate that cities develop typologies to target investment efforts in their communities and identify prescriptive measures to address changing communities. Cities relied heavily on socioeconomic and housing characteristic indicators to understand neighborhood conditions.

Neighborhood Classification Systems in 1980s

Neighborhood classification systems (NCSs) led to typologies. This section provides a historical overview of the development and examples of NCSs. During the Johnson administration, NCSs were used by cities after a federal mandate for municipalities to target specific neighborhoods in reinvestment strategies to access CDBG funding. Goetze and Colton (1980) explore examples of cities which used NCSs to demonstrate how cities were using systems to guide reinvestment strategies. Memphis, Tennessee, is studied by the authors as a city which used the NCS to direct CDBG funds to transitional neighborhoods, demonstrated by active real estate markets as a criterion. The criteria are also used to select areas with non-tangible assets such as areas with active neighborhood organizations. The presence of active organizations indicates the communities' capacity to be self-sustaining. Specifically for distressed neighborhoods, functioning organizations demonstrated the capability to improve based on housing value and neighborhood quality.

Milwaukee, Wisconsin, was another city chosen for Goetze and Colton's (1980) analysis, in that this city used NCSs to target areas with low homeownership rates and high vacancy percentages. Neighborhoods were classified to a Relative Residential

Status. This status is based on an analysis of the 208 census tracts in the city and a collection of ten variables. Their findings identify the most stable neighborhoods (i.e., those with the highest assessments, highest owner occupancy rates, and lowest vacancy rates) and the least stable neighborhoods (i.e., those with the lowest assessments, lowest owner occupancy rates, and highest vacancy rates). Milwaukee began participating in the CDBG Program in 1974. Within the first ten years, 121 of the city's 218 (55 percent) census tracts had been targeted for CDBG funding using their NCS criteria (Gleiber and Steger, 1983).

By the late-1980s and early-1990s, the use of NCSs were discontinued in a number of cities due to flexible regulations under CDBG that no longer required targeting and the fact that cities viewed this classification system as a catalyst for generating negative perceptions of neighborhoods labeled as distressed. While some cities continued to use NCSs to guide investments, others abandoned the practice altogether. NCSs did not resurface until the late-1990s and early-2000s.

Typologies in the 2000s

Prompted by economic changes and increased disinvestment in urban and suburban neighborhoods, cities have returned to the use of NCSs to understand neighborhoods and guide reinvestment decisions with fewer federal resources and local dollars. However, since the 1970s, the data, methods, and purpose of classification systems have changed. Increases in vacant housing, foreclosures, and property disinvestment due to economic changes have prompted some cities to discontinue the use of classification systems that focus almost exclusively on socioeconomic and housing conditions, instead opting for variables that specifically address housing-related factors.

While some cities still use socioeconomic factors to develop NCSs, the focus of those policy tools tended to be on the structural factors and the physical conditions of nearby properties. Currently, these classification systems are known as NHMTs, which represent a classification of neighborhood housing markets whose purposes can vary, but are generally used to identify areas with the potential to present the greatest return on limited investment.

Table 2 identifies six cities and indicates how they employ NHMTs. These cities were selected to represent a variation among typologies used by different cities, based on the number and identification of market types, the units of analysis, the indicators used to determine market types, the methodology, the scaled strategies to improve or stabilize markets, and how the typology will be used to inform decisions. The section of the literature review following will briefly discuss the differences among typology types and the indicators used to define typologies.

Housing and Socioeconomic Indicators

Indicators used to determine neighborhood types provide a purpose for the development of a typology. For example, the use of foreclosure indicators may inform the user that the purpose for the typology is to determine which areas contain a high percentage of foreclosed properties. These indicators may include structural conditions of homes, house sales price or assessment value, household tenure, or other housing-related characteristics. In addition, typologies may also include variables that demonstrate neighborhood characteristics including dis-amenities such as foreclosures, or amenities such as the percent of home sales, the percent of permits issued, and the percent of property zoned for commercial use. Socioeconomic and demographic variables may also

Table 2: Sample city examples of NHMTs

City	Market Typologies	Unit of Analysis/Timeframe	Indicators	Strategy	Methodology	Purpose
Baltimore, MD	Competitive, Emergining, Stable, Transitional, Distressed	Census Block Group/2008	Median Home Value Sales, Percent Commercial Land, Percent Rental Subsidies, Percent Foreclosure, Percent Vacant Homes, Percent Home Ownership, Percent Single Family Homes, and Percent Vacant Lots	Preventative measures for competitive/emerging typologies; stabilization efforts for stable and transitional markets; and demolition and substantial redevelopment in distressed markets.	Factor analytic cluster analysis	Guide city's investment strategies for both daily operations and long-term planning; use of data to target HUD Neighborhood Stabilization program dollars.
Philadelphia, PA	High Value/Appreciating, Steady, Transitional, Distressed, and Reclamation	Census Block Group/2001	Median Sale price, variance in sales price, percent rental subsidies, percent vacant, percent foreclosure, percent commercial use, percent owner occupied, housing units per acre, new construction	Invest in areas with the greatest potential, close to strong markets or with stable real estate market; and extensive redevelopment in distessed areas.	Factor analytic cluster analysis	Program was designed to renew and strengthen Philadelphia's urban neighborhoods through specific public action.
Kansas, MO	Developing Areas, Conservation Areas, Stabilization Areas, and Redeveloping Areas	Census Tract/2007	Population change, median household income, unemployment; percent household on public assistance, persons below poverty level, persons with high school education, rate of crimes, single headed households; median house value, housing unit change, percent vacant housing, residential building/demolition permits ratio, percent owner occupied housing, household income to housing payment ratio	Preserve what is valuable and prevent decline by addressing problems and their root causes. Undertake many actions simultaneously to address housing maintenance/rehabilitation, code enforcement	z-score; final score calculated as the average of all z-scores for each variable within each block group	Provide neighborhood assessments for long term planning intiatives, which strategically apply public and private resources in a way that is based on the existing conditions, trends, opportunities, strengths and needs of diverse areas.
Cleveland, OH	Regional Choice, Stable, Transitional, Fragile, Distressed	Census Tract/2008	Median assessed value, percent change in median value, net change in number of single family housing, foreclosure rate, homeownership rate, boarded up/condemnation rate, housing rate below fair, vacant and distressed structure rate, demolition rate	Encourage rehabilitation in strong and stable markets; use NSP funds in conjunction with HOME, CDBG and LIHTC resources to rebuild areas; create sustainable homeownership rehabilitation markets	z-score; final score calculated as the average of all z-scores for each variable within each block group	Provide information to assist the Department of Community Development, City of Cleveland, and other stakeholders in the development of program strategies that promote urban revitalization.
Indianapolis, IN	A: Attractive, high end residential, B: Healthy areas with above average property values, C: Visible Signs of decline but not highly concentrated, D: Significant deterioration of housing stock with dense concentrations of vacant buildigns	Census Block Group/2005	House vacancy rate (90-day postal vacancy), total assessed housing value, and percent owner occupied (certified property ownership)	A: Regional market; B: active code and nuiance reinforcement; C: selective demolition, target resources, and limit concentrated subsidized housing; and D: site acquisition and land assembly	Factor analytic cluster analysis	Guide more efficient decision making by matching resources, policies, and strategies with neighborhood conditions
Memphis, TN	Zone 1: Classic distressed neighborhoods; Zone 2: Vulnerable "swing" neighborhoods; Zone 3: Stable neighborhoods of choice; and Zone 4: Uptrending traditional neighborhoods	Census Tract/2007	Socio-economic variables, variables related to community development essentials, housing and neighborhoods factors, such as: crime, school quality, and health indicators	Encourage scaled intervention of code enforcement, rehabilitation and new construction development, demolition, and cosmetic repairs based on neighborhood conditions	Zones geographically categorized based on market criterion.	Stabilize neighborhoods and develop intervention for foreclosures; overlay zones with foreclosure data to guide investment decisions

Source: City of Baltimore NHMT, 2008; The Reinvestment Fund Philadelphia NHMT, 2001; Kansas City, Missouri 2007-2011 Consolidated Plan; City of Cleveland, Ohio Neighborhood Typology, 2008; City of Indianapolis, Indiana; and, the Center for Community Building and Neighborhood Action, University of Memphis be included in typologies to describe neighborhood housing conditions. The current literature supports these indicators as factors that affect neighborhood health (Ellen and Turner, 1997; Ellen et al., 2003).

Property values or home prices are common indicators used in all typologies as measures of neighborhood health or quality (Aaron, 1973; Ding and Knaap, 2003; and Galster et al., 2005). Bates (2006) suggests that many factors contribute to the quality of housing, but that the principal indicator of quality is price. Still, other factors are also considered important, including the physical condition of the housing stock, especially in terms of structure type, maintenance (as demonstrated by "good" or "fair" housing conditions), and unit structure material, such as brick (Accordino and Johnson, 2000; and Rohe and Stewart, 1996). The percent of owner-occupied units is also a common indicator included in typologies, as it is considered a gauge for neighborhood stability. Owner-occupied units tend to be cared for to a higher degree than renter-occupied units, and upkeep and maintenance affect property values and neighborhood health (Aaronson, 2000; Green and White, 1997; Harkness and Newman, 2002; Haurin et al., 2002; and Rohe and Stewart, 1996).

Socioeconomic factors are not widely used in typologies, as shown in Table 2. Only two cities, Memphis and Kansas, use these indicators in their typologies. Empirical studies that analyze the impacts of neighborhood characteristics on property values suggest that race, ethnicity, and poverty rates affect neighborhood conditions. These studies note that race and ethnicity define housing submarkets because minority residents as a group tend to have limited access to capital and other financial resources, which in turn affects their ability to invest in the maintenance and upkeep of their housing (Kain and Quigley, 1975; Galster, 1996; and Yinger, 1998). Based on these factors, Yinger (1998) suggests these households may be compelled to operate in separate housing markets due to their inability to access better housing or adequately invest in the upkeep of their current housing. When maintenance and upkeep of the housing stock is neglected, property values and the overall quality of a neighborhood tend to decline.

Other neighborhood conditions, such as crime, are also not widely used in the typologies listed in Table 2, with the exception of Memphis and Kansas. Empirical studies suggest that crime is an important factor because high rates of crime affect property values and therefore influence neighborhood health. Crime indicators include violent crimes, property vandalism, juvenile crime rates, and drug arrest rates in a neighborhood; however, these factors are generally under reported (Hellman and Naroff, 1979; Lynch and Rasmussen, 2001; Pandey and Coulton, 1994; and Schwartz et al., 2003). In addition, schools are also considered factors that may create separate submarkets within typologies based on achievement test scores, racial composition, and completion rates. School quality is only included in Memphis's typology. Studies suggest that neighborhoods with high achievement scores will positively influence property values (Haurin and Brasington, 1996; Jud and Watts, 1981; Schwartz et al., 2003; and Weimer and Wolkoff, 2001).

The percent of tax delinquencies and foreclosures are very common indicators used in all typologies in Table 2, with the exception of Memphis. The negative impacts of tax delinquencies and foreclosures have been the impetus behind other cities to develop NHMTs, such as Chicago, Illinois; New Orleans, Louisiana; and Cleveland, Ohio. Since 2005, the percent of tax delinquencies and rates of foreclosure have risen significantly in numerous cities, particularly those in the Midwest and Northeast. Increases in these factors have not only impacted poor neighborhoods but also stable communities. Other common typology indicators include housing structural characteristics, real estate loan data, and the percent of code violations and condemnation rates.

Lastly, neighborhood change indicators may also be used in typologies, as in Kansas's and Cleveland's typologies. Indicators may include population percent change and housing unit percent change at the census tract or block level. These factors provide an assessment of the condition of the neighborhood at multiple times. Changes in various indicators may show that the neighborhood is improving, worsening, or remaining the same. In most cases, cities that use percent change indicators in their typologies employ z-score methodology to place neighborhoods into market categories. This method enable analyst to standardize the comparison of neighborhoods with the rest of the city. Details about the z-score methodology are discussed below in the next section.

Geographic level and neighborhood boundaries

The unit of analysis is an important factor in the development of typologies. Cities may represent neighborhoods or submarkets in typologies by census blocks, census tracts, and other statistical geographic boundaries. The unit of analysis for typologies is based on two factors, which include the need for detail to differentiate among neighborhood markets or access to data. Empirical studies that develop submarkets for analysis use census block groups because they provide a relatively homogenous area to capture locational qualities of housing conditions (Bates, 2006). Cities may use larger geographic levels based on access to data at that level; however, this level of analysis may lead to obscure or inaccurate data outputs. For example, a neighborhood may be considered a census tract but may include three or more district types of market activity, which may result in misleading neighborhood market type assignments and present a different level of aggregation of the data. The city may be led to make an investment decision that may lump a stable neighborhood among distressed neighborhoods based on proximity. Submarkets tend to be built up from the smallest possible spatial unit (McClure, 2005). The smaller the statistical unit of analysis, the more accurate and detailed the submarket.

Methodology and Identification of Market Categories

Methods to identify neighborhood market types also differ among cities developing and using typologies. As presented in Table 2 above, various methods are employed to develop NHMTs. The cluster method is a commonly used statistical method in the development of typologies by cities and researchers (Abraham et al., 1994; Bourassa et al., 1999; and Bourassa, Hoesli and Peng, 2003). This method allows the researcher to separate primary housing and socioeconomic data into distinct categories within geographic areas. In addition, cluster statistical methods allow the researcher to see variations and ranges of the data at the neighborhood level. Z-score calculations are another method used to differentiate markets. This method allows cities to standardize neighborhood indicators and represent neighborhood categories based on criteria such that neighborhoods are fitted within zones based on percentages or thresholds among the data (Betts, 2008). The Z-score method is used to calculate the averages of each variable at the neighborhood block or census tract level.

Upon the identification of distinct neighborhoods or geographic area types, cities can then classify neighborhoods based on indicator conditions. This classification of neighborhoods consists of the city ranking areas by house prices, socioeconomic indicators, or neighborhood characteristics within a geographic boundary. The method of ranking neighborhoods allows the city to capture the quality of the neighborhood based on the range of the data in each cluster. Each cluster receives a market type based on the conditions of housing and socioeconomic indicators. Common market labels include stable, transitional, or distressed categories.

As shown in Table 2, market classifications vary and communicate different purposes. Baltimore; Philadelphia, Pennsylvania; and Cleveland use classification labels to infer how housing markets compare with citywide and regional markets. Kansas City's classification system exhibits the direction and intervention strategies for neighborhoods, including developing areas, redeveloping areas, or stabilization areas. Memphis puts its neighborhoods in zones based on neighborhood conditions. The range in market labels among sample cities in Table 2 is not indicative of variables used to develop typologies. Regardless of the variables used in the typology, each city employs very similar labels.

Matching Strategies to Market Conditions or Taxonomies

In general, typologies are used under the assumption that neighborhood conditions vary across the city and that different strategies are relevant to different neighborhoods based on the unique conditions of communities. The identification of market categories allows cities to take next steps and prescribe revitalization or preservation strategies to each category. This step assists cities in prioritizing resources and investment decisions based on market conditions. Revitalization strategies in more distressed areas tend to include massive redevelopment of vacant properties, rehabilitation of deteriorated housing stock, improvements to commercial façade treatment, and other physical and structural changes. Based on the magnitude of the investment, cities may direct this strategy to areas exhibiting lower levels of disinvestment. Other strategies include preservation, which focuses on addressing problem properties through code enforcement. This strategy tends to be used in less distressed neighborhoods because governmental intervention is minimal. Stabilization emphasizes the need to support homeownership and property maintenance. This strategy may be employed in transitional areas.

General Discussion of Typologies and Theories

Empirical studies suggest that housing submarkets are composed of socioeconomic and structural housing variables (Bourassa, Hoesli and Peng, 2003; Goodman and Thibodeau, 1998). Additionally, studies assert that location variables, inclusive of socioeconomic variables and the physical conditions of nearby properties, also influence the formation of housing submarkets (Goodman and Thibodeau, 2007; Bourassa, Cantoni and Hoesli, 2007). Literature on submarkets presents discrepancies in whether variables comprehensively define submarkets or whether variables in isolation are best to define markets (Day, 2003; Fik, Ling, and Mulligan, 2003; and Brasington, 2005).

In review of the six sample cities included in Table 2, all cities presented a variation of variables to define neighborhood housing markets based on different purposes. For typologies with the purpose to provide a general overview of the neighborhoods to guide investment strategies, policy makers relied on housing related variables such as home sales values, type of home (i.e., single family), and home tenure. Cities that used typologies for stabilization strategies to counteract a specific event in the city, such as a sudden upsurge in foreclosures, relied on both housing and socioeconomic variables. In this case, foreclosures may be tied to household socioeconomic status, to track predatory lenders; or housing condition, to track homes in later stages of abandonment. These sample cities included change variables such as population or housing unit change to reflect change from one time period to another. This technique may be useful to allow cities to determine the direction of change and impacts of the event on neighborhoods. However, the inclusion of different variables may have influenced the methodology employed to cluster neighborhoods into distinct categories.

The z-score method may be a more simplified tool used by cities without access to or capacity to run statistical cluster methodologies. However, the limitation of the method is based on the fact that cases are not compared to nearest neighbor but to city-wide averages. The inclusion of socioeconomic or percent change in socioeconomic variable may obscure the analysis. For example, the city may lose a large percent of the population and therefore gains at the census block level may allow the tract to rank at a higher level in the analysis. This gain may be in a neighborhood of a lower housing quality but compared to city-wide changes in the z-score method, the neighborhood may be seen as a higher quality. Strong neighborhoods may lose population and gain population at similar rates as more distressed neighborhoods. Additionally, housing conditions may not reflect the socioeconomic status of residents. For example, a low-income neighborhood may be improving due to massive redevelopment but still contain a high percent of low-income households, high unemployment rates or a significant percent of households receiving public assistance. If these variables are included in the z-score analysis based on city-wide averages, neighborhoods with stronger housing values but low socioeconomic conditions may be misrepresented.

The proper identification of variables to assist in tracking and analyzing the key dimensions of their neighborhood housing markets is important for neighborhood monitoring purposes and to guide reinvestment strategies. In this review of the literature, scholars present mixed assertions of which indicators are useful in the development of distinct submarkets, and method used to explore submarkets vary. Some scholars claim socioeconomic variables are indicators of housing markets while others argue that housing characteristics alone are important indicators. There is also more recent literature on the construction of typologies or submarkets which employ hedonic regression models, and other spatial statistical method for defining housing submarkets (Bourassa et al., 1999; and Bourassa, Hoesli and Peng, 2003; Goodman and Thibodeau, 2007; Bourassa, Cantoni and Hoesli, 2007). However these studies do not include many of the observable variables used by the sample cities in their construction of typologies. There are numerous gaps in the review of other cities' selection of variables and few studies that evaluate the indicators used to construct typologies.

1.5. REDEVELOPMENT IN BALTIMORE AND NEIGHBORHOOD HOUSING MARKET TYPOLOGIES

The Study Area

To assess the impact of housing investment on property values, data from the city of Baltimore was used in this study. The beginnings of Baltimore's population decline began in the 1970s due to significant job losses in the commercial, shipping, and steel industries (Schumacher and Lietner, 1997). Between 1970 and 1990, the city lost approximately 170,000 residents, representing a 23 percent decline in population. Mirroring most post-industrial cities, Baltimore has suffered a mass outmigration of residents to surrounding suburban communities. In the 1990s, the city's population represented just 25 percent of the regional population (Baltimore Housing Report, 2005). Higher levels of unemployment and population losses in the 1980s adversely affected Baltimore's residential and commercial districts, causing the city's downtown to empty out, leaving abandoned warehouses and vacant Harbor properties. These effects brought a wave of redevelopment in the city in the late 1960s.

Redevelopment in Baltimore

City-wide abandonment and spreading decline presented opportunities for Baltimore's downtown with the development of urban renewal plans and activities. In 1963, a redevelopment plan was created for Charles Center, a disinvested area located just north of downtown. This plan was followed by another urban renewal plan for Baltimore's Inner Harbor. The Charles Center plan focused on redeveloping existing commercial and housing sites through an aggressive mixed-use strategy, while the Inner Harbor plan demolished existing housing and businesses for a new vision that included a significant amount of retail and commercial office space. The plans focused heavily on commercial redevelopment because the private sector investors felt there was little residential demand given the city's persistently declining population.

In the 1980s, neighborhoods adjacent to the harbor began to turn around due to spillover from the Inner Harbor development. The city directed heavy acquisition and redevelopment into areas directly east and west of the harbor, including Federal Hill, Fells Point, Locust Point, Canton, and Little Italy. Additionally, the city provided over

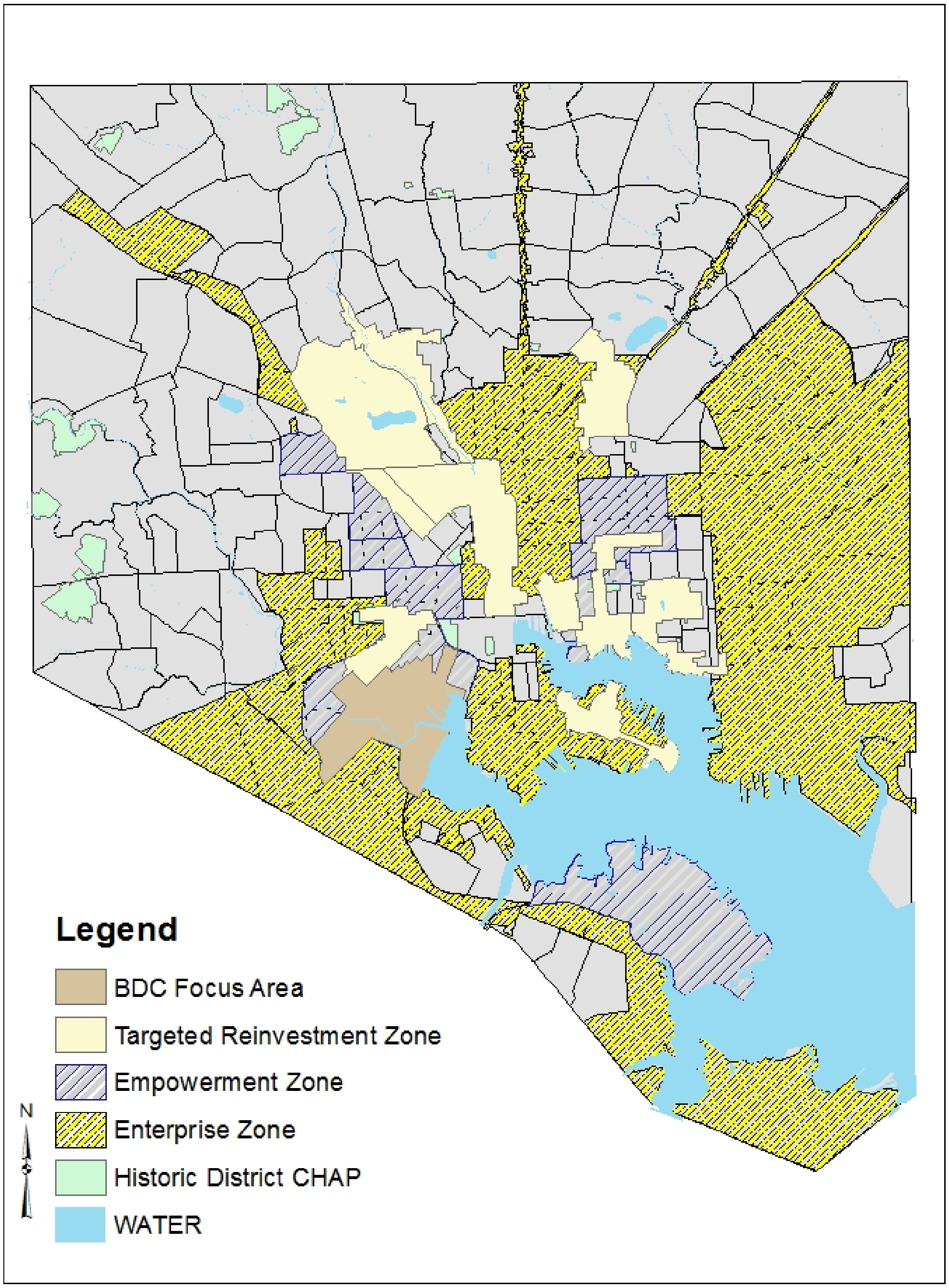
100 residential properties to private developers for rehabilitation projects in accordance with area design guidelines and regulations. By the 1990s, these neighborhoods experienced rapid physical improvement and ultimately gentrified. Commercial businesses, especially in the technology industries, also begin to relocate to the downtown area.

In Baltimore's Westside area, neighborhoods adjacent to Charles Center also experienced positive effects in the 1990s, like Mt. Vernon and Seton Hill. Areas around the Mt. Vernon neighborhood were targeted with commercial and retail development led by the Baltimore Development Corporation (BDC). BDC was incorporated as a non-profit organization in 1991 to focus on economic development initiatives in the city. In Baltimore's downtown area, BDC activities included the installation of a light rail station, commercial center, and the Lexington market, a large food market near the downtown. BDC also administered Enterprise Zone incentives, Tax Incremental Financing (TIF), and assistance in the development of urban renewal plans. Tax incentives in the form of property and employment tax abatements were offered to business located within BDC service area. In addition, BDC developed partnerships to attract mixed use commercial and retail, University of Maryland medical school support services, and the rehabilitation of the Hippodrome Theatre.

Figure 2 maps the redevelopment target zones created in the city, including Empowerment Zones, designed to address economic and community revitalization; Target Investment Zones, prioritized areas that receives incentives to generate private investment; and other zones related to heritage preservation and state-wide priority areas. While some areas revitalized in these zones, neighborhoods just three to five blocks away from the Harbor were still plagued with poverty disinvestment and high crime rates. For example, the Canton neighborhood, a historically Non-Hispanic White working class neighborhood with a strong industrial base, experienced population increases and an infusion of new private development (Hopkins Institute, 2005). However, Hampton, a similar neighborhood located in Northern Baltimore, experienced population decline and property disinvestment in spite of slight revitalization efforts in the 1980s. Between 1980 and 2000, Canton experienced a 19 percent population increase, while Hampton's population declined by 17 percent. At the same time, contrasting characteristics of the two neighborhoods are significantly linked to the surplus of housing in the city. Unemployment and population losses had only triggered the predominate challenges affecting Baltimore since the 1970s, including neighborhood blight, abandonment, and disinvestment. Ten years later, in 2010, Canton experienced increases in foreclosures and drops in home values due to extensive speculation, while Hampton experience slight increases in foreclosure based on risky mortgages by new homebuyers.

Since Baltimore's population began to decline in the 1950s, the city was classified as "under-crowded," defined by Rae and Calsyn (1996) as the pattern of persistent of population loss that leaves behind a large surplus of unused buildings and land. Much of the new development in neighborhoods surrounding the Inner Harbor and Charles Center in the 1980s and 1990s allowed stable and affluent households to filter up into better housing, leaving behind even more vacancies in neighborhoods north of downtown.

Figure 2: Reinvestment Zones in Baltimore (Including BDC target Area, Historic areas, Empowerment Zone, Enterprises Zone, TIF (Target Reinvestment Zone)).



Source: Data collected from Baltimore City's GIS department.

In 2000, the city's abandoned housing units ranged from 12,700 to 42,480 based on the city's count of units and the 2000 decennial census (Cohen, 2001). Baltimore had nearly 6,000 vacant properties through tax foreclosures, and once it factored in other city-owned properties, that number increased to 10,000 (Baltimore Housing Report, 2005-2010). Some of the hardest hit neighborhoods were located just outside of Baltimore's Inner Harbor and downtown, with poverty rates over 40 percent and median household incomes at $10,000 to 15,000 (Baltimore Housing Report, 2005-2010). By 2010, the impacts of the economic crises and ten years of disinvestment in the most distressed neighborhoods caused foreclosure rates to increase by approximately 10,000 additional properties, further exasperating declining conditions in neighborhoods.

To counteract increasing neighborhood disinvestment and address the mounting number of vacant units, the city used numerous housing programs to create better quality housing opportunities for its residents; these include CDBG funding (since 1980, approximately $28 million annually); HOME Program investments (since 1992, approximately $8 million annually), HOPE VI (1994); LIHTC (since 1992); and a host of others. CDBG dollars provide blight elimination funds, such as housing construction, counseling, and supported community development initiatives in neighborhoods. HOME Program dollars are used for new construction and rehabilitation of rental properties in neighborhoods. Other housing programs, such as Section 108 loan funds, were also used to address property acquisition and demolition. The city used more than $6 billion of federal funds to transform major public housing developments plagued with crime and poverty into HOPE VI Program projects (Baltimore Housing Report, 2005-2010). The HOPE VI program was established in 1993 by the Department of Housing and Urban

Development to de-concentrate public housing developments and combine market rate and subsidized housing in one development. Two sites, Lexington Terrace and Lafayette Court, now known as The Townes at the Terraces and Pleasant View Gardens respectively, were redeveloped in 1995 and 1997.

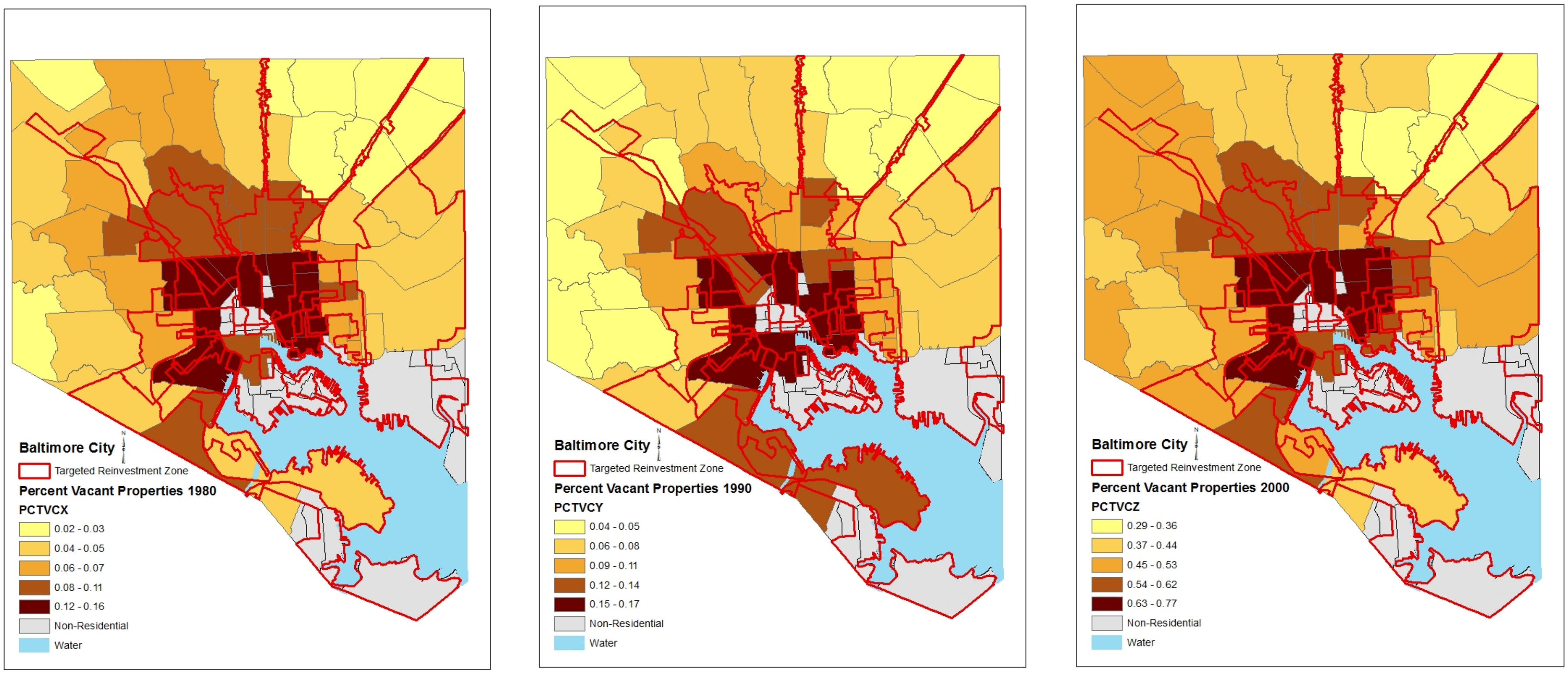
Despite decades of federal funding, few areas in Baltimore have experienced improved conditions. Figure 3 below maps the percent of vacant properties for 52 neighborhoods in Baltimore for years 1980, 1990, and 2000. Targeted reinvestment zones are highlighted on these maps. Using vacant properties as an indicator of neighborhood conditions, these maps show that over 30 years, vacant properties increased in neighborhoods near the downtown area. Between 1990 and 2000, only neighborhoods near the Inner Harbor showed improvements, while areas further north showed increased abandonment.

In the late-1980s and early-1990s, Baltimore neighborhood organizations began to strategically target public investments on a block-by-block method near neighborhood assets such as community parks. The Patterson Park neighborhood started a community development corporation and is an example of a neighborhood organization that reinvested in vacant and problem properties owned by absentee landlords on selected blocks near the neighborhood park.

By 2000, the downtown area began to thrive again with redevelopment around the Harbor. However, neighborhoods only two to three blocks away were still considered blighted,

abandoned, and racially segregated. Between 2000 and 2010, Baltimore's population continued to decline as shown in table 3 below. However, population losses during this

Figure 3: Percent Vacant Properties for 1980, 1990, and 2000



Source: Geolytics, U.S. Census data

ten-year period were not as significant as in the past. The city's total population declined only 2 percent, while population totals in the region increased by approximately 4 percent.

Table 3: Baltimore Socio-Economic Change from 1970-2010

	Total Population		City population	Poverty Rate		Median HH Income (%)		Unemployment Rate (%)	
Years	City	MSA	as % of Metro	City	MSA	City	MSA	City	MSA
1970	905,759.00	2,089,092.00	0.43	18	11.1	$30,851.00	$ 39,289.00	4.6	3.4
1980	786,775.00	2,199,531.00	0.36	22.9	11.9	$29,398.00	$ 42,949.00	10.7	6.6
1990	736,014.00	2,382,172.00	0.31	21.9	10.1	$32,306.00	$ 49,107.00	9.2	4.8
2000	651,154.00	2,552,994.00	0.26	22.9	9.8	$30,078.00	$ 49,938.00	10.7	4.9
2010	620,961.00	2,642,928.00	0.23	20.9	7.6	$38,458.00	$ 64,812.00	11.7	6.0

Source: Baltimore Housing Report 2010 and 2000 and 2010 U.S. Census

According to table 3, unemployment in the city dropped from 10.7 percent in 1980 to 9.2 percent in the 1990s, and continued to decrease to 6.8 percent in 2000. A 2010 Baltimore Housing Report stated that high wage manufacturing jobs were no longer the major employment sectors in Baltimore in 2000, with job declines from 11.5 percent in 1985 to 7.8 percent in 2000, representing a significant drop from 34.1 percent in 1950. In this report, between 2005 and 2010, unemployment rates fluctuated with increases in 2005 to 8.3 percent, declines in 2008 to 6 percent, and a jump in 2010 to 11.7 percent. The 2010 unemployment rate did not change significantly between 2000 and 2010, but it was still higher than the region.

Although many distressed neighborhoods did not improve in the city, between 2005 and 2008, housing prices and sales in Baltimore underwent drastic changes. In 2005, the number houses sold in the cities peaked, and in 2007, homes sales prices were the highest ever recorded for the city. After 2007, even though the city experienced gains in per capita income in 2008 and declines in the number of households in poverty, the city was still affected by the national economic crisis. The house price bubble hit

Baltimore shortly after 2008, causing prices to plummet well into 2009. In 2008, the number of homes that sold in the city dropped to 38 percent from the previous year in 2007 (Baltimore Housing Report, 2010).

Lower home values coupled with high rates of unemployment caused a rise in foreclosure filings. In 2009, the city recorded 5,902 foreclosure filings compared to 3,062 filings in 2006. Figure 3 show that between 2007 and 2009, vacant properties increased by 800 units (4 percent) to a total of 16,594 properties. While many of these units were suitable for rehabilitations, most were located in distressed areas with little to no market value. Most sales and the largest increases in median prices between 2001 and 2007 occurred within these weaker markets due to speculative buying, which pushed up prices in 2006 and 2007. This period of the bubble not only affected housing prices but also raised rents. While the number of sales and home prices dropped significantly, the average monthly rent in the city increased from $650 to 900 with new demand from previous homeowners impacted by foreclosures (Baltimore Housing Report, 2010). Though many aggressive efforts were initiated in the city, waves of foreclosures seem to keep efforts from being successful.

The Healthy Neighborhood Initiative (HNI), established in 2001, was one progressive effort the city used to impact declining neighborhoods. Through a partnership with philanthropic groups and later with the city, HNI used approximately one percent of CDBG and HOME dollars and Neighborhood Improvement grants to develop a neighborhood-based initiative to target neighborhoods on the brink of transitioning towards economically distressed areas. These neighborhoods were represented by areas that exhibited few vacant properties, initial signs of disinvestment, and declining property values. HNI selected just 15 or 29 percent of Baltimore neighborhoods to concentrate investments. Neighborhoods were selected through a data-driven process that focused on housing structural conditions, sale prices, vacancy rates, and neighborhood potential. Housing rehabilitation and acquisition were the focus of HNI efforts, along with capital for homeownership assistance and neighborhood empowerment efforts on selected blocks in HNI neighborhoods.

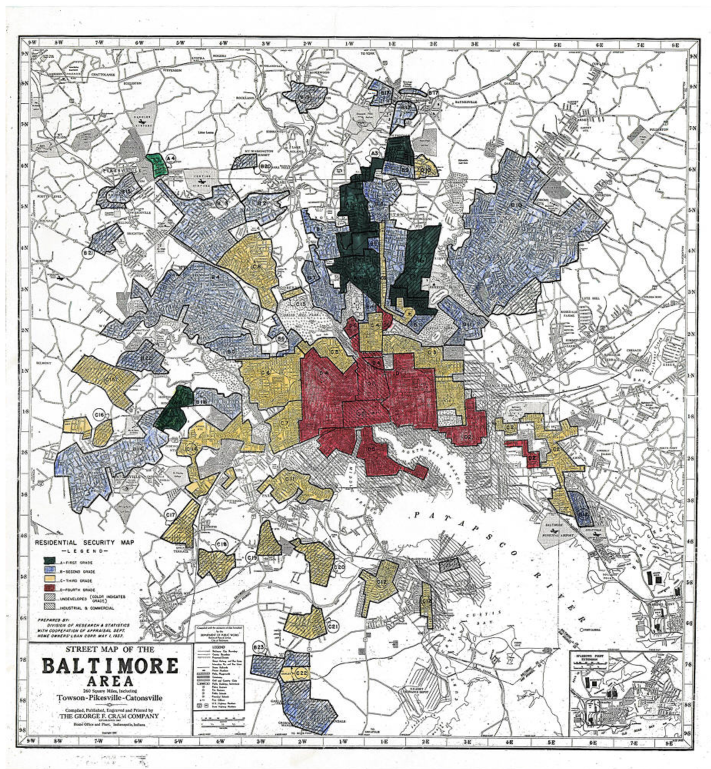
Based on a real estate analysis of HNI efforts at the census block level, between 2000 and 2006, selected neighborhoods demonstrated positive impacts. Favorable effects included increases in home sale prices, declines in the number of vacant units, decreases in homes remaining on the market for more than 120 days, and increases in the number of homes sold in target blocks (Boehlke, 2002). With such successes, the city began to use data driven processes to prioritize neighborhoods for intervention strategies. One such method was the development of NHMTs.

Baltimore's NHMTs

HNI was the first initiative to use data driven analyses to select neighborhoods to target housing investments. In 2002, an NHMT was developed for Baltimore, which categorized neighborhoods into classifications based on housing type and neighborhood characteristics. For each neighborhood classification, a specific government intervention was identified. HNI used the typology to identify middle market neighborhoods to target reinvestment strategies. The 2002 typology was not the first time the city mapped its neighborhoods into market categories. Baltimore neighborhoods were first categorized in 1937 to provide a market understanding of its neighborhoods to real estate agents. Figure 4 below shows a hand drawn map developed by the Home Owners Loan Corporation

(HOLC). Areas coded as red were neighborhoods considered devalued and areas coded as yellow were areas where the government recommended the issuance of mortgages with caution and strict terms. Areas coded as green were given the highest grades, meaning mortgages were available for qualified buyers at liberal terms.

Figure 4: 1937 Hand drawn redline map of the City



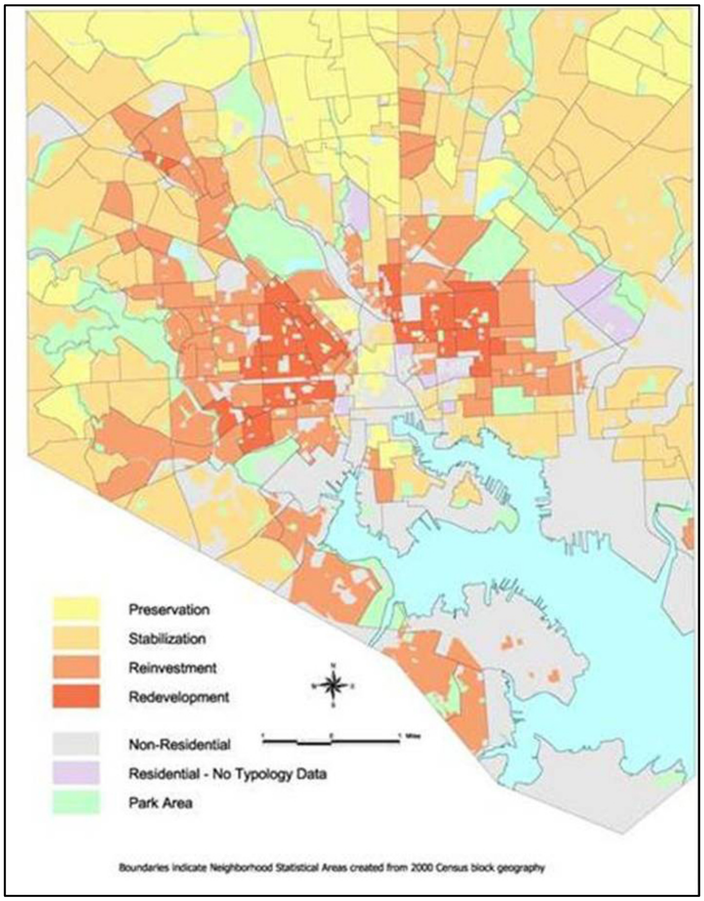
Source: Pietila, 2010

The implication behind color-coding neighborhoods led to negative impacts for the city, as predominately Jewish and Black neighborhoods were redlined. Most Jewish and Black households resided in areas labeled as red on the map. Wealthier areas like Roland Park were excluded from green areas due to housing age, while areas like Guilford, Homeland, and Northwood were given high grades because the housing was newer and the population consisted of young, middle class Protestant families. The latter neighborhoods contained deeds that excluded Black and Jewish households.

Unlike the neighborhood classifications developed in the late 1930s, Baltimore's 2002 typology was developed strictly based on data analysis for community statistical areas, which were agglomerated census tracts, and each classification was given a revitalization strategy to stabilize neighborhood conditions. Three indicators—abandonment rate, median assessed home value, and percentage of homeownership rate—were used in the initial typology. To categorize neighborhoods based on these indicators, the city used the cluster statistical analysis method to compare neighborhoods. Neighborhoods were grouped into four categories, including preservation, stabilization, reinvestment, and redevelopment. This snapshot of Baltimore neighborhoods, as shown in Figure 5 and Table 4 below, assisted policymakers in prioritizing and targeting public intervention (i.e., code enforcement, property rehabilitation, and demolition) according to market conditions. Unfortunately, the reliance on census tracts creates an analytical constraint.

Census tracts tend to have a population size between 1,200 and 8,000 people, with an optimum size of 4,000 people or 2,500 households (U.S. Census Bureau, 2010). A census tract will cover a contiguous area; however, the spatial size, in terms of square mile distances of the census tracts, varies widely depending on the density of area. Even with an average of 4,000 people, this geographic area still obscured the typology and skewed the results, which were originally intended to help create distinct housing markets. One census tract could contain several different markets not captured based on the aggregation of data at the tract level. This limited the usefulness of the analysis and made it difficult for policymakers to decide how to intervene in the neighborhoods.

Figure 5: Baltimore 2002 Neighborhood Housing Market Typology



Source: City of Baltimore Planning Department. Unit of analysis are census tracks with only four market categories.

Table 4: Baltimore Neighborhood Statistics by the NHMT

Type	# Neighs.	% 2000 Pop.	% City Pop.	Population Change 1990-2000	% Female Headed HHs	% Vacant	% Owner Occupied	% HS Grad	% BA+	% Not In Labor Force	% Poverty
Preservation	36	73,711	11	2.6	3.9	7.8	49.2	85.8	52.7	38.4	13
Stabilization	103	291,866	45	-6	11.3	9.3	57.5	73.6	20	38.6	15.9
Reinvestment	69	192,309	30	-18.3	17.8	17.3	46.7	59.4	9.4	46.1	29.2
Redevelopment	21	71,656	11	-43.5	21.6	28.4	31	51.5	4.7	52.7	41.5
Residential - No Typology Data	10	18,881	3	5.4	20.5	15.2	30.3	57.4	6.9	73.4	44.2

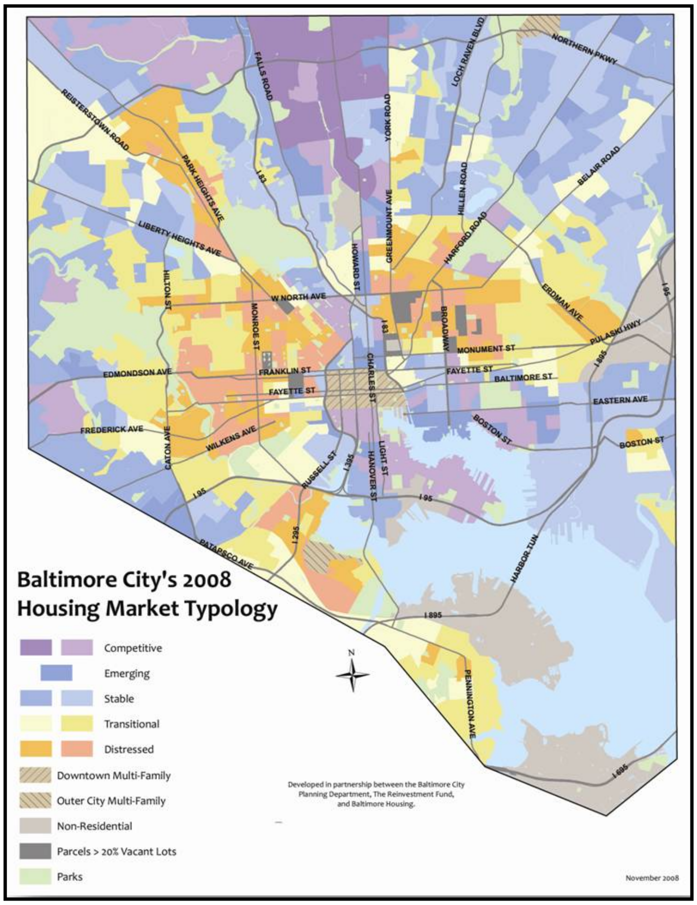
Source: U.S. Census adapted from the Baltimore Housing Consolidation Plan (2005)

In 2005, the city revised the typology, based on census blocks, a smaller unit of analysis, in order to encompass more market variations, as well as additional housing related variables. The city's updated NHMT included additional variables to better explain neighborhood housing markets and conditions. The new typology included the following additional variables: percent of vacant homes and lots; percent of foreclosures, percent of single-family homes; percent of commercial land; and percent of residential rental subsidies. Three years later, in 2008, the city experienced substantial increases in vacant properties and mortgage foreclosures with the collapse of the local housing market. The city owned approximately 15,000 vacant housing units and listed approximately 6,000 vacant property filings. Although house prices in the city continued to rise, the number of home sales dropped for the first time in six years since 2001 (Baltimore Housing Report, 2005-2010). As such, in 2008, the city added additional market types with labels that demonstrated neighborhood markets as shown in Figure 6 below. Previous labels referred to intervention strategies. An increase in the number of different market types allowed the city to develop more refined descriptions of neighborhood conditions.

HOME Partnership Program in Baltimore

This study will focus on the HOME Program in Baltimore and its impact on neighborhoods. The HOME Program will be described from a national perspective and then within the context of Baltimore. It is important to understand how HOME dollars have been used for the production of affordable rental housing to provide a framework for how local communities should allocate these federal dollars in their neighborhoods.

Figure 6: Baltimore 2008 Neighborhood Housing Market Typology



Source: City of Baltimore Planning Department. Unit of analysis are census blocks with nine market categories.

HOME: National Perspective

The HOME Program debuted in 1992 as one of the largest federal block grant programs. It supported state and local government efforts to salvage and preserve the aging housing stock, build affordable housing, and provide homeownership opportunities for low- and moderate-income households. The HOME Program is a block grant that consists of multiple categorical grant programs bundled into one large program. These program areas include the Rental Rehabilitation Program, the Urban Homesteading Program, the Section 312 Program, and the Nehemiah Program. As a block grant, the HOME Program gives recipient state and local governments the discretion and flexibility to spend funds as they see fit.

The purpose of the HOME Program is to increase affordable housing in communities through property acquisition, new construction, rehabilitation, home-buyer assistance, and tenant-based rental assistance (US Department of Housing and Urban Development, 2004). The guiding principles of the program include: (1) provide flexibility to design and implement revitalization strategies tailored to the needs and priorities of a community; (2) consolidate planning efforts to facilitate public and private sector partnerships; (3) build neighborhood-based capacity by providing local technical assistance for non-profit groups; and (4) require grantees to leverage at least 25 percent of the total grant award through cash match or in-kind services. Based on these principles, HOME funds are used in a number of ways, supporting low-interest loans, deferred loan payments, and loan guarantees (US HUD, 2004). The HOME Program also offers assistance with property acquisition and new construction, with particular focus on rental unit renovation and new construction. These services will be the focus of this analysis.

HOME Eligibility

Beyond providing affordable housing to low-income households, the HOME Program is intended to improve and maintain the quality of existing housing stock. The program was designed to target poor households to ensure that populations demonstrating the greatest need can access these federal funds. At the same time, the flexibility of the program allows persons in other income brackets to also access funds, just as long as their income does not exceed 80 percent of the area median income (AMI).

Nationally, a large portion of households earning above 50 percent AMI used HOME funds. For HOME homebuyer units, approximately 46 percent of households earn between 60 to 80 percent of the AMI. As such, this Program targets more than just the most distressed households. HOME funds are also targeted according to household types, to include homeless individuals and families, families with children, large households, senior families, persons with disabilities, and those that rely on public assistance.

HOME Activities

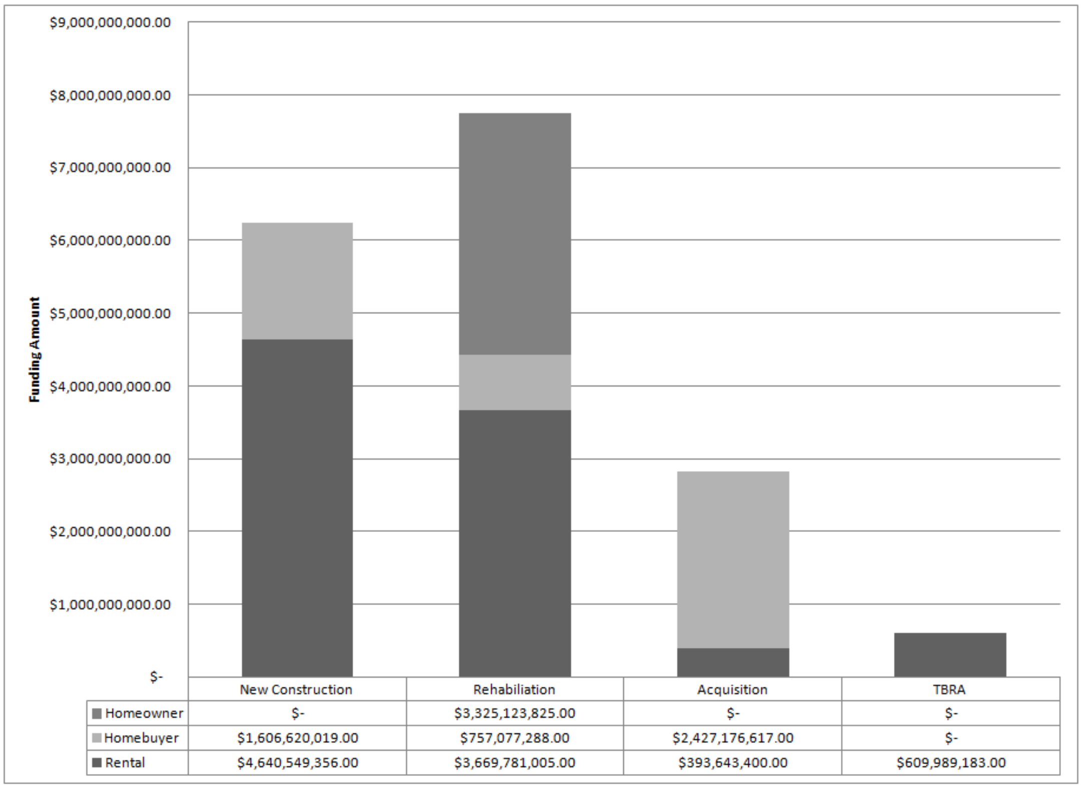
The HOME Program provides resources to individuals through supply-side assistance and works to improve place though production-side assistance. For owners who cannot afford to maintain their homes, HOME funds can be used to cover the cost of necessary repairs. The Program is also designed to restore vacant properties to improve neighborhood conditions. Nationally, 42 percent of HOME funds are used for housing rehabilitation, 24 percent of HOME funds are used for new construction, and 34 percent of funds are used for property acquisition. Of this total, roughly 42 percent are rental, 38 percent are homebuyer, and only about 20 percent are homeowner tenure (HOME Investment Partnership Program, 2004).

HOME funds may be used to assist new and existing homebuyers, but the Program's main focus is renters or rental property owners. Fifty-four percent of HOME funds as a total of dollars for all activities are used for rental housing and 28 percent is used towards homebuyer programs. Since 1992, the HOME Program has produced 217,121 new construction housing units and assisted in the rehabilitation of 385,075 units, representing 24 percent and 42 percent of all HOME activities, respectively. Figure 7 below show total cost of HOME activities by type and tenure nationally from 1992 to

2009. Table 5 below shows the cost-per-unit of HOME activities by type and tenure.

The average cost for a new construction rental unit requires $29,430 in HOME funds, while new construction homebuyer units are slightly lower, at an average of $27,029. The average cost for the rehabilitation of a rental unit is $21,432, while the

Figure 7: HOME Activities by type and tenure



	New Construction	Rehabiliation	Acquisition	TBRA
Homeowner	$-	$3,325,123,825.00	$-	$-
Homebuyer	$1,606,620,019.00	$757,077,288.00	$2,427,176,617.00	$-
Rental	$4,640,549,356.00	$3,669,781,005.00	$393,643,400.00	$609,989,183.00

Source: U.S. Department of Housing HOME Dashboard for funds committed from 1992 to 2009. This figure illustrates the total cost of HOME activities based on the total number of HOME production units funded (includes rental units produced, new homebuyers, and existing homeowners assisted) nationally in billion. TBRA is Tenant-based rental assistance. Areas are blank in columns because dollar amount does not apply.

rehabilitation of a homebuyer unit costs $23,435. HOME dollars are leveraged with other HUD programs, including Low Income Tax Credits and Section 8. Each HOME dollar is able to leverage $3.75 in public and private investment, which ensures community buy-in for housing redevelopment projects (US HUD, 2009).

To use HOME funds effectively, recipients must have an understanding of the local housing market, including characteristics of the household's socioeconomic status, housing conditions and tenure, and other market conditions to prioritize and direct public resources to urgent housing challenges. The targeting of households based on socioeconomic conditions and family type is a requirement of this program. Spatial targeting of resources is not a requirement of the program, but since 2000, a growing number of cities with declining budgets have begun to target resources in areas for visual impact and to leverage neighborhood resources.

In 2004, the HOME Program encouraged participating jurisdictions (PJs) to consider concentrating HOME funds at the neighborhood level based on the availability of buildable land, neighborhood anchors and assets, and infrastructure to support community development and growth of the community. HUD program offices cautioned PJs that investments should be targeted in small redevelopment zones for greater visible impact to avoid dispersed activities and investments. PJs were encouraged to target areas

Table 5: HOME Cost per Unit by Activity Type and Tenure

Activity	Rental	Homebuyer	Homeowner	Average
New Construction	$ 29,430.00	$ 27,029.00	N/A	$ 28,773.00
Rehabilitation	$ 21,432.00	$ 23,435.00	$ 18,316.00	$ 20,131.00
Acquisition	$ 23,632.00	$ 8,269.00	N/A	$ 8,094.00
Average	***$ 25,188.00***	***$ 12,435.00***	***$ 18,316.00***	***$ 18,435.00***
TBRA	$ 2,502.00	N/A	N/A	$ 2,902.00

Note: Tenant based rental assistance (TBRA) programs are not available for homebuyer and ownership programs because this activity only support rental. Homeowner grants are not supported by new construction activities or acquisition. Costs are average dollars listed as of 2009.

within a quarter-mile radius from the neighborhood center; areas near existing neighborhood strengths, such as schools to attract potential homebuyers; areas with few tax delinquencies; and areas with supportive infrastructure for home designs and amenities to attract mixed used development.

HOME Partnership Program in Baltimore

Baltimore uses HOME funds as the major funding to target poor households and provide suitable and affordable housing options. Since 1992, HOME funds have been the city's major investment vehicle to address suitable housing needs for low-income households through new construction and rehabilitation. Of the total HOME dollars, approximately $47 million has been allocated to the city for housing and community development since 1992. According the City of Baltimore's dashboard report, in 2005, HOME represented just 6 percent or approximately $7 million of this total funding. The city has allocated a total of $138,036,051 between 1992 and 2010. In this time period, approximately 78 percent of HOME dollars had been used for the new construction of rental units and 22 percent for homebuyer units, and only eight percent for homeowner-rehab units. Of these units, HOME funds have served 14.2 percent and 5.5 percent of Non-Hispanic White households for rental and homebuyer units respectively. HOME dollars have been used to serve 84.5 percent and 87 percent of African American households for rental and homebuyer units, respectively. Hispanic/Latino households represent a small percentage of HOME fund recipients, with less than one percent of households receiving assist for rental units and two percent for homebuyer units.

The disbursement of HOME dollars among groups is reflective of Baltimore's racial and ethnic composition. In 2010, the City contained 28 percent Non-Hispanic White households, a slight decline from 31 percent in 2000, compared to 63 percent African American households, also a slight decline from 64 percent in 2000. Hispanics/Latinos Inner Harbor have experienced positive impacts due to downtown redevelopment and new businesses, most of the neighborhoods three blocks north of the

Harbor still exhibit high levels of abandonment and blight. Most HOME investments are located within these neighborhoods, which include Heritage Crossing, Harlem Park, Franklin Square, Barclay, and Hollins Market. HOME investments are also in more affluent- to moderate-income neighborhoods, such as Canton, Butcher's Hill, Midtown, Fells Point, and Beliar-Edison.

Since 2001, much of Baltimore's HOME dollars have declined, and the city's CDCs have had an increasingly prominent role in the allocation and use of HOME funds. Some organizations use funds on scattered site developments, while others use funds on a block-by-block basis in a more targeted effort. Unfortunately, the magnitude of blight in distressed neighborhoods and market factors in less distressed neighborhoods present questions about the impact of the program across the city. In this light, it is important to understand the effects of investments in various neighborhoods given their different market conditions or market types.

HOME Policy Challenges and Limitations

Two analyses of the HOME Program have been completed to date; one following the inaugural year of the program, and another four-year analysis of how PJs used program funds and how they understood new requirements as an amendment of the program (Nelson and Khaddurri, 1992; Khuddurri and Rodda, 2004). However, a thorough analysis of the HOME Program has not been conducted to evaluate its effects in neighborhoods.

Nelson and Khaddurri's (1992) analysis of the HOME Program found that HOME resources are insufficient to address problems facing poor households. They assert that "the efforts to remedy all housing problems will always fall short because the solutions require more funding than can be made available. These programs cannot produce enough units to generate sufficient filtering to provide adequate housing for all the poor who are in need" (Nelson and Khadduri, 1992, p. 33)." Nelson and Khadduri claim that the HOME Program remains insufficient in that production subsidies fall short of meeting the housing supply needs of the urban poor. The authors argue that there is a significant gap between households with the greatest need and the intent of the housing programs. In review of housing programs similar to the HOME Program, Apgar's (2008) evaluation of housing policies finds that the best housing policies are programs that targeted areas based on household needs, in a manner that needier households benefit from the intervention, instead of being displaced due to area-wide gentrification.

Beyond determining whether poor households are the recipients of housing policy efforts, scholars have long debated whether HOME dollars and other housing programs can actually lead to neighborhood revitalization (Khadduri, Burnett, and Rodda, 2003; and Galster et al., 2004). The HOME Program appears to have two conflicting goals. The first goal is to provide affordable housing for lower-income households, by targeting subsidies with income restrictions based on household income level. The second goal is to promote neighborhood revitalization through the rehabilitation and development of housing to address neighborhood quality and improvement. According to Nelson and Khadduri (1992), the current structure of the Program cannot provide affordable housing opportunities for low-income households without negatively impacting households who were to benefit from the Program. New investments may increase surrounding property values, and therefore, displace poor households. However, the authors conclude that investments may positively influence surrounding properties. Despite this, there is reason to believe that such subsidies may not lead to the revitalization of distressed neighborhoods. Increased housing values may indicate that the housing investment was successful, but few studies have found that housing investments have improved the quality of distressed neighborhoods (Galster et al., 2002; Cummings et al., 2002; and Briggs et al., 1997). These scholars assert that public subsidies can be used to stabilize neighborhoods, but extremely distressed neighborhoods may be beyond the point where revitalization can occur with the support of production subsidies. These subsidies may present only modest improvements to a portion of the neighborhood's housing units, but as single investments, they do not constitute a critical mass of resources (Khadduri, Burnett, and Rodda, 2003).

1.6. TYING IT ALL TOGETHER - CONCLUSIONS

This review of the literature provided an overview of the evolution of government policies and investment impacts on neighborhoods; the research, theory, and use of NHMTs; and to develop a framework to evaluate the impact of housing production programs such as the HOME Program in Baltimore. According to the existing literature, it is apparent that it remains unclear of whether government investments, particular housing production programs, have significant effects on neighborhoods.

In review of PBPs from 1950 to the present, it is evident that investments that were targeted in smaller areas based on market conditions present clear measurable impacts. The larger the geographic target area, the less likely impacts will be perceived. This was evident in the comparison of PBPs in the 1950s through the early 1990s, and those in the 2000s. PBPs in the 2000s were market conscious, data driven efforts that guided investment in smaller areas. This smaller geographic focus presented positive effects on neighborhoods and was easily measured, while PBPs before 2000 present mixed or few results, such as EZs.

A review of empirical studies that evaluate the impact of these PBPs on neighborhoods found that the measurable impacts of investments on property values are linked to neighborhood conditions and the scale of the investments. Other empirical studies find distances, such as property located within 150 to 300 feet of investments, are statistically significant. These studies also reveal that larger investments tend to have greater impacts on surrounding property values. Furthermore, the social and economic composition of the neighborhood also affects the impacts of investments. One study found that low-income and non-minority neighborhoods benefit from government investments. Amidst all of this information, however, there are still questions related to neighborhood housing markets and where to target housing investments.

The examination of NHMTs draws on research and theory related to neighborhood change and housing submarkets. This review of the literature concludes that neighborhoods are a set of bundled goods as a measure of housing characteristics, quality, and residents' socioeconomic conditions. Most analyses of housing markets rely on housing related data to develop market typologies and tend to negate social and economic characteristics of residents. This method is a common strategy used by practitioners to develop typologies of neighborhood markets. While some typologies include social economic variables, others only include housing related variables. Empirical studies in this area are conflicting. Some studies assert that social and economic factors are important to understand neighborhood markets because residents' ability to investment in property affects housing conditions and therefore influences market conditions. Other scholars claim that markets are influenced to a greater degree by housing type and quality, as opposed to social and economic factors. This disconnect must be understood to address the question of whether typologies provide an accurate image of neighborhood markets.

Equally important is the discussion of scale. The literature on government investments identifies the neighborhood scale as an important factor to consider neighborhood impact. Yet, literature in this review of the HOME Program concludes that many neighborhoods are too distressed for such investments to have an impact. The authors suggest that HOME funds in distressed neighborhoods are only effective when matched with other resources, like commercial redevelopment, improved public safety and schools, and other social services. They assert that housing redevelopment alone does not constitute a critical mass and is therefore ineffective as a revitalization effort. Factors of scale may be impacted by the spatial effects of neighborhood investments and market types, although much of this is missing in empirical studies that measure government investments.

The gap in empirical studies related to housing and community development investments in neighborhoods are the misrepresentation of neighborhood markets. Numerous typologies exist but there is little understanding of which indicators marginally affect neighborhood housing markets, or more specifically, housing prices. These markets are composed of more than social and economic factors, and may include housing quality indicators. Additionally, little has been concluded about scale of investments and their impacts across market types. It is important to resolve these factors as practitioners determine whether to invest in neighborhoods in the early stages of decline versus areas that represent distressed neighborhoods. Impacts may differ across market types, and even more, it may be necessary to consider other mitigating factors to determine the impact of investments, including the proximity to neighborhood amenities and dis-amenities.

This study will focus on NHMTs. It will examine the impacts of the HOME Program across Baltimore housing market types for 2005, and then attempt to address spatial effects and determine if neighborhood amenities or dis-amenities affect investment impacts.

ESSAY ONE:
DEVELOPING A NEIGHBORHOOD HOUSING MARKET TYPOLOGY: A FOCUS ON BALTIMORE, MARYLAND

INTRODUCTION

Since the 1980s, federal agencies have encouraged cities to develop data driven methodologies to target programs in their neighborhoods and identify prescriptive measures to address changing communities. Policy tools such as neighborhood classification systems were used by cities during the 1980s to provide a basis for the government to distribute federal Community Development Block Grant (CDBG) resources. Cities relied heavily on these systems to understand socioeconomic and housing conditions citywide.

Three decades later, in 2000, these systems are now called Neighborhood Housing Market Typologies (NHMTs) with a focus on indicators which impact housing markets, such as housing sale prices, percent of foreclosures, and homeownership rates. These typologies allow cities to evaluate existing conditions and forecast future changes that may affect neighborhood stability. The results from these analyses are used by cities to develop public investment strategies intended to stabilize and improve neighborhood conditions. While, typologies' purposes may vary, these tools are generally used to identify areas with the potential to leverage public section investments with limited government resources.

The number of cities employing NHMTs has increased significantly since 2000. Cities like Baltimore, Maryland; Philadelphia, Pennsylvania; and Cleveland, Ohio, now use NHMTs as a precursory step in the planning process to better understand local market conditions, and in more recent years, to help cope with rising foreclosure rates and economic instability. In the past ten years, more than 20 different cities have used neighborhood housing market typologies.

With growing interest and reliance on NHMTs, it is important to critically evaluate the validity of typologies to assist communities to measure neighborhood conditions and change. Two questions are at the forefront of this concern. First, how should practitioners construct NHMTs, given a set of observable variables? And second, are these variables useful to help define spatial housing submarkets?

The first part of this study reviews neighborhood change and housing market theories, and provides an overview of the theoretical foundations of NHMTs. Then, using Baltimore neighborhoods as the study area, indicators discussed in the literature and commonly used in typologies are assessed. First, neighborhood indicators are identified in terms of their validity as a component of NHMT. Second, the indicators are used to develop a 2005 typology for Baltimore, Maryland. The purpose of the typology is to provide an overview of how variables are selected and clusters are developed to create Baltimore submarkets. Finally, this typology is tested to determine if the cluster method provides separate submarkets given the selected data set.

LITERATURE REVIEW

Neighborhood typologies are the systematic and structural classification of variables into a simpler form to allow scholars and field practitioners to understand similarities or dissimilarities of groups under analysis (Hunter, 1979). Categories or clusters of variables are developed to simplify or explain complex phenomena. Fields ranging from the social sciences to biology have used typologies to classify data and explain patterns developed from the data. For fields like public health, sociology, and geography, a *neighborhood* is “a social unit of social organizations… that is larger than a household and smaller than a city” (Hunter, 1979, p. 5). Census geographic boundaries and the common statistical cluster methodology (explained below) are used in these fields to classify neighborhoods according to racial and ethnic variables. In addition, ranking and ordering of the neighborhoods may be based on other factors, which include socioeconomic status, familial composition, condition of housing stock, and a number of other variables that reflect the quality or condition of the neighborhood (Hunter, 1979). The results of these classifications are used to explain how neighborhoods evolve over time or how neighborhood indicators positively or negatively affect residents (Hunter, 1983). In essence, neighborhood-level typologies provide a simple representation of demographic and compositional characteristics of residents and their housing within a spatial context.

NHMTs differ from classification methods used in the social sciences in that these typologies focus on housing stock quality and housing-related neighborhood characteristics that give minimal consideration for residents’ socioeconomic status. Instead neighborhood characteristics are defined by the quality and status of surrounding housing conditions, such as percent of foreclosed properties or housing permit activity in a neighborhood. The purpose of NHMTs is to identify housing submarkets and develop solutions to positively impact market conditions. The theoretical development of typologies is based in urban housing theories and models.

Theoretical Foundation of NHMTs

Scholars such as Park and Burgess (1921) and Hoover and Vernon (1930) within the Chicago School presented the early beginnings of ranking and ordering socioeconomic characteristics of residents by geographic boundaries to understand neighborhood composition. They defined neighborhoods as different natural areas that experienced a set of sequential stages of change, and concluded that change was inevitable and beyond the reach of government intervention. Numerous studies followed, analyzing change and patterns at the neighborhood level to explore racial stability and diversity as causes of neighborhood change (Shevky and Bell, 1955; and Berry, 1967).

Neighborhood Stage Models

In 1980, Downs complemented these studies by refining neighborhood life cycle theories which is the foundation of NHMTs. Downs suggested that neighborhoods were in fact influenced by outside factors and susceptible to experience decline if intervention methods were not used to slow or stop the process of neighborhood disinvestment. Downs placed neighborhoods into stages of change, which included stable, transitional, decline, and in some cases renewal, and claimed that at any one of these stages neighborhoods could move up or down between stages. Stages of neighborhood life cycles were determined based on population, socioeconomic status of residents, and housing conditions.

Downs asserted that local government reinvestment strategies should be scaled with neighborhood conditions. For example, neighborhoods exhibiting heavy decline due to significant population losses, would require drastic government investment such as massive demolition and redevelopment. More stable areas, determined by high property values with few vacant properties would receive less government attention. Downs further cautioned that interventions were influenced by a neighborhood's capacity to improve, and therefore, the effectiveness of policies relied heavily on the neighborhood's current stage at the time when a given policy is applied. Downs's assertion was espoused by other scholars' work in the 1980s and well into 2000, as they also claimed policies must be customized to fit the specific conditions of a neighborhood (Goetz an Colton, 1980; and Mallach, 2000).

Since 2000, neighborhood stage models have evolved into housing submarkets, defined as a "bundle of spatially based attributes associated with clusters of residences" (Galster in eds. O'Sullivan and Gibbs, 2003, p. 155). This contextualization of housing markets implies that neighborhoods are heterogeneous of each other but contains homogenous characteristics of adjacent properties. More specifically, a submarket is defined as a set of dwellings that are reasonably close substitutes for one another and yet poor substitutes for dwelling in other submarkets (Day, 2003). This definition is included in the literature of housing market segmentation.

Housing Submarkets

Market segmentation theorists posit that a housing market is in reality a series of submarkets consisting of clusters of housing units that share common housing and locational characteristics. Clusters represent different segments and are composed of different dynamics of housing supply and demand within the housing market (Maclenana and Tu, 1996; Borassa et al, 2001; Borassa and Hoesli, 1999; Bourassa, Hoesli, and Peng; 2001, 2003; and Bates, 2006). According to the literature, the challenge has been to identify those characteristics which are useful to define and distinguish different housing segments. Cluster statistical methods and hedonic regression models are two common methods used by scholars to determine housing submarkets. A small body of research uses cluster analysis to identify separate housing markets, and this method has become a major tool used by practitioners in the planning field. Hedonic regression models, alternatively, are widely analyzed among scholars to determine the distinctiveness of submarkets. Both methods are reviewed in detail below.

Cluster Methods

Cluster analyses are becoming a common tool used by both scholars and practitioners as a method to systematically define submarkets by housing units' physical characteristics and spatial location. Since 2000, it has been widely used by practitioners to understand housing market conditions and determine where and how to invest limited resources. This method was used by the Reinvestment Fund in 2000 as a market value analysis approach in Philadelphia to identify area local strengthens and to direct private capital. TRF later duplicated this methodology in other cities including Baltimore, MD; Washington, DC; Wilmington, Delaware; and Camden, New Jersey (Federal Reserve, December 2011).

In developing a cluster analysis, two key factors are considered which include indicators and cluster analysis. The selection of indicator is generally based on access to data and the purpose of the market analysis. Some cities may rely on data reflective of housing conditions and exclude socioeconomic data, while other cities may include both datasets. Additionally, some cities may attempt to understand the direction of neighborhood change by including neighborhood change variables. The selection of administrative and census data are important to evaluate the condition of neighborhoods and to scale intervention strategies. In general, the unit of analysis is either the census tract or the census block as both provides a fixed geographic area, but the latter is presents a smaller geographic area to detect greater market differences.

Cluster analyses are and methods employed to develop these analyses are equality important in the development of submarkets. Cluster analyses are based on a measure of variance between spatial data to divide a dataset into groups of observations, where similarities exist within groups. Two basic processes are used to complete cluster analysis, including portioning methods and hierarchical methods. For the partitioning method, the researcher decides upon the number of cluster to be identified in the dataset. In this case, K represents the number of clusters, and the portioning algorithm seeks to find the distance between k locations. This distance is minimized during the portioning process and each observation is placed within its nearest cluster.

The hierarchical method works a little differently, in that a number of clusters are not predetermined. This clustering technique merges data through various iterations for a natural process of grouping and the software provides the optimal number of clusters based on the grouping of the data. In this process, K clusters are merged together to the nearest cluster to form larger clusters. The hierarchical algorithm starts with one large cluster and splits smaller clusters based on dissimilarities among different characteristics and spatial locations. Each split represents a branch and separate cluster. The advantage of the hierarchical method is that a predetermined number of clusters are not imposed, but this is also the disadvantage of the method, as researchers must attempt to determine a small set of clusters in a large dataset. In most cases, scholars propose a hybrid method in which 100 clusters are specified using the partitioning method and the data is divided into smaller cluster from this point. Upon the final grouping of the data, cluster solutions are interpreted.

Steps of a cluster analysis are simple. First, variables are identified to be incorporated in the cluster analysis. In most studies the factor analysis method is used to narrow down the number of variables used in the study. This method is used to extract a small number of factors from a larger data set where multi-collinearity is a known challenge. Cluster analyses are then used to define submarkets based on a smaller set of variables. The limitation of this method is that information is excluded during the factor analysis extracting process. When data is placed into factors and allocated based on their score, only factors with the highest score are incorporated into the cluster analyses excluding other relevant variables.

The cluster analysis is still an emerging statistical method and is not extensively supported by a body of statistical reasoning (Julnes, 1999). A formal theory has not yet been developed to ensure cluster classifications are validated. Further, the ability of the technique to determine a structure, or cluster in the data set, means clusters will be identified whether there is a real basis for the developed cluster or not. Therefore, this method must be validated with both qualitative and quantitative analyses to ensure clusters are statistically significant and mirror real world conditions. Empirical studies validate cluster methods by analyzing estimates and levels of variance between submarkets using hedonic price functions and other statistical tests, such as the WALD and Chow tests (Day, 2003; Turner and Kaye, 2006).

Z-score methods

Z-score calculations are another method used by practitioners to differentiate markets. Based on the z-score method each variable in an analysis is standardized prior to aggregation at the geographic analysis level representative of observation cases. A case may represent a census block group or tract by which the variable data is aggregated. The use of z-scores shows the relative position of each case in relation to every other case within the City. The z-score method for a particular observation (x_i) within a distribution is calculated as follows (Cleveland Typology, 2009):

$$Z_i = (x_i - AVG/\ STDEV) \tag{1.1}$$

The final score is calculated as the average of all z-scores for each variable within each case. The ranking of cases are based on city-wide averages. This method may present constraints when socioeconomic variables and even change variables are included in the analysis. This approach is not as robust as the cluster approach because it relies on the average of each variable at the neighborhood block or census tract level in comparison to city-wide averages. Cities which use this method represent neighborhood categories based on thresholds within the dataset (Memphis foreclosure typology, 2005). The z-score methodology is not preferred by scholars over the cluster method, because identified submarkets cannot be statistically validated. Practitioners' descriptively validate both z-score and cluster methodology by graphically mapping analyses output.

Hedonic Regression Models

Hedonic regression models are commonly used by scholars to determine the impact of various factors that make up housing markets, particularly housing sale prices. In these models housing is assumed to be a differentiated good, which is composed of a variety of characteristics that command different prices (Galster, 1998; Day, 2003; and Bourassa, et al. 2008). For example, homes with more than one full bathroom may show a premium in sale prices than a home with only one full bathroom. Therefore, a hedonic regression model provides scholars the abilities to sparse housing characteristics into separate elements to determine the price of each element that contribute to the sales price of the housing unit. This method also allows scholars to identify various indicators which may make up a housing market and determine the value of the indicator's impact on the sale prices.

In review of hedonic regression analyses, the challenge, similar to the cluster method, is to determine which indicators make up a residential submarket. Some scholars claim that physical characteristics of housing stock, such as property type, structural materials, and housing amenities are defining factors of housing markets (Maclenan et al, 1987; Schnare and Struyk's, 1976; and Goodman and Thibodeau, 1998). Other scholars argue for a broader interpretation of housing submarkets, and suggest that markets are influenced by socioeconomic variables representative of consumers income levels, employment status and occupation, and household composition (Galster, 1979; Palm, 1978; Gabriel,1984; Kain and Quigley, 1975; Yinger, 1998; and Bourassa, Hoesli, and Peng, 2001).

The hedonic regression method also differs among analyses. The work related to identifying NHMT submarkets and boundaries employ numerous hedonic price regressions modeling such as hierarchical models, geographic fix effects and other spatial econometric models (Goodman and Thibodeau, 1998, 2002, 2003; Borassa, Hoesli and

Peng, 2003; Watkins, 2001; Schnare and Struyk, 2004). Some models tend to use factor analysis to identify variables for inclusion in cluster analysis (Bourassa et al., 1999).

The unit of analysis to define submarkets is the research question in these empirical studies. Scholars attempt to delineate submarket by zip codes, census tracts or block groups (Goetzmann and Spiegel, 1997, Goodman, 1977, 1981). More recently, scholars have used school districts and other municipality boundaries determine distinct housing submarkets (Brasington, 2000, 2001). Econometric models are tested against geographic areas generally defined by real estate appraisers to determine the best fit of the data and evaluate the prediction accuracy of the alternative housing submarket constructions (Goodman and Thibodeau, 2003, Bourassi, Hoesli, and Peng, 2003, and Goodman and Thibodeau, 2007). Among the hedonic regression methods used, studies find that hierarchical models provide a useful framework for delineating housing submarkets, which indicate submarkets are determined based on school districts or locations within municipalities (Goodman and Thibodeau, 1998). Other studies claim that house price prediction is an appropriate specification method (Schnare and Struyk, 2004, Goodman and Thibodeau, 2003). In general, these studies conclude that housing submarkets matter, and location or spatial factors of housing units play a major role in why they matter. Locational factors may include views, the proximity of the housing unit to high crime rates, the proximity to the central business district or other neighborhood dis-amenities such as areas with high percent of mortgage defaults or vacant properties.

In conclusion, scholars find that both social and economic variables affect housing markets and are equally important to define housing submarkets. However, practitioners tend to include variables in cluster analyses based on imminent challenges in the community and few employ statistical analyses of the data before conduction cluster techniques. Empirical studies rely on factor analysis as first steps to identify uncorrelated variables for cluster analysis but are unclear if variables affect local housing markets. Hedonic regression models are only used to test the validity of separate clusters or use locational variables to control for possible submarkets, such as proximity to the central business district. Understanding which variables impact housing markets and how these variables are used to define spatial neighborhood markets is important and requires further attention.

RESEARCH QUESTIONS

This study will use data from the City of Baltimore and construct a series of NHMT to assess whether: a comprehensive set of variables, including both social economic and housing variables, can enhance the NHMT work to define distinctive neighborhoods, and second, determine if the cluster method will produce distinct submarkets. The study will specifically analyze observable socioeconomic and neighborhood change (i.e. percentage change) variables to determine whether these variables improve the capability of NHMTs to reflect neighborhood market conditions.

THE STUDY AREA

The City of Baltimore, Maryland, will be the focus of this research. In 2002, Baltimore developed its first NHMT. By this time, the city had experienced a significant decline in its population of approximately 50,000, or 11.5 percent of its residents since 1990, and the population decline again in 2000 with a net loss of 84, 000 residents (Baltimore Housing Report, 2005). Though housing prices had increased and construction was on the upsurge in the housing market, Baltimore still suffered from high percentages of foreclosures and vacant properties in its neighborhoods. Lower housing values and high rates of joblessness only exacerbated Baltimore's housing challenges.

To address decline in its neighborhoods and provide intervention methods to counteract citywide problems, the city's 2002 NHMT was developed based on community statistical areas (CSA). CSAs are an agglomeration of adjacent census tracts into one geographic boundary and were used in Baltimore's typology to classify neighborhoods into submarket clusters. The cluster method was used and three indicators—abandonment rate, median assessed home value, and percentage of homeownership were the basis for this typology.[4] The city used the cluster statistical technique to define the different housing submarkets and grouped Baltimore neighborhoods into four categories, labeled: (1) preservation; (2) stabilization; (3) reinvestment; and (4) redevelopment. The typology presented a snapshot of the city neighborhoods to assist policy makers in prioritizing and targeting public intervention (i.e., code enforcement, property rehabilitation, demolition) into areas based on market conditions. However, the size of the CSAs obscured the typology and skewed the results, which were originally intended to help create distinct housing markets. The challenge with the CSA size was that the geography encompassed more than one neighborhood and areas representing different housing submarkets. This issue led to more than two submarkets consolidated within one market category based on this geographic level and

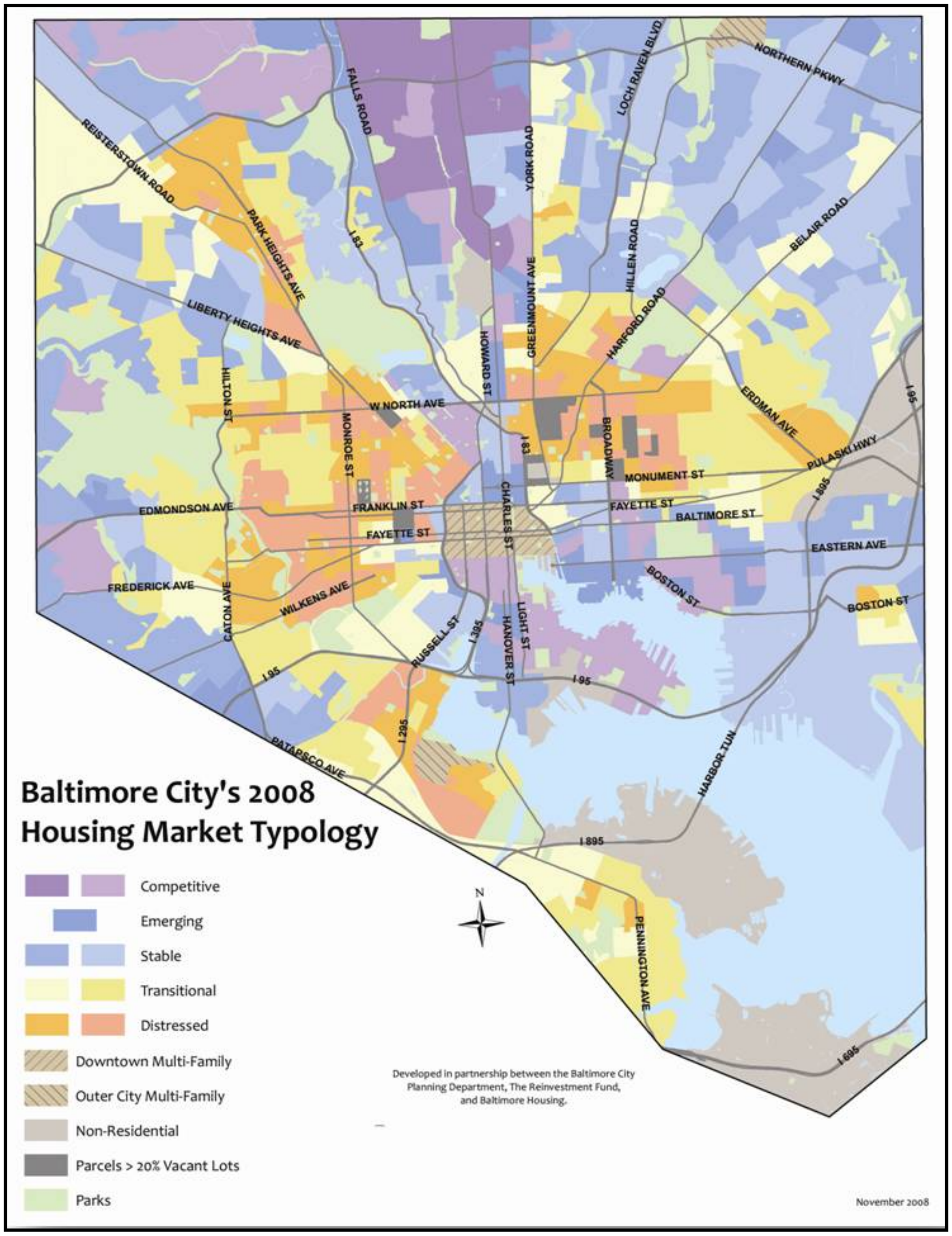
[4]The variables homeownership was included in Baltimore's 2002 typology based on the 2000 U.S. Census data.

limited the usefulness of the analysis for policymakers to decide, based on market conditions, which strategies to use in the neighborhoods.

In 2005, the city revised the typology, with the help of the Reinvestment Fund, and instead of CSAs, census blocks, a smaller unit of analysis, was used because it presented greater variance in market conditions and additional housing related variables. Presumably, the finer detail provided by the census block would allow policymakers to recognize market variation within a given area. In 2008, following the nation-wide collapse of the housing finance systems and housing markets, the city experienced substantial increases in vacant properties and mortgage foreclosures. By the end of 2008, the city owned approximately 15,000 vacant housing units and listed approximately 6,000 vacant property filings. The City reported that though housing prices in the city continued to rise, the number of housing sales dropped for the first time since 2001 (Baltimore Housing Report, 2005).

The city revised its NHMT again in 2008 to include additional variables to better explain neighborhood housing markets and conditions. The new typology included the following variables: percent vacant homes and lots; percent homes foreclosure; percent of single-family homes; percent commercial land; and percent residential rental subsidies. Further, the city expanded the number of clusters in recognition of the diversity of neighborhood housing markets and the variety of intervention strategies. An increase in market types allow for more variation in the number of clusters, from five to nine. Markets now included: (1) competitive; (2) emerging; (3) stable; (4) transitional; and (5) distressed. Additional clusters did not result in more market categories, but additional

Figure 8: Baltimore 2008 Neighborhood Housing Market Typology



Source: City of Baltimore Planning Department. Unit of analysis are census blocks with nine market categories.

clusters in each market type. Two additional clusters were represented by competitive markets, as well as additional clusters for distressed and transitional markets.

The Baltimore typology will be used as a benchmark to compare results for an alternative typology. An alternative typology is developed to evaluate the inclusion of variables (e.g., change variables) and determine if the Baltimore model can be improved selecting variables based on the cluster method, geographic mapping, and statistical methods to test results.

THE DATA AND SELECTION OF VARIABLES

The selection of variables to include in the development of a typology is very important. Neighborhood indicators inform the user of the purpose for the typology and assist to distinguish markets within cities. To identify indicators to incorporate in a NHMT for Baltimore, six cities were analyzed. These cities reflect a variation in market typologies categories, unit of analysis to determine market types, variables, strategies, methodologies, and purposes for the typology. As presented in Table 6, the cities include Baltimore, Maryland; Philadelphia, Pennsylvania; Kansas City, Missouri; Cleveland, Ohio; Indianapolis, Indiana; and Memphis, Tennessee. Common variables used in this analysis was selected based on the correlation among the data, and importance of the variables to impact housing sale prices, as discussed in the current literature.

Table 6: Sample city examples of NHMTs

City	Market Typologies	Unit of Analysis/Timeframe	Indicators	Strategy	Methodology	Purpose
Baltimore, MD	Competitive, Emerging, Stable, Transitional, Distressed	Census Block Group/2008	Median Home Value Sales, Percent Commercial Land, Percent Rental Subsidies, Percent Forclosure, Percent Vacant Homes, Percent Home Ownership, Percent Single Family Homes, and Percent Vacant Lots	Preventative measures for competitive/emerging typologies; stabilization efforts for stable and transitional markets; and demolition and substantial redevelopment in distressed markets.	Factor analytic cluster analysis	Guide city's investment strategies for both daily operations and long-term planning; use of data to target HUD Neighborhood Stabilization program dollars.
Philadelphia, PA	High Value/Appreciating, Steady, Transitional, Distressed, and Reclamation	Census Block Group/2001	Median Sale price, Variance in sales price, Percent Rental Subsidies, Vacancy factor, Percent Foreclosure, Percent Commercial use, Percent Owner Occupied, Housing Units per Acre, New Construction	Invest in areas with the greatest potential, close to strong markets or with stable real estate market; and extensive redevelopment in distessed areas.	Factor analytic cluster analysis	Program was designed to renew and strengthen Philadelphia's urban neighborhoods through specific public action.
Kansas, MO	Developing Areas, Conservation Areas, Stabilization Areas, and Redeveloping Areas	Census Tract/2007	Population change, median household income, unemployment, household on public assistance, persons below poverty level, persons with high school education, rate of crimes, single headed households, median housing value, housing unit change, vacant housing, residential building/demolition permits ratio, owner occupied housing, household income to housing payment ratio	Preserve what is valuable and prevent decline by addressing problems and their root causes. Undertake many "standard actions" simultaneously to address housing maintenance/rehabilitation , code enforcement	z-score; final score calculated as the average of all z-scores for each variable within each block group	Provide neighborhood assessments for long term planning intiatives, which strategically apply public and private resources in a way that is based on the existing conditions, trends, opportunities, strengths and needs of diverse areas.
Cleveland, OH	Regional Choice, Stable, Transitional, Fragile, Distressed	Census Tract/2008	Median Assessed Value, Percent change in Median Value, Net Change in number of single family housing, Foreclosure rate, homeownership rate, boarded up/condemnation rate, housing rate below fair, vacant and distressed structure rate, demolition rate	Encourage rehabilitation in strong and stable markets; use NSP funds in conjunction with HOME, CDBG and LIHTC resources to rebuild areas; create sustainable homeownership rehabilitation markets	z-score; final score calculated as the average of all z-scores for each variable within each block group	Provide information to assist the Department of Community Development, City of Cleveland, and other stakeholders in the development of program strategies that promote urban revitalization.
Indianapolis, IN	; of decline but not highly c	Census Block Group/2005	Housing Vacancy (90-day postal vacancy), total assessed housing value, and owner occupied (certified property ownership)	A: Market regionally; B: active code and nuiance reinforcement; C: selective demolition, target resources, and limit concentrated subsidized housing; and D: site acquisition and land assembly	Factor analytic cluster analysis	Guide more efficient decision making by matching resources, policies, and strategies with neighborhood conditions
Memphis, TN	Zone 1: Classic distressed neighborhoods; Zone 2: Vulnerable "swing" neighborhoods; Zone 3: Stable neighborhoods of choice; and Zone 4: Uptrending traditional neighborhoods	Census Tract/2007	Socio-economic variables, variables related to community development essentials, housing and neighborhoods, crime, school quality, and health indicators	Encourage scaled intervention of code enforcement, rehabilitation and new construction development, demolition, and cosmetic repairs based on neighborhood conditions	Zones geographically categorized based on market criterion.	Stabilize neighborhoods and develop intervention for foreclosures; overlay zones with foreclosure data to guide investment decisions

Source: City of Baltimore NHMT, 2008; The Reinvestment Fund Philadelphia NHMT, 2001; Kansas City, Missouri 2007-2011 Consolidated Plan; City of Cleveland, Ohio Neighborhood Typology, 2008; City of Indianapolis, Indiana; and, the Center for Community Building and Neighborhood Action, University of Memphis

Baltimore and Philadelphia's typologies were similar in that they were developed by the same organization, the Reinvestment Fund, but the typologies presented different categories and variables. The other four cities all presented very different typologies, developed for various reasons, which include: to target reinvestment strategies and housing redevelopment programs, to assess long-term planning initiatives, to inform the city and promote urban revitalization, and to stabilize neighborhoods and develop intervention against rising foreclosures.

In review of indicators used by the six cities selected for this study, each cities list of indicators were divided into four categories which include: (1) census indicators; (2) housing indicators; (3) neighborhood character indicators; and (4) neighborhood change indicators.

For census data, cities included population change; median household income and households on public assistance; percentage of persons below the poverty level; percentage of college graduates or other proxies for individual education; number of crime; single headed households; and household tenure. These indicators were used by Kansas City, Cleveland, and Memphis. Kansas City and Cleveland used socioeconomic indicators to provide neighborhood assessments for long-term planning efforts, while Memphis used indicators to identify areas to target foreclosure intervention strategies.

Data initially analyzed for this study include: median household income; percent of owner-occupied units; percent of unemployed residents; percent of African American households; and average commute time. Demographic and socioeconomic data, such as employment and household income, were collected from the 1990 and 2000 U.S. Census. Geographic Information System (GIS) analysis was used in this investigation to link and aggregate structural, demographic and other neighborhood data to the census block group level. Some variables were dropped during the analysis due to high correlation and lack of meaningful implication to the cluster analysis. In 2000, 88 percent of Baltimore's population were African American households and spanned all income brackets. In this light, we did not expect to see significant variation between race and housing market conditions. As such, race was dropped from the analysis since it would not distinguish market conditions across different Baltimore housing markets. Unemployment was found to be highly correlated with household income, so this variable was also dropped from the analysis. Housing variables are included in all sample cities, but were relied heavily on in the Baltimore, Philadelphia, and Cleveland typologies. Housing variables included median home value or sale prices, variance in sale prices, and percent of single-family homes. Homeownership rate is the only census data included in these typologies. In some cases, cities obtained this data from current administrative sources other than the U.S. Census, such as the city assessor's office.

In this study, housing variables included housing condition; age of housing unit; percent of single-family housing unit; proportion of housing sales; and square footage of housing units. These variables were obtained from the Maryland Property View database, which collects data from assessors' offices throughout the state.

Neighborhood characteristics vary among the cities' typologies. All typologies included variables reflective of the condition of housing and housing-related activities in the neighborhood, such as percent foreclosures; percent vacant homes; percent vacant lots; percent rental subsidies; proportion of commercial land; proportion of permits; and crime rates. The percent of tax delinquencies and foreclosures are very common indicators used in all typologies in Table 6, with the exception of Memphis. The negative impacts of the percent of tax delinquencies and foreclosures have been the impetus behind other cities NHMTs, such as Chicago, Illinois; New Orleans, Louisiana; and Cleveland. Since 2005, the percent of tax delinquencies and rates of foreclosure have risen significantly in numerous cities, particularly cites in the Midwest and Northeast. Studies find that these factors negatively influence housing sale prices. Housing structural characteristics, mortgage loan activity, percent of housing code violations and condemnation rates are also commonly included in typologies. For this study housing data include: percentage permits; sales; foreclosures; vacant building; vacant lots; subsidized homes; and commercial land uses. These data were obtained from the City of Baltimore and the Baltimore Neighborhood Indicator Alliance.

Several typologies included neighborhood change variables to indicate direction of neighborhood markets. Few empirical studies include neighborhood change indicators in their hedonic analyses. Zielenbach (2000) examines gentrification in Chicago using neighborhood change indicators. Using index scores and cluster analyses, he included the percent change in racial groups, percent change of individuals with college degrees and changes in crime rates. Galster (2002) also examines neighborhood change variables in a national analysis to identify parsimonious indicators to include in neighborhood monitoring system for practitioners to track key dimensions of neighborhoods. However, few empirical studies have examined whether these indicators affect housing markets and present distinctive market types in cluster analysis.

This study explore neighborhood change variables for median household income, percent of foreclosed properties, and proportion housing sales and permits. Neighborhood change variables were calculated as the percent change in collected administrative data for 2000 and 2005. For census data, percent change was calculated using 1990 and 2000 data. Census data percent change variables include: race; median income; employment; and age.

METHODOLOGY

For this study, a 2005 NHMT is created for Baltimore using a variation of indicators identified among the sample cities in table 6 above. The goal is to identify indicators that can be used to construct NHMTs based on explanatory variable impacts on house sale prices in Baltimore and their capability to present distinct market types. This process consists of several steps which include a statistical cluster analysis. The cluster analysis was used to determine which indicators presented spatial variation based on the location of housing sales and associated neighborhood indicators. Final clusters were analyzed based on regression models for extensive testing to validate cluster submarkets. Additional field analysis, inclusive of photos of the neighborhoods and informal interviews with community leaders were completed to further test cluster outputs. These steps are explained in detail below.

Step 1: Identifying Typologies

The initial list of variables was based on indicators used by the six sample cities' NHMTs. Variables included in the analysis were sub-divided into four groups presented in table 7 and 8, which include: census data indictors, administrative housing indicators, neighborhood characteristics indicators and neighborhood change indicators. For this study, five typologies were tested which included selected variables. These typologies and data included in the study represented data sets presented by the sample cities.

Highly correlated indicators and inaccessible data (i.e. proprietary data) were not included in this study.

In the development of this typology sample cities variables were considered.

Table 7: List of NHMT Variables

Census Data Indicators	Administrative Housing Indicators
Median household income	Housing Condition (Excellent, Good, Fair, Poor)
% Owner occupied housing units	Age of housing unit
% Unemployed, labor force aged 16+ years	% Single Family housing unit
% Population African American	Proportion housing sales
Average commute time	Violent crime rate
	Proportion of Commercial land use
	Square footage of unit

Table 8: List of NHMT Variables (cont.)

Neighborhood Characteristics Indicators	Neighborhood Change Indicators
Proportion of Permits	% change in median household income
Proportion of subsidized housing units	% change in African American population
Percent of foreclosed housing units	% change in unemployment
Percent of vacant building housing units	% change in foreclosed properties
Percent of owner occupied housing units	% change in home sales
	% change in permits

Additional locational variables were considered in the analysis, such as proximity to downtown, based on the literature of housing markets which assert that spatial factors such as location matter in determining neighborhood submarkets. However, preliminary analysis based on geographically mapping outcomes of clusters did not yield logical results; therefore locational variables were not included in this model. Following are the typologies examined in this study:

- Typology 1: Inclusion of socioeconomic and housing-related variables;

- Typology 2: Inclusion of socioeconomic, socioeconomic and housing-related percent change variables, and housing-related variables;
- Typology 3: Inclusion of housing-related variables; and
- Typology 4: Inclusion of housing-related and housing-related percent change variables.

Typology 1 and 2 represented a combination of data presented in Kansas City, Memphis and Cleveland typologies. Typology 3 represented Baltimore's 2008 typology and variations of Philadelphia and Indianapolis typology. Typology 4 was included to determine if housing and decennial change in housing characteristics presented distinct market types.

Each typology was tested using Baltimore data. The summary of data used in this analysis is summarized in table 9. Descriptive statistics including box plots were used to identify outliers in sales data and housing sales above $400,000 or below $11,000, as well as arms-length transactions, were omitted from the analysis.[5] In total, the final data set consists of 14,276 total sales from 2004 to 2005 housing sales. For the cluster analysis, data were aggregated at census block groups to perform the cluster analysis. In the analysis, 94 census block groups of the total 653 block groups, were excluded due to missing data for either socioeconomic or housing data. Much of this missing data was a result of limited and inconsistent data provided for both 1990 and 2000 decennial data. In total, 559 of the city's 653 census block groups were included in the cluster analysis.

Step 2: Cluster Analyses

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[5] Arm's length transactions were identified based on labels provided by the Baltimore assessor's office. Additionally, this study assumed that sales less than $5,000 were arm's length transactions.

Based on five typologies determined, a cluster analysis was completed for each. The five cluster analyses were computed with a non- hierarchical k-mean cluster method. The k-means method allows the analyst to choose the number of clusters to create and the initial centers or threshold for which the data is sorted into cases through a series of iterations until it converges to a stable partition of k clusters. For this analysis, five market types was selected through an analysis of the cluster trees in which four to 15 clusters could be determined based on the dataset. Five market types presented a small number by which a variation among neighborhood submarkets could be perceived and provide enough observations if the data set was divided into market categories for additional analysis.

Euclidean distance was chosen as the clustering criterion to converge the data. This criterion allows the cases to be compared to all of the clusters by calculating the squared Euclidean Distance formula as shown below:

$$d^2 = \sum_{i=1}^{n} (x_{1i} - x_{2i})^2 \qquad (1.2)$$

Each variable distance from the initial center is calculated based on the means of the nearest cluster. In this cluster analysis the initial center was the first case in the dataset. If a case is identified to be nearest to a cluster of another than the one it was initially converged with, then the k-Means process will move it to its nearest cluster. The

Table 9: Summary Statistics and Definition of all Variables

Summary Statistics						
Variable	**Label**	**Unit of Measure/Analysis**	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Sales Price	PRICE	dollar/individual unit	$114,400.68	$ 2.08	$11,000.00	$1,548,816.62
Log (Sales Price)	XLOGPRICE	dollar/individual unit	5.0584286	0.3183562	4.0413927	6.19
Structural Characteristics (2004,2005)						
Housing Condition Excellent	DGEXC	binary/individual unit	0.0042684	0.0651958	0	1
Housing Condition Fair	DGFAIR	binary/individual unit	0.7862991	0.4099324	0	1
Housing Condition Good	DGGOOD	binary/individual unit	0.0880274	0.2833447	0	1
Brick	XBRICK	binary/individual unit	0.7001609	0.4582033	0	1
Basement	XBASEMENT	binary/individual unit	0.8986775	0.3017659	0	1
Square Footage of Unit	XSQFTSTRC	feet/individual unit	1276.31	731.425957	0	16920
Square Footage of Unit (squared)	XSQFTSTRC2	feet/individual unit	2163926.36	3778635.29	0	286286400
Age of Unit	XAGE	number/individual unit	88.408229	147.285339	1	2005
Age of Unit (Squared)	XAGE2	number/individual unit	29507.47	301972.28	1	4020025
Aircondition	XAIRCON	binary/individual unit	0.2752781	0.44667	0	1
Half Bath	XHBTH	number/individual unit	0.2237772	0.4475546	0	3
Finished Basement	XBASEMFN	binary/individual unit	0.2381219	0.425949	0	1
Garage	XATGR	binary/individual unit	0.0370163	0.1888083	0	1
Fireplace	XFIRE	binary/individual unit	0.1092296	0.311938	0	1
Porch, Deck, Patio	XDECK_PRCH	binary/individual unit	0.7336785	0.5852383	0	3
Socio-Economic Characteristics (1990,2000)						
Average Income of Census Block	XINCOME	average/census blgrp	$ 35,405.97	$ 1.54	$ 1.00	$ 169,824.37
Log of average income in census block	XLOGINCOME	average/census blgrp	4.5490765	0.1886841	0	5.23
Percentage Change in Log of average income in census block	XCHINCOME	percentage/census blgrp	0.4396893	1.0528108	-0.8	7.3
Percent of African American	XPCTBLK	percentage/census blgrp	0.4379533	0.3734201	0	1
Percentage change in African American population	XCHGBLK	percentage/census blgrp	-2.4988874	11.7449926	-151.6	1
Percentage unemployed	XPCTUMEPLY	percentage/census blgrp	0.0632118	0.050498	0	0.33
Percentage change in unemployment	XPCTUMEP_1	percentage/census blgrp	0.0619551	0.0617479	0	0.3
Commute Time	XCOMMUTE	rate/census blgrp	30.2543559	7.8091315	10	83
Housing Value and Type (1990, 2000)						
Percentage of single-family housing units	XPCTHSGSF	percentage/census blgrp	0.1994185	0.3026405	0	0.99
Percentage of owner occupied housing units	XPCTOWNER	percentage/census blgrp	0.6445595	0.1938919	0	1
Percentage of home sales	XPCTSALES	percentage/census blgrp	0.1126501	0.051346	0	1.55
Neighborhood Characteristics (2005)						
Percentage of permits (permits greater than $5,000 exterior rehabs for	XPCTPERM	percentage/census blgrp	0.0227785	0.0275561	0	0.22
Percentag of subsidize housing (including public housing projects)	XSUBHSG_1	percentage/census blgrp	0.0012735	0.028902	0	1.1
Proportion of commercial land (as a percentage of square miles of land uses)	XPCTCOMM05	Proportion/census blgrp	0.0141348	0.1180506	0	1
Percentage of foreclosed housing units	XPCTFOR	percentage/census blgrp	0.0152841	0.0122052	0	0.25
Percentage change in foreclosed housing units	XPCTCHGFOR	percentage/census blgrp	-0.1383122	0.93083	-1	6.61
Percent of vacant housing units	XPCTVCT05	percentage/census blgrp	0.0257773	0.0468287	0	0.42
Percentage of home sales	XPCTCHGHSG	percentage/census blgrp	356.6279477	159.537377	0	936
Percentage change in home sales	XPCTCHGSAL	percentage/census blgrp	-0.0015639	0.1093465	-5.38	0.3
Percentage change of permits (permits greater than $5,000 exterior rehabs for housing units)	XPCTCHGPER	percentage/census blgrp	1.1943883	3.2359629	-1	25.916
Rate of crime among all residents (number of crime per 1000 people in the city in 2005)	XRTCRIME	rate/census blgrp	2.4219873	15.6360877	0	262.42
Percentage change in rate of crime among all residents (number of crime per 1000 people in the city in 2005)	XPCTCHGCRM	percentage/census blgrp	0.093889	0.5845559	-0.565	6.476

cluster model is continuously calibrated over numerous interactions until all cases are placed into a cluster and a stable partition is constructed. The cluster convergence is predetermined based on the maximum number of iterations specified for the cluster process. In this process, 100 iterations were specified.

In this analysis, data for each cluster was examined based on typologies identified in step 1 using Baltimore data prior to the cluster analysis. Data for the cluster analysis were standardized using z-scores. As a result, the set of indicators (e.g., housing sales, percentages, and number values) were normalized to common units relative to city averages. The significance of the clusters were determined by analyzing cluster trees, looking for the maximum value of the pseudo-F statistic and observing the minimum of the R^2 (Finch, 2005). During the cluster analysis, if a block group was categorized as an outlier and included in cluster 0, they were not included in the final typology.

Step 3: Mapping the Clusters

Based on the cluster analysis output, clusters were ranked by average house prices of each cluster category. Clusters 1 and 2, which contained the highest house prices, comprised of those block groups that would be defined as stable markets; Cluster 3, included those block groups viewed as middle markets; and, Clusters 4 and 5, which contain the lowest house prices, represented those block groups considered distressed markets. Geographic maps of the distribution of these block groups defined by each cluster type was created to assess the spatial variation of the market data.

Step 4: Validating Clusters

The spatial mapping of the clusters was validated with existing conditions in Baltimore through field analysis in which neighborhoods were driven and visually observed. Photos were taken of neighborhoods which represented different cluster types. In addition, informal interviews were conducted with community development organizations to assess whether neighborhoods should be considered in respective cluster types.

To further ensure consistency in results, GIS was used to link socioeconomic data and other descriptive variables for each cluster type to determine if socioeconomic, housing and change variables were consistent with the literature or dynamics of Baltimore neighborhoods. For example, clusters with the highest range of housing values were examined to ensure they also contain the highest range in income groups, a low vacancy rate, and high homeownership rate.

Hedonic regression analyses were completed to further validate the clusters. In the regression equation, social and economic, housing, and neighborhood change variables were consolidated into cluster dummy variables and were regressed on the dependent variable, sale prices of single-family houses sold in 2004 and 2005. The rationale for using sale prices in 2004 and 2005 is to capture housing sales for the 2005 typology.

The following regression equation was used test whether the typology contained distinct clusters.

$$\ln P = \beta_0 + \beta_1 S_{1i} + \beta_2 C_{2i} + e_i \qquad (1.3)$$

Where:
P= sale price;
S = Structural characteristics;
C = Clusters (1 through 5)

e = error term

In Typology 1, C represented a vector of socioeconomic and housing condition variables; Typology 2, C represented a vector of socioeconomic, housing condition variables and socioeconomic percent change variables; Typology 3, C represented a vector of socioeconomic, housing condition variables, socioeconomic and housing condition percent change variables; and, Typology 4, C represented a vector of housing condition and housing condition change variables. Each regression model was analyzed in detail.

The separate submarkets in the final cluster analysis were then tested to determine their statistical validity. The limitation of running a hedonic regression model on the full data set is that it assumes that the entire area is a single property market (Brett, 2003). This assumption is not correct. Therefore a regression equation was compared using a Chow test. The Chow tests or f-test determines whether, among the regression equations, there is a significant difference between the clusters under the null hypothesis, and that there is a structural break in the data. The test static provides the following formula:

$$\mathbf{F}_{chow} = \frac{(\hat{\mathbf{u}}'\hat{\mathbf{u}} - \hat{\mathbf{u}}_1'\hat{\mathbf{u}}_1 - \hat{\mathbf{u}}_2'\hat{\mathbf{u}}_2)/k}{(\hat{\mathbf{u}}_1'\hat{\mathbf{u}}_1 + \hat{\mathbf{u}}_2'\hat{\mathbf{u}}_2)/(n_1 + n_2 - 2k)} \tag{1.4}$$

where $\hat{\mathbf{u}}$ is the regression residual vector from the full set model, $\hat{\mathbf{u}}_1$is the regression residual vector from the first set model, and $\hat{\mathbf{u}}_2$is the regression residual vector from the second set model. Under the null hypothesis, the Chow test statistic has an *F* distribution with k and $(n_1 + n_2 - 2k)$degrees of freedom, where k is the number of elements in β. The Chow test statistic is used to test the null hypothesis $H_0 : \beta_1 = \beta_2$conditional on the same error variance $V(\mathbf{u}_1) = V(\mathbf{u}_2)$. If the test presents significance at the 1% level of confidence, then it is assumed that the clusters represent district submarkets.

Next, a final model was determined based on this review and a cluster analysis was completed based on the set of variables selected. The model included the comprehensive set of social economic and housing variables that presented the greatest variation in the spatial cluster output.

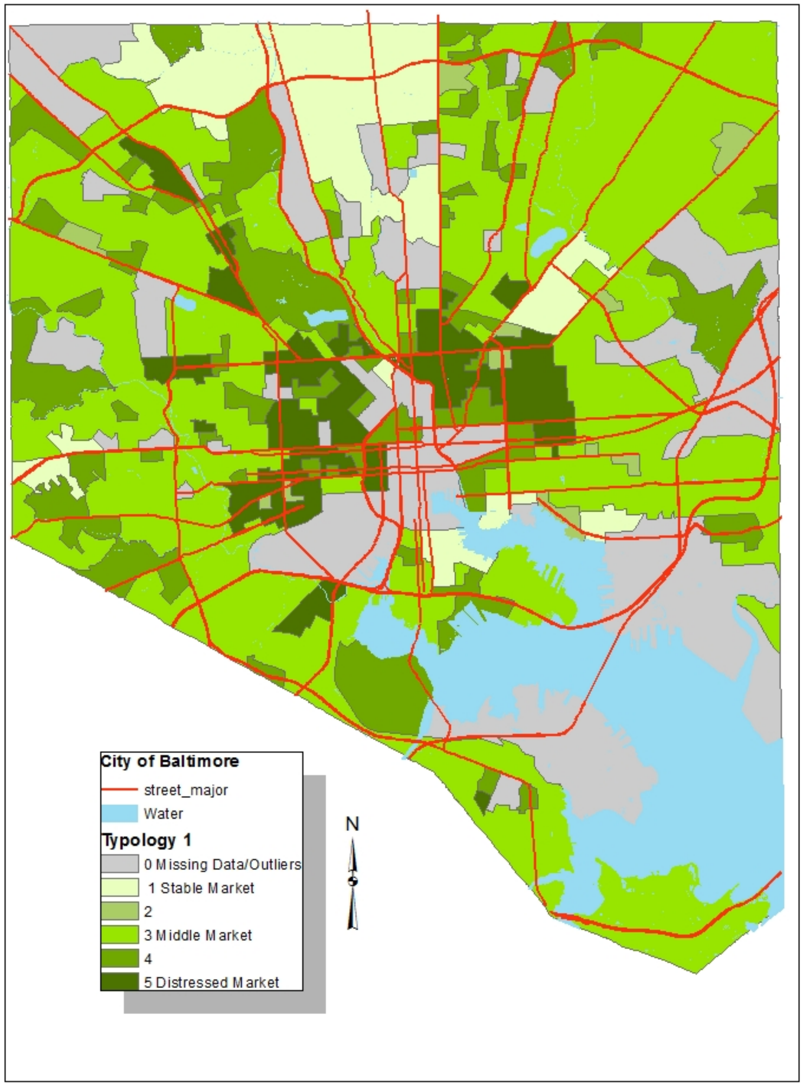
ANALYSIS

The first part of the analysis examines the output of the cluster and reviews the results of the GIS analysis to determine the spatial variation of the typologies. The second section reviews the final typology and provides discussion from the output and field analysis.

Results of Mapping Cluster Outputs

Figure 9 and 10 below provides five cluster maps for each typology (1 to 4). In the analysis, typologies 1 and 3 show the greatest variation in overall cluster distribution in the city, while typologies 2 and 4 shows the least amount of variation. Typology 2 includes both socioeconomic and housing related variables and percentage change variables, and typology 4 includes housing related variables and percent change of housing related variables. The discrepancies in typology 2 represent stable areas along the edges of the city and a similar cluster type for the northeast section and the northern section of the city. The northern section of the city contains affluent neighborhoods like Roland Park, represented by large homes and higher household income. This area is distinctively different from the northeast section and edges of the city which contain lower home values and household incomes.

Figure 9: Cluster Outputs for Typologies 1 and 2



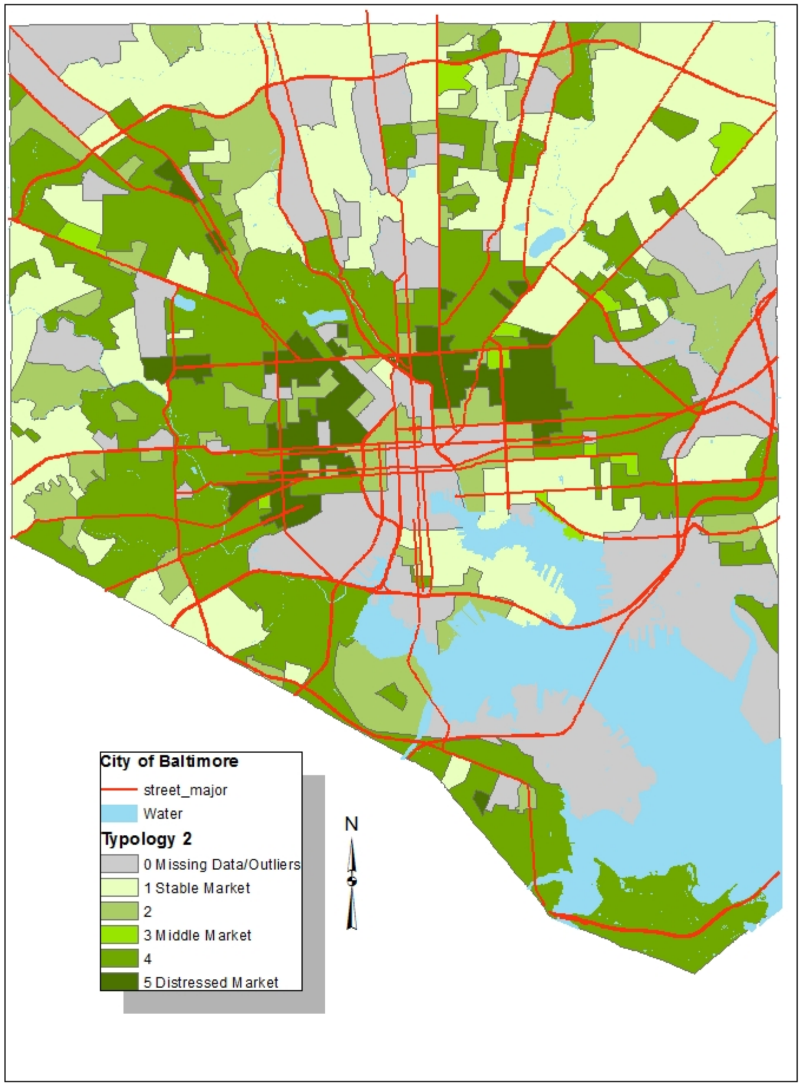
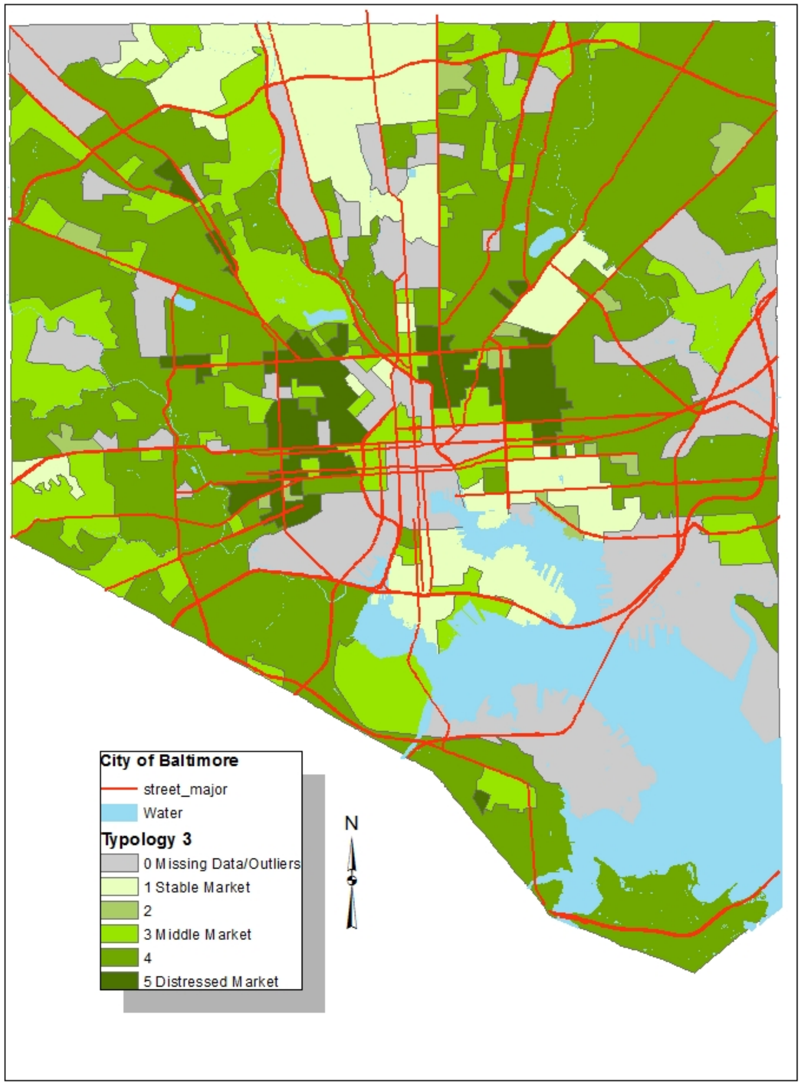
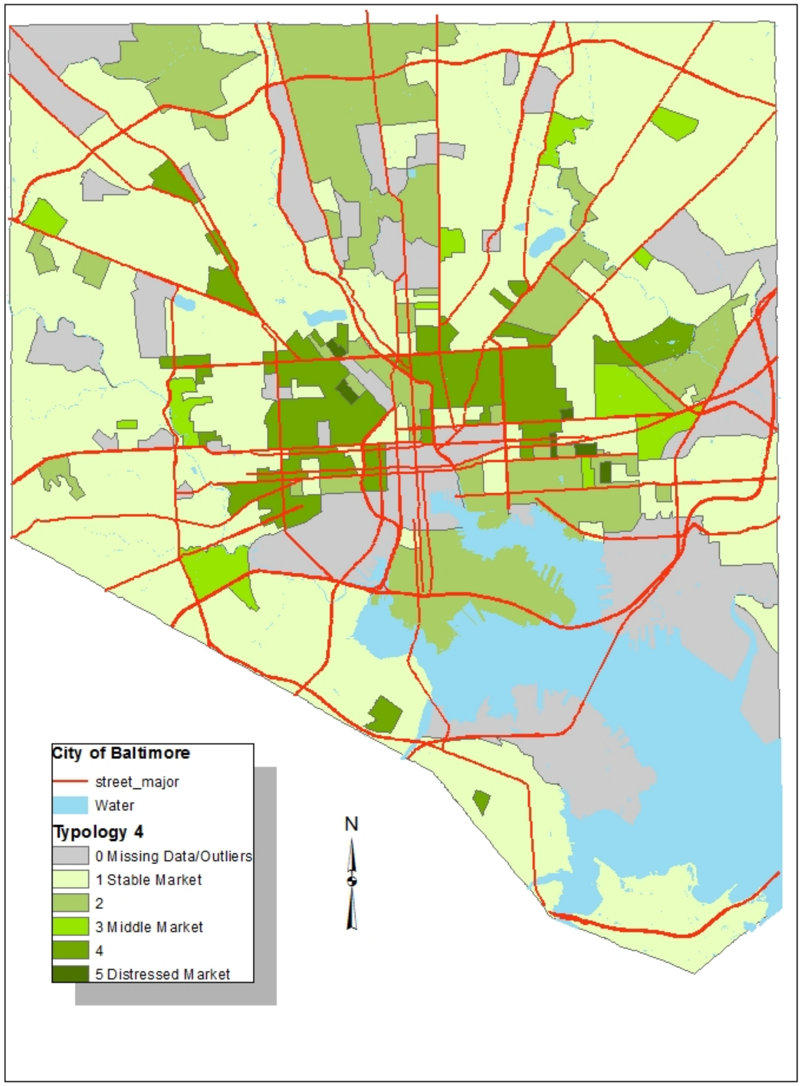


Figure 10: Cluster Outputs for Typologies 3 and 4





Typology 4 also presented similar findings as Typology 2. In this model most of the city was classified as stable and the affluent are represented as cluster 2, indicating that it is the second quality level lower than stable based on market conditions even though this area contains the highest home values in the area. Therefore, cluster outputs from typology 2 and 4 are not consistent with ground level housing and socioeconomic conditions.

Typology 1 and 3 presented more variation and distribution in the data. Typology 1 contained both socioeconomic and housing related indicators, and typology 3, contained only housing related indicators. For typology 3, areas between middle market and distress presented some discrepancies. Neighborhoods along the northeast edge of the city and areas which surround the more distressed market represented in this typology were classified at one level higher than distressed, however these neighborhoods based on field observation contain more stable housing market conditions with the second highest home values in the city. In typology 3, the cluster output aggregate median home value is approximately $88,000 while in typology 1, these neighborhoods aggregate median home value is approximately $100,000. These differences are based on the number of cases converged into the same category during each cluster analyses. In typology 1, there are more variables in category 2 based on the cluster output which include additional socioeconomic variables and this may be the cause of different average home values.

Based on this analysis, typology 1 was selected as the final model to test distinction in market. In the final typology, socioeconomic variables were excluded with the exception of household income. Percent African American do not indicate market condition and unemployment rates appear to be a proxy for housing value. Figure 11 provides the final typology. Table 10 summarizes the results.

Results of Validating Clusters

This final typology was tested to validate that each cluster represented a distinctive and separate cluster. A hedonic regression was used to test the significance of these clusters. Specifically, the unit sale prices were regressed on unit characteristics, such as building conditions, age, garage, fireplace, and structural characteristics.

Next, cluster dummies were added to the model to determine if the clusters improve the estimation price and second, if the submarkets are significantly different from one another. For the final typology, added cluster dummies presented a R^2 advanced from .38 to .65, improving the model's fit. The clusters substantially and significantly altered the unit price as shown in Table 10. The clusters are statistically significant demonstrating distinct differences among the submarkets. For certainty, each submarket is estimated separately, and the standard errors of the hedonic equations were then compared for each model to determine if each submarket were distinctive from the next. The regression equations are compared using a Chow test. The Chow test determines whether, among the regression equations, there is a significant difference between the clusters under the null hypothesis that the two models are equivalent. Table 11 presents the result of this test for the five clusters of properties. The test presents significance at the 1 percent level of confidence.

Table 12 provides the cluster summary output from the GIS analysis. This step was completed to ensure that clusters presented accurate representation based on descriptive variables. For example, cluster 1 in the final typology contained the highest home values and median household income. This cluster also contains lower vacancy and crime rates, low percent of rental housing and subsidized housing. These descriptive statistics are consistent with the current literature on housing markets. Cluster 5, represented of distressed markets contained the lowest home values and median household income, with higher crime rates and percent of vacant housing.

Table 10: Hedonic Regression for Clusters

Hedonic Regression on individual-unit sale price, 2005				
	R squared	*0.646*		
	b	std *b*	sig	sig
Intercept	4.90291	0.02875	***	<.0001
Structural Characteristics				
DGEXC	0.16885	0.02532	***	<.0001
DGFAIR	-0.09763	0.00591	***	<.0001
DGGOOD	0.05531	0.00763	***	<.0001
XBRICK	-0.06383	0.00393	***	<.0001
XBASEMENT	0.00734	0.006		0.2211
XSQFTSTRC	0.0001977	4.24E-06	***	<.0001
XSQFTSTRC2	-1.37E-08	7.31E-10	***	<.0001
XAGE	9.621E-05	8.641E-05		0.2656
XAGE2	-1.35E-08	4.17E-08		0.747
XAIRCON	0.07345	0.00411	***	<.0001
XHBTH	0.01403	0.00409		0.0006
XBASEMFN	0.03046	0.00411	***	<.0001
XATGR	0.04094	0.00901	***	<.0001
XFIRE	0.04875	0.00607	***	<.0001
XDECK_PRCH	0.00636	0.00303		0.0357
Clusters				
CL1	0.21325	0.02731	***	<.0001
CL2	0.20869	0.02653	***	<.0001
CL3	-0.09172	0.02651	**	0.0005
CL4	-0.16171	0.02676	***	<.0001
CL5	-0.22707	0.0309	***	<.0001
Note: *n* = 14291				

Table 11: Clusters Chow Test

Note: Chow test were perform for each cluster to determine differences between clusters. Test was significant at the 1 percent level

Ordinary Least Squares Estimates			
SSE	4169.091	DFE	14278
MSE	0.29199	Root MSE	0.54036
SBC	23003.72	AIC	22958.3182
MAE	0.417444	AICC	22958.3241
MAPE	3.625935	Regress R-Square	0.4568
Durbin-Watson	0.9367	Total R-Square	0.4568

Structural Change Test					
Test	Break Point	Num DF	Den DF	F Value	Pr > F
Chow	13408	6	14272	27.44	<.0001

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	11.7566	0.0788	149.16	<.0001
CL1	1	1.0613	0.0809	13.12	<.0001
CL2	1	0.4709	0.0793	5.94	<.0001
CL3	1	-0.3684	0.0791	-4.66	<.0001
CL4	1	-0.623	0.0799	-7.8	<.0001
CL5	1	-1.0203	0.0908	-11.24	<.0001

Figure 11: Final 2005 Typology

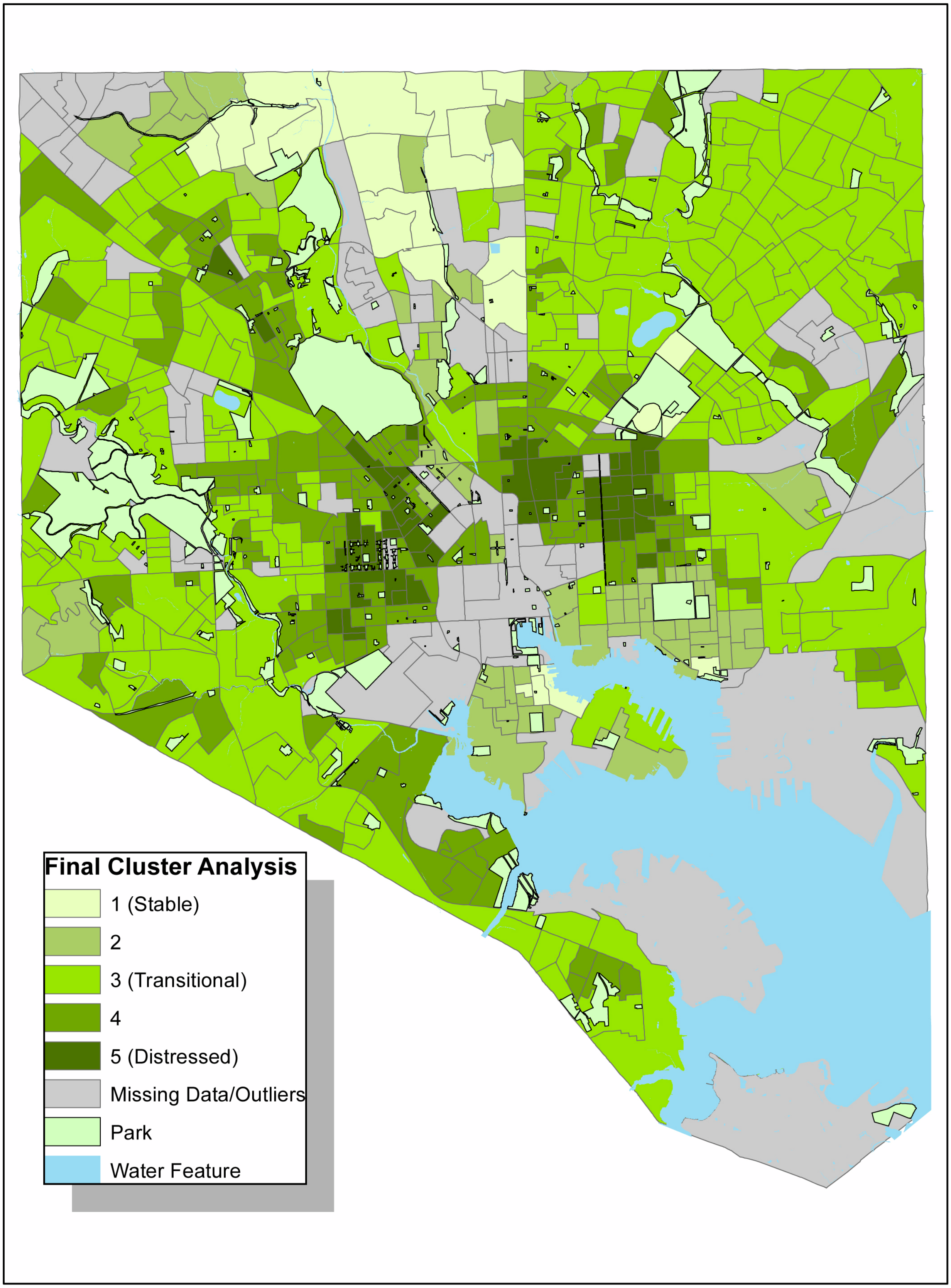


Table 12: 2005 Typology Summary Statistics

Neighborhood Indicator	Level of Data	Data Source	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Population Density (people per square miles)	Census block	US Census	10147.03	17490.95	14206.49	15525.25	13525.26
Percent change in population in 1990 and 2000	Census block	US Census	-0.77	-0.63	-0.21	-0.27	0.14
Percent of White Households	Census block	US Census	0.86	0.71	0.30	0.13	0.03
Percent change of White Households	Census block	US Census	0.09	-0.09	0.32	0.14	0.05
Percent of African American Households	Census block	US Census	0.09	0.20	0.66	0.83	0.94
Percent change of African American Households	Census block	US Census	-0.16	-0.54	-2.14	-0.57	-0.01
Percent unemployment	Census block	US Census	0.02	0.05	0.07	0.12	0.12
Percent change of unemployment	Census block	US Census	0.21	0.07	-0.24	-0.29	0.19
Average Household income	Census block	US Census	$ 88,794.05	$ 35,466.33	$ 36,740.33	$ 21,670.01	$ 19,075.55
Percent of owner occupied housing units	Census block	CPD	0.81	0.50	0.71	0.36	0.33
Percent of renter occupied housing units	Census block	CPD	0.19	0.49	0.29	0.63	0.65
Average age of housing units	Census block	MPV	56.23	54.13	52.59	50.90	51.24
Average values of housing unit (based on sale prices)	Census block	MPV	$ 434,505.05	$ 246,903.38	$ 95,487.19	$ 60,861.84	$ 37,850.78
Percent of foreclosed housing units	Census block	CPD	0.01	0.01	0.02	0.02	0.01
Percent of home sales	Census block	CPD	0.09	0.12	0.09	0.10	0.06
Percent of permits (permits greater than $5,000 exterior rehabs for housing units)	Census block	CPD	0.03	0.05	0.01	0.01	0.01
Rate of crime among all residents (number of violent crime per 1000 people in the city in 2005)	City district	CPD	0.69	1.54	1.51	4.09	3.79
Percent of vacant housing units	Census block	CPD	0.00	0.03	0.01	0.11	0.25
Percent of vacant lots	Census block	CPD	0.00	0.00	0.00	0.01	0.11
Proportion of commercial land (as a Percent of square miles of land uses)	Census block	CPD	0.07	0.13	0.09	0.12	0.22
Proportion of subsidize housing (including public housing projects)	Census block	CPD	0.00	0.00	0.00	0.02	0.02
**MPV: Maryland Property View Assessor Data							
**CPD: Baltimore City Planning Department							

DISCUSSION

The 2005 final typology for Baltimore is comprised of five distinct housing submarkets. Figures 12 and 13 provide visual examples of housing represented in this typology.

Stable Cluster: Cluster 1 and 2

Census block groups in Clusters 1 and 2 are defined as stable submarkets in the city. Cluster 1 neighborhoods contain the highest housing sales values in the city, followed by Cluster 2. Clusters 1 and 2 present the highest percentage population changes of all other clusters since 1990. Based on 2000 decennial data, these neighborhoods contained approximately 86 percent Non-Hispanic White residents and only nine percent African American residents, with small gains in the white population and significant declines in the African American population. These two clusters also contained the highest percentage of college graduates, and enjoyed the highest average household income of $89,000 among the five markets. Neighborhoods in this category also contained over 80 percent owner-occupied housing. Clusters 1 and 2 contained a low percent of foreclosures (1 percent) and zero vacant housing units, lots, or subsidized housing.

The socioeconomic characteristics of Clusters 1 and 2 demonstrate some similarities. Non-Hispanic White households make up 71 percent of Cluster 2 and African American household represent 20 percent. Cluster 2 presents a 9 percent decline in Non-Hispanic White households, with 54 percent decline in African American households. Cluster 2 contains 26 percent senior population (65 and over), which is less than all other clusters.

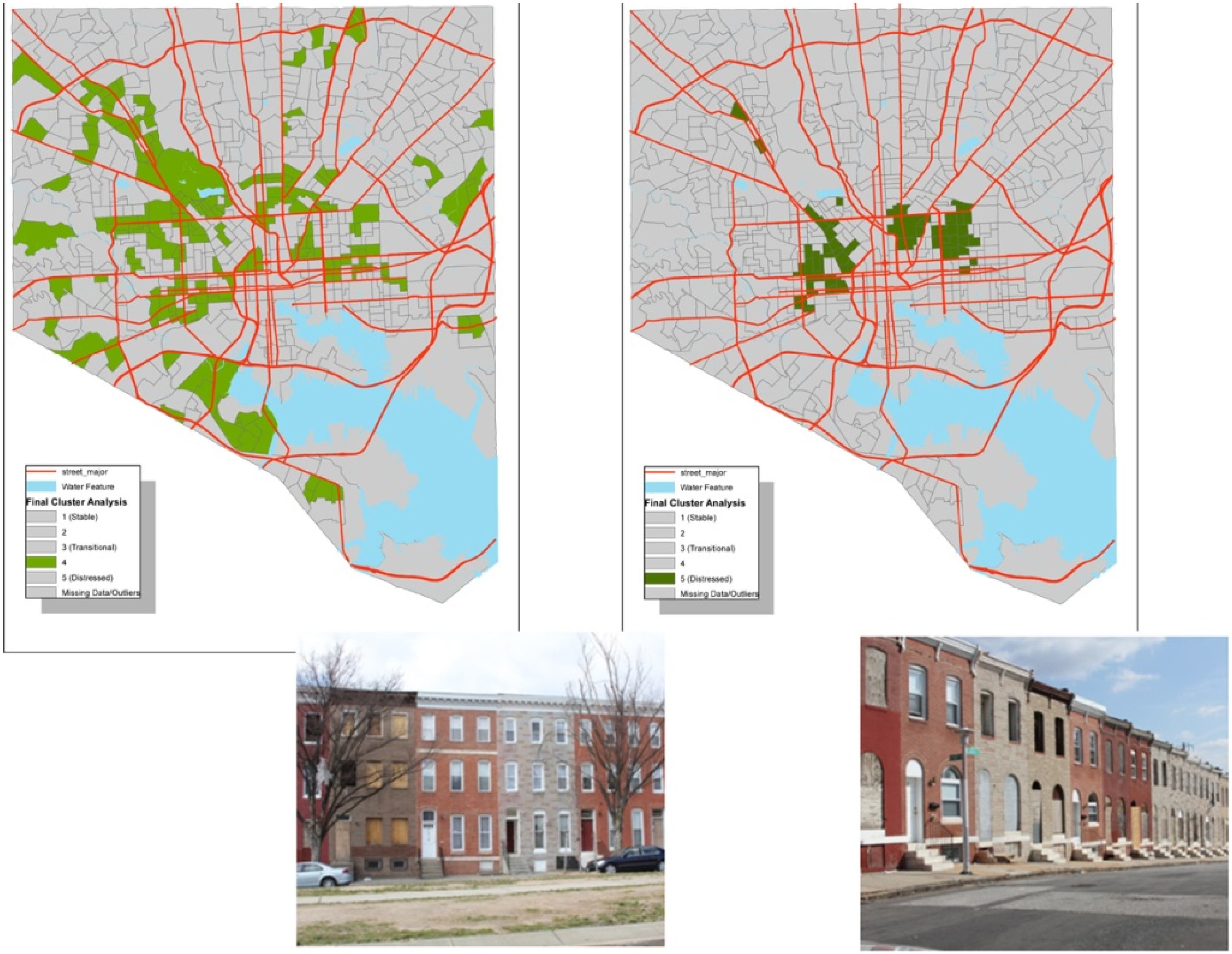
These two stable submarkets also had some differences. Cluster 1 showed a nine percent decline in Non-Hispanic White households, with 54 percent decline in African American households, however it contained the largest percentage of seniors than any other cluster. Cluster 2 also contained a high percentage of rental occupied units, 49 percent. Additionally, more homes were sold in cluster 2 than Cluster 1. Cluster 2 also contains more permit activity than Cluster 1.

Baltimore’s 224 neighborhoods were classified in the study. Fourteen (six percent of clustered neighborhoods) and 31 (14 percent of clustered neighborhoods) neighborhoods were classified in Clusters 1 and 2, respectively. Examples of these neighborhoods included Federal Hill, Clifton Park, Little Italy, Roland Park, and Montebello. These neighborhoods are characterized as historical areas in the city with high property values, large homes, and well-maintained property near universities and other city institutions. Federal Hill and Little Italy are both located near large commercial and retail districts in the central area near the Harbor. Roland Park and Montebello contain some of the city’s largest housing stock by square footage, with large lots. Cluster 2 neighborhoods are represented by Mount Vernon, Fells Point, Canton, Brewer, and Butcher Hill. These neighborhoods represent historic areas located near the city’s downtown area and near the Harbor. Neighborhoods also contain a diverse mix of populations from students to young professionals accounting high percent of rental population. Neighborhoods in Cluster 2’s proximity to downtown decrease its housing values below Cluster 1.

Figure 12: Field Analysis, neighborhood photos 1, 2, and 3

Notes: Listed from left to right, neighborhoods included in this Figure are Roland Park, Mt. Vernon, and Belair Edison.

Figure 13: Field Analysis, neighborhood photos for clusters 4 and 5



Notes: Listed from left to right, Neighborhoods included in this Figure are Broadway East and Greenmount.

Middle Market Cluster: Cluster 3

The Cluster 3 housing submarket suffered a 20 percent decline in population between 1990 and 2000. It is defined as the middle market cluster. Census block groups in this category contain 30 percent Non-Hispanic White households and 66 percent African American. This cluster is made up of 30 percent college graduates and reflects a 5 percent unemployment rate. It had a slightly higher average income than Cluster 2, at $36,000. This higher income may be a reflection of a higher percentage of young professional residents. Few foreclosures exist in this cluster. Crime rates are higher than Cluster 1 but slightly lower than Cluster 2. Cluster 3 contains a lower percentage of vacant properties than Cluster 2. Unemployment rates in this cluster are higher than previous clusters, and income is slightly higher than Cluster 2, at $36,000. There are a limited number permits in this cluster (similar to conditions in more distressed clusters), but more housing sales than in the most distressed cluster. Crime rates are higher than Cluster 1, but slightly lower than Cluster 2. Cluster 3 contains a lower percentage of vacant properties than Cluster 2. Additionally, this cluster contains a lower percent of commercial land uses in comparison to other clusters.

Nineteen percent (or 109) of Baltimore neighborhoods are represented in the Cluster 3 submarket. Examples of these neighborhoods include Belair-Edison, Baltimore-Linwood, Greek town, Gwynn Falls, and Northwood. These neighborhoods are composed of mainly brick row homes and high density of housing units.

Distressed Clusters: Cluster 4 and 5

In Clusters 4 and 5, the distressed housing submarkets comprise 37 percent of all block groups in the City. Cluster 4 contains 13 percent of Non-Hispanic White households and 83 percent of African American households. This cluster has a higher unemployment rate than clusters above it (1 through 3). It had a lower income ($21,607) than cluster 5 ($19,075). Cluster 4 was predominantly renter-occupied (63 percent). In addition, vacant buildings made up 11 percent of the stock, exceeding the percentages for other clusters (1 through 3), while also significantly lower than Cluster 5. In a similar fashion, the distressed markets in Cluster 4 contain a larger percentage of subsidized housing (2 percent) than the stable or transitional markets. Foreclosure represents two percent of housing stock, and crime rates are high in this submarket relative to the more stable or middle markets. Permit activity was also relatively low in this market. Neighborhoods in Cluster 4 are located along the western border of the city and along York Road from the edge of the central core to the northern border of the city. Neighborhoods in this cluster include Waverly, Hollins Market, Charles Village, Reservoir Hill, and Westport.

Cluster 5 was defined as the most distressed cluster, accounting for 9 percent (or 51) of the census block groups in the city. Surprisingly, this cluster did not experience substantial population change from 1990 and 2000, and increased by 14 percent in ten years. Some of this increase is due to the gradual influx of the Non-Hispanic White population. Regardless of this influx, Cluster 5 continues to be predominantly African American (94 percent). This cluster has the smallest percent of college graduates, and 12 percent unemployment rate. The average household income is also the lowest of all clusters at a little less than $20,000. This cluster also has the lowest housing values. The rental population is 65 percent, with housing values the lowest of all clusters, approximately $37,000. This cluster contains a higher percentage of vacant lots and subsidized housing than the other four clusters, which is the highest of all clusters, at 22 percent. The crime rate is also higher than all other clusters, except Cluster 4. Housing sales of only six percent are the lowest of all other clusters and permit activity is approximately one percent.

Neighborhoods in Cluster 5 are the most disinvested areas and, based on field research, contained blocks of vacant buildings and lots. Field analysis also presented some findings in terms of spatial geography. Small pockets within neighborhoods in Cluster 5 appear to be undergoing gentrification with new development along major corridors, such as Charles Village. However, due to proximity to other rapidly declining areas, progress within neighborhoods in Cluster 4 and 5 is not captured even at the parcel block level. Other neighborhoods within this cluster include Greenmount West, Jonestown, Barclay, and Sandtown. Many of these neighborhoods are notorious for crime and continually failed reinvestment, as these areas are the focus of the city's target zones. These neighborhoods continued to experience negative changes between 1990 and 2000, despite their location in reinvestment zones.

CONCLUSION

In the first section of this analysis, the variables to include within a NHMT for the City of Baltimore were identified. Using cluster analyses, it was determined that change variables were questionable indicators because of inconsistency with the typologies which included these variables. The cluster results of this analysis were mapped in GIS and presented mixed findings. Change variables appeared to cloud the model, did not provide meaningful outputs, and presented little variation or an inaccurate representation of neighborhoods. This preliminary analysis of the data led us to question typology models employed by cities as reviewed in Table 6.

Output from the GIS spatial analysis presented questions related to cluster technique and the quality of variables used to develop typologies. The final typology model developed for this analysis included few socioeconomic variables as presented in models for Kansas City and Memphis and the final model. Upon testing the clusters included in the final hedonic price function model, it was determined that these housing variables, including income, provided a statistically significant representation of neighborhood submarkets in Baltimore. This analysis raises questions as to the role of socioeconomic variables on housing markets.

The results of the GIS mapping of cluster outputs suggest that population change and other change variables may not reliably distinguish housing submarkets. Kansas City and Memphis's typologies use change and socioeconomic variables to represent submarkets. However, they rely on z-scores methods rather than our cluster approach. Using a z-score methodology may allow more flexibility to define markets with change or socioeconomic variables, because data is normalized relative to citywide averages. The statistical cluster methodology may not present similar results because it is based on spatial distances rather than city averages.

The unit of analysis is central in the evaluation of neighborhood clusters because it explains the usefulness of typologies to provide an accurate image of neighborhoods. During field analysis, it appeared that small pockets of stability or emerging neighborhoods were not captured once data was aggregated to the census block group level. Even though the census block level was the smallest unit of analysis, it still appeared that other submarkets either existed within one submarket or overlapped into another market. This presents similar obscurity as the use of larger geographic units of analysis and evidences the difficulty of defining submarkets. According to the final cluster summary Table 10, the cluster method is able to capture market differences, but the analysis output still presented opportunities for further variation (e.g., inclusion of additional clusters) to explain submarket conditions.

In Hunter's (1979) analysis of typologies, he concluded that there was a central utilitarian debate of whether clusters were a useful way to differentiate neighborhoods for the purposes of specific policies and programs. This analysis does not attempt to address intents of policies, but has determined that further research is necessary to address units of analysis and the usefulness of socioeconomic variables to differentiate submarkets. Based on this analysis, socioeconomic variables and change variables do not show spatial submarkets. Their effects may be gleaned or internalized from housing condition variables. However, these findings must be addressed with great caution.

In the manner of citywide and block level targeting efforts, the focus on housing characteristics to distinguish submarkets makes it easier to target government resources. Conclusions from this study suggest that cities' should focus on housing market conditions to target resources and not be confounded or blinded by socioeconomic characteristics.

As typologies are used to illustrate market conditions in a neighborhood, the exclusion of social indicators may negate population characteristics, such as residents' ability to improve housing conditions, risk of mortgage defaults, access to capital, and other factors demonstrated in the housing market but not controlled by local governments. Additionally, based on the technical methodology used to develop a typology, socioeconomic indicators may not be used in the development process, but they are essential to tell an accurate story of the multi-dimensional dynamics of neighborhoods.

Further analysis is necessary. Additional testing of submarkets may be warranted to test how clusters in different typologies present varying representations of submarkets. The literature on submarkets continues to evolve including spatial proximity. Though these factors did not present significant finding in initial analysis other steps or statistical models may be necessary to explore locational factors in the development of typologies. These location variables may include amenities like proximity to parks or retail, in addition to proximity to the downtown. The influence of locational amenities is important to determine their usefulness in defining housing submarkets.

ESSAY TWO:
DO NEIGHBORHOOD HOUSING MARKET TYPOLOGIES MATTER? EXAMINING THE EFFECT OF THE HOME PARTNERSHIP INVESTMENT PROGRAM IN BALTIMORE, MARYLAND

INTRODUCTION

For decades, scholars and practitioners have sought to determine the most effective method to spatially allocate scarce financial resources to produce measurable improvements in economically distressed communities. Cities continue to question which public investments strategy will allow them to leverage private investments and lead to the revitalization of depressed neighborhoods. Scholars have been unable to conclusively answer this question and others relevant to the impact of federal housing subsidies in distressed communities (Ding et al., 2000; Ellen et al., 2001; Galster et al., 2001; and Galster et al., 2006). They point to different factors and strategies to determine which investments will be most effective, and where they will produce the greatest returns. To further complicate the situation, for the first time in over a decade, distressed neighborhoods are not the only areas showing signs of hardship. With the recent housing market crisis and economic downturn, even once-stable communities are now experiencing signs of disinvestment and abandonment. The debate is no longer about *where* to strategically invest in distressed, low-income neighborhoods, but *how* cities should spatially allocate program resources to address the unique needs of diverse communities and different housing market types.

Empirical studies that review housing programs' impact on neighborhoods find that federal housing subsidies and programs tend to have positive impacts in distressed communities when investments are large and concentrated in specific areas (Ding et al., 2000; Ellen et al., 2001; and Galster et al., 2006). Positive effects on surrounding property values vary based on whether the investments are new construction or rehabilitation. Additionally, studies suggest that effects may vary based on the distance of the investments from the property sale and the scale of federal investments. Studies find that investments are most effective within 150 feet of the housing sale (Ding et al., 2000; and Ellen et al., 2001). Other factors such as neighborhood characteristics have also been identified in the current literature as factors that influence investment impacts.

Neighborhood characteristics, generally identified in the literature by income, race, and ethnicity, play a role in the impact of investments on surrounding properties. While numerous studies focus solely on distressed neighborhoods, some studies evaluate the variation of impact in distressed versus non-distressed areas. In a review of investment impacts on surrounding property values, these studies find that investments are significant and have a positive impact in lower income neighborhoods, while these investments are not significant in minority neighborhoods (Ding et al., 2001). However, additional literature on housing market segmentation suggests that social and economic demographics of neighborhoods are not the only factors that make up housing submarkets. Scholars identify housing type, structure, and other neighborhood elements that affect housing markets, as opposed to neighborhoods' household characteristics (Bourassa et al., 1999; Tu et al., 2007; and Fik et al., 2003).

There is a need among empirical studies to broaden the scope of analysis to measure additional factors which impact housing submarkets to estimate the effects of federal housing production programs' on neighborhoods. Few housing program studies analyze investment impacts based on neighborhood housing market conditions beyond distinguishing markets according to income and racial composition. It is important to question whether neighborhood housing markets, as clusters of similar social, economic, and housing conditions, present different outcomes related to the effects of housing program investments. This study provides answers to the aforementioned issues and uses Baltimore, Maryland, as the study area.

Over the past 20 years, Baltimore has employed housing production programs in its neighborhoods to provide affordable housing for disadvantaged households and revitalize its most distressed areas. Coupled with economic development programs and strategies, the city has funded numerous subsidized unit rehabilitation and new construction projects with programs such as Section 8 New Construction/Substantial Rehabilitation, HOPE VI, Section 202, Section 811, the Low Income Housing Tax Credit (LIHTC), and the HOME Investment Partnership Program (HOME Program). Baltimore relies heavily on the HOME Program to help transform neighborhoods and support affordable housing efforts. However, little is known of the Program's true impacts in Baltimore. In this study, I will examine the impact of the HOME Program in Baltimore neighborhoods, focusing on production subsidies, such as rehabilitation and new construction investments.

The first section of this study will examine Baltimore's social and demographic trends and patterns of its neighborhoods in the context of neighborhood change theory. The second section will evaluate the impacts of the HOME Program based on the scale and concentration of investment. Finally, this study will test the impacts of investments across neighborhood housing market types to determine whether the effects of investments change based on the overall condition of neighborhoods.

LITERATURE REVIEW

Much of the literature related to the impacts of housing programs on surrounding properties and neighborhoods surfaced among housing policy analysts in the late 1990s. Studies reviewed major housing programs such as HOPE VI, LIHTC, the Nehemiah Housing Program, and the Community Development Block Grant (CDBG) Program related to the production of housing programs. The purpose of such analyses was to determine if federal housing programs affected neighborhoods based on increases in housing property values. The common thought was that subsidized housing programs negatively influenced property values; however, empirical studies have offered conflicting evidence. The literature that evaluates the impacts of housing programs is divided into two areas. The first area tests the impacts of investments in the form of vouchers and homeownership programs; these programs represent demand-side housing programs. The second area examines the impact of housing investments in the form of new construction or rehabilitation of housing; these programs represent production or supply-side housing programs (Schwartz, 2010). This literature review will focus on production housing programs.

Studies that evaluate the impacts of subsidized housing investments in neighborhoods suggest three factors that influence surrounding housing prices. Housing sale prices in this literature are used as a proxy for neighborhood quality (Galster, 2000; and Knapp and Ding, 2001). The factors include the scale of the investment, the distance of the investment from the property, and neighborhood socioeconomic and housing characteristics.

Lyons and Loveridge's (1993) analysis of subsidized housing programs in Ramsey County, Minnesota find that the dollar amount per subsidized housing unit and the total number of units involved in an investment project has a significant impact on surrounding housing values. In their analysis, they found that a greater number of subsidized development units were associated with a positive impact on property values. Ellen et al. (2001) used a difference-in-difference model to analyze the New York Nehemiah Program and the Partnership New Homes program and reached the same outcome that all large-scale investment projects (as measured by the number of units) have significant impacts on property values. Galster, Santiago, and Tatian (2001) found that large-scale investment projects in Denver, Colorado positively affect housing sale prices if they are within a certain distance of a property. These findings are similar to Ding et al. (2000), who conclude that large-scale investment projects have a positive impact on housing sale values, and that the impact on neighboring properties diminishes as the distance from the investment increases.

Galster, Tatain, and Accordino (2006) concluded that there is a concentration effect based on the total dollar amount of an investment. In their analysis of Richmond, Virginia, the authors suggest that an investment project valued over $25,000 that is concentrated at the block level will positively affect the surrounding area. Alternatively, there is little evidence that the size of the development has significant effects (Briggs, Darden, and Aidala, 1999; Lee, Culhane, and Wachter, 1999). An examination of rehabilitated public housing sites of 14 to 48 units in Yonkers, New York, returned few significant findings. Lee, Culhane, and Wachter (1999) assert that values of surrounding homes may be impacted by the distance between the property and the investment. In their analysis of Section 8 certificates and vouchers in Philadelphia, the authors concluded that higher distances may diminish the impact of the investment.

Other empirical studies that examine the effects of new construction and rehabilitation of subsidized housing attempt to determine if there is a spillover effect. These studies have mixed findings. Ding et al.'s (2000) analysis of residential subsidized investments on nearby property values in Cleveland, Ohio, suggests that the effects of investments on property values are based on geography. The authors conclude that residential investments of new construction and rehabilitation have positive impacts on surrounding property values located within a 150-foot radius of the investment site. Schill et al.'s (2002) analysis of a ten-year plan in the City of New York indicates that prices of homes within a 500-foot radius of subsidized units' increases relative to those located beyond 500 feet, but within the same census tract. Johnson and Bednarz's (2002) analysis of LIHTC suggest that impact is significant within a 1,000-foot radius of the property, while finding that there is no impact if a property is outside of that radius. Other studies associate neighborhood conditions as factors that affect investment impacts.

Past work on housing subsidy programs suggests that neighborhood conditions matter and influence investment impacts. Green et al. (2002) analyze the effects of LIHTC on surrounding property values and found that the impact depends on the quality of the neighborhood as defined by household socioeconomic status. The authors found that areas with a high percentage of low-income households, high poverty rates, and high percent of African Americans overshadowed the effects of federal housing investments. In contrast, Green et al. (2002) found that investments had either positive or neutral effects when located in areas with more affluent characteristics. Lee et al. (1999) found that subsidized units had negative effects on property values; whileBriggs et al.'s (1999) analysis of subsidized housing found no price effect on the development of small-scale investments. Galster (2002) asserts that the areas surrounding the selected sites influence the effects of investments, concluding that many areas selected for subsidized housing tend to be in areas with low and declining property values.

Despite a significant body of literature on the negative impacts of subsidized housing, other studies have presented different outcomes. Ding et al.'s (2002) study of subsidized housing investments in Cleveland, Ohio, found that new construction and rehabilitation have positive impacts on low-income areas, as well as predominately non-minority neighborhoods. Galster el al. (2006) also present positive impacts in distressed neighborhoods, but caveat that investments must be large scale. The authors find that the greatest impacts in distressed neighborhoods occur when the public investment is over $21,000 per block. This analysis indicates a need to concentrate investments for measurable impact. Other scholars also find similar positive effects of investments in distressed neighborhoods (Ellen et al., 2001; and Santiago, Galster, and Tatian, 2001).

Gaps in the Literature

Much of the past empirical work on subsidized housing impacts concludes that scale, distance, and neighborhood characteristics affect the impacts of investments on surrounding property values. These works present mixed evidence of positive and negative effects in distressed neighborhoods. A few studies have examined the differential effect of subsidized housing investments across neighborhoods based on housing market conditions. Ding et al. (2000) is one of the few studies that evaluate the impact of housing investments in low-income neighborhoods and areas with high concentrations of African American households. However, other factors affect housing markets.

Downs's (1980) early examination of factors that cause neighborhoods to change discovered that the effectiveness of specific policies is dependent upon a given neighborhood's stage at the time the policy is applied. In today's terms, neighborhood stage refers to neighborhood housing market types. These types are identified by placing neighborhoods into distinct categories according to social, economic, and housing conditions. These categories are then classified using aggregate neighborhood conditions, including stable, transitional, and distressed. The emphasis of recent work on the impacts of subsidized housing has been directed toward neighborhoods in general. Few studies evaluate different neighborhood types outside of Ding et al.'s (2000) work that classified neighborhoods as low-income or affluent areas, and measured the different magnitude of investment impacts.

The literature on housing market segmentation suggests that neighborhoods are a bundle of similar social, economic, and housing characteristics. Identified market types are based on the social and economic characteristics of households. However, scholars claim that these are not the only factors that make up markets. They suggest that housing types, quality of housing units, and other neighborhood effects (e.g., percent of vacant properties) create distinct housing markets and are more likely to influence market segmentation than social and economic household characteristics (Bourassa et al., 1999; Tu et al., 2007; and Fik et al., 2003). These findings are important because much of this analysis is not included in studies related to subsidized housing units and measures of impact. Income, race, and ethnicity remain central in these analyses to differentiate neighborhood markets. Additionally, few comparative studies are provided.

Time of redevelopment, scale of redevelopment, and the strategy employed all affect the impacts of investments. Cities going through major reinvestment and revitalization may target critical portions of dollars in their more distressed areas. This massive amount of investment funneled into a few select areas may present greater impacts versus funding in a non-strategic manner to provide assistance to all eligible households. Aggressive and concentrated investments by a municipality may yield different results from scattered site investments. In addition, the city's size, composition, and housing stock may also present different findings.

This research will focus on the city of Baltimore and empirically examine the impacts of the HOME Program and determine whether impacts are based on the scale of the investment, the distance of the investment from property values, or other factors related to neighborhood characteristics and housing markets. Before this project can focus on the empirical analysis and findings, the HOME Program will be described from a national perspective and then within the context of Baltimore.

STUDY AREA

This analysis will focus on the city of Baltimore which lost approximately 170,000 residents between 1970 and 1990, a 23 percent decrease in 30 years (National League of Cities, October 2005). As with most postindustrial cities, Baltimore suffered significant population losses, with residents moving to surrounding suburban communities, as a result of major declines in port activities and the steel industry. In the 1990s, the city's population represented just 25 percent of the regional population (Urban

Renewal and Inner Cities). Unemployment in the city dropped in the 1990s to 8.3 percent from 10.8 percent in 1980, and continued to decrease until 2003. Manufacturing jobs, represented as high-wage employment, were no longer the major employment sector in the city. This industry experienced a 3.7 percent decrease in jobs from 11.5 percent in 1985 to 7.8 percent in 2000; in 1950, the number was 34.1 percent.

Unemployment, coupled with population losses, were the culprits of significant neighborhood blight and disinvestment in the city. In 2000, the city's abandoned housing units range from 12,700 to 42,480 based on the city's count of units and the 2000 census (Cohen, 2001). During this time, the city had nearly 6,000 vacant properties through tax foreclosures, and once it factored in other properties owned by the city, that number increased to 10,000 properties (Baltimore Housing, 2005). Some of the hardest hit neighborhoods were located near Baltimore's Inner Harbor and central downtown, with poverty rates over 40 percent and median household incomes at $10,000 to $15,000 (Baltimore Housing, 2005).

To counteract increasing disinvestment in neighborhoods and address the mounting number of vacant units, the city began to employ a number of initiatives to tackle its excess supply of abandoned homes. Empowerment zones were established in the central core neighborhoods along with other targeted reinvestment zones in the early 1990s for the purpose of attracting businesses in the central core of the city. To address housing needs, the city employed numerous housing programs including CDBG funding (since 1980), HOME investments (1992), HOPE VI (1994), LIHTC (1992), and a host of other housing related programs. Much of these initiatives were targeted towards Baltimore's most distressed areas in the core of the city. The city uses HOME funds as the major funding to target poor households and provide suitable and affordable housing options for its disadvantage populations.

HOME Partnership Program

The HOME Program debuted in 1992 as one of the largest federal block grant programs. It supports state and local government efforts to salvage and preserve aging housing stock, build affordable housing, and provide homeownership opportunities for low- and moderate-income households. The HOME Program is a block grant, meaning that it consists of multiple categorical grant programs bundled into one large program. These program areas include the Rental Rehabilitation Program, Urban Homesteading Program, Section 312 Program, and the Nehemiah Program. Because it is a block grant, the HOME Program gives recipient state and local governments, identified as participating jurisdictions (PJs) the discretion and flexibility to spend funds as they determine necessary.

The purpose of the HOME Program is to increase affordable housing in communities through property acquisition, new construction, rehabilitation, home-buyer assistance, and tenant-based rental assistance (US HUD, 2004). The guiding principles of the program include: (1) provide flexibility to design and implement revitalization strategies tailored to the needs and priorities of a community; (2) consolidate planning efforts to facilitate public and private sector partnerships; (3) build neighborhood-based capacity by providing local technical assistance for non-profit groups; and (4) require grantees to leverage at least 25 percent of the total grant award through cash match or in-kind services. Based on these principles, HOME funds are used in a number of ways, to support low-interest loans, deferred loan payments, and loan guarantees (US HUD, 2004,

p. 6). The HOME Program also offers grants to communities with a particular focus on rental unit renovation and new construction. The analysis will address these services.

The HOME Program is designed to target poor households to ensure that populations demonstrating the greatest need can access these federal funds. At the same time, the flexibility of the Program allows persons in other income brackets to also access the funds, just as long as their income does not exceed 80 percent of the area median income (AMI). Nationally, for occupied or soon-to-be occupied dwellings, a large percent of households earn above 50 percent AMI. For homebuyer units, approximately 46 percent of households earn between 60 to 80 percent AMI. This demonstrates the flexibility of the Program to target more than just the most distressed households or neighborhoods. HOME funds are also targeted according to household types, to include homeless individuals and families, families with children, large households, senior families, persons with disabilities, and those that rely on public assistance.

To use HOME funds effectively, HOME recipients must have an understanding of the local housing market, including characteristics of household socioeconomic status, housing conditions and tenure, and other market conditions to prioritize and direct public resources to urgent housing challenges. The targeting of households based on socioeconomic condition and family type is a requirement. Spatial targeting of resources is not a requirement of the Program. However, since 2000 a growing number of cities with declining budgets have begun to target resources in geographic areas for visual impact and to leverage neighborhood resources.

In 2004, the HOME Program encouraged PJs to consider concentrating funds at the neighborhood level based on the availability of buildable land, neighborhood anchors and assets, and infrastructure to support community development and growth of the community. HUD program offices cautioned PJs that investments should be targeted in small redevelopment zones for greater visible impact to avoid dispersed activities and investments. However, HUD also discouraged PJs from targeting zones that are too small. They suggest that zones that are too small limit neighborhood boundaries and provide benefits to few residents, thus failing to generate the intended neighborhood impacts. PJs were encouraged to target areas within a quarter-mile radius from the neighborhood center; areas near existing neighborhood strengths, such as schools to attract potential homebuyers; areas with few tax delinquencies; and, areas with supportive infrastructure for home designs and amenities to attract mixed used development. Few cities have aggressively implemented target area allocations with HOME funds. The next section looks specifically at Baltimore's use of HOME funds.

HOME Partnership Program in Baltimore

Since 1992, HOME funds have been the city's major investment vehicle to address suitable housing needs for low-income households through new construction and rehabilitation. Of the total $47 million allocated to the city for housing and community development from HUD, HOME represents six percent or $7 million. The city has allocated a total of $138,036,051 in HOME funds between 1992 and 2010. Approximately 78 percent of HOME dollars have been used for new construction of rental units and 22 percent for homebuyer units, with only 8 percent for homeowner-rehabilitation units. Of these units, HOME funds have served 14.2 percent and 5.5 percent of Non-Hispanic White households for rental and homebuyer units respectively. HOME dollars serve 84.5 percent and 87 percent of African American households for rental and homebuyer units, respectively. Hispanic households represent a small percentage of HOME funds recipients, with less than one percent of households receiving assistance for rental units and two percent for homebuyer units. Additionally, the elderly population represents 45.7 percent of households recipients of rental units developed with HOME funds, while single non-elderly households represent 45 percent of recipients of homebuyer units.

HOME investments in Baltimore are located near the central core of the city near the Inner Harbor. Many neighborhoods along the Inner Harbor have experienced positive impacts due to downtown redevelopment and new businesses; however, most of the neighborhoods slightly on the edge of the downtown still exhibit high levels of abandonment and blight. Additionally most HOME investments are located within these neighborhoods, though; HOME funds are not only targeted toward distressed neighborhoods.

In 2002, Baltimore developed an NHMT to better understand housing conditions across the city. NHMTs are a statistical tool that clusters neighborhoods into rankings based on housing related characteristics (e.g., percent of single family housing, foreclosures, or permit activities) at the census tract or block level. Rankings result in labels to classify neighborhood types, such as stable, transitional, and distressed. NHMTs are used by cities to guide citywide investment strategies and target areas based on their unique conditions. Baltimore has revised its typology numerous times since 2002. Based on the city's 2008 typology HOME investments are located in both distressed and stable areas. Baltimore's community development corporations (CDCs) and community housing development organizations (CHDOs) have been the primary users of HOME funds. Each year the city sets aside 15 percent of HOME allocations for CDCs to implement new construction and housing rehabilitation on a block-by-block basis. Additional funds are given to CDCs/CHDOs for scatter-site developments. Nonetheless, there are a few organizations use these funds on a more targeted block-by-block effort. One such organization is the Healthy Neighborhood Initiative (HNI), established in 2000. HNI targets investments to Baltimore's ”transitional” neighborhoods or those that exhibit moderate neighborhood conditions. This block-by-block strategy has resulted in some successes. However, for many neighborhoods in the city, 30 years of disinvestment has caused housing program investments to appear small or insignificant. The magnitude of blight in these distressed neighborhoods and market failures in less distressed neighborhoods present questions about the impact of the program across the city.

RESEARCH QUESTIONS

This study seeks to address three specific questions within the context of the HOME Partnership Program in Baltimore:

(1) Which neighborhoods in Baltimore, based on a historical cluster analysis of economic and housing conditions, are more likely to change, and in which direction?

(2) Do HOME investments have positive impacts on surrounding housing sale prices?

(3) Are the impacts of HOME investments based on the following factors?

   a. Do household incomes impact the magnitude and direction of the investments?

   b. Is the impact based on the scale of the investment?

c. Do other factors such as neighborhood housing markets influence the impact of investments based on scale and concentration?

Question 1 will be addressed through a decennial descriptive analysis of Baltimore neighborhoods for 1980, 1990, and 2000. Questions 2 and 3 will be analyzed using a multivariate analysis and other statistical analyses to determine the impact of HOME investments on surrounding property values and test past empirical findings which suggest that scale, concentration, and neighborhood characteristics are causation factors which may influence the effects of investments.

DATA

This study uses three methods to analyze the aforementioned research questions, which include the cluster method, transition matrix, and hedonic regression model, all discussed in more detail in the methods section. The initial cluster analysis, decennial census data was collected for 1980, 1990 and 2000. As noted in Tables 7 and 8 above, these variables included percent home owners, median household income, median sale prices, and percent vacant properties. Variables were selected based on the literature of factors that are neighborhood change drivers. Data was aggregated to the census tract level using Neighborhood Change Database (NCDB) created by Geolytics, Inc. Census tracts were used because decennial data collected for these years are not provided at the census block level, as is the case for 1980 data. Geolytics provides tabulated United States Census long form decennial data at the census tract level and normalizes the data for all decennial years observed based on 2000 census tract boundaries using geographic apportionment (Tatian, 2003). Normalization of the data allows for consistent geographic boundaries when analysts use the method to create clusters. For this analysis, census tracts that contained missing data or population densities of less 300 people per square mile were excluded from this analysis. In total, 197 census tracts of were included in this analysis.

Data collected for the 2005 typology and hedonic regression analyses included a more recent data set. The structural data for sale prices of single-family units were obtained from the Maryland Property View database, which collects data from assessor offices throughout the state. Structural variables include building age, house style, date of the sale, garage presence, and size, square footage of the house, and types of utilities. Other housing data were obtained from the City of Baltimore and the Baltimore Neighborhood Indicator Alliance. Neighborhood data include: percent permits, proportion sales, percent foreclosures, percent vacant building, percent vacant lots, proportion subsidize homes, and portion of commercial land uses. These data were collected from the city of Baltimore Planning Department and Baltimore Neighborhood Indicator Alliance for 2005.

Sale prices for single-family houses and rental units sold in 2004 and 2005 were selected as the dependent variable. Data with missing recordings, arm's length transactions, and outliers were removed from the data set. Arm's length transactions are generally recorded for each assess properties, and for those properties were the information is not recorded, this study assumed properties sold for less than $5,000 were arm's length sales. Sales of more than $400,000 and less than $10,000 were identified as outliers and excluded from the analysis. Box plot analyses were used to descriptively identify outliers based on the median and the lower and upper quartiles (defined as the

25th and 75th percentiles). Rental properties were included in the analysis due to the distances to HOME Program investments Baltimore has approximately 51 percent homeowners and 48 percent rental households (Baltimore HOME dashboard (www.hud.gov)). Lastly, only sales that occurred within 5000 feet of HOME investments were included in the analysis, this threshold was determined because the average distance of housing sales from investments was approximately 2,000 feet. The total data set included 16,151 sales for 2004 and 2005.

As shown in Tables 12 and 13, the typical unit sold for $109,000, and contained approximately 1,200 square feet of living space. Most units were built in the mid-1920s as is common for housing located in post-industrial cities. Units are generally brick material, with porches, but few contained fireplaces, half-baths, and garages. This is based on the row house type in Baltimore.

Investments range from $4,000 per unit to $2.2 million and from one to two units to 200 units. One to two unit new construction investments cost an average of approximately $39,000. New construction investments greater than two units' development cost an average of $756,000. Over 50 percent of newly constructed investments were one to two units. One to two units receiving extensive rehabilitation funds cost an average of $28,934. For rehabilitated projects greater than two total units, investments cost an average of approximately $462,000. Over 50 percent of rehabbed units were one to two unit investments.

GIS was used to calculate distance measures between HOME investments and property sale centroids. Initially, this research calculated 150, 300, and 500 feet distance

Table 13: Summary statistics and definitions of all variables for Investments

Variable	Label	Unit of Measure/Analysis	Mean	Std Dev	Minimum	Maximum
Sales Price	PRICE	dollar/individual unit	$ 109,362.74	$ 1.93	$ 13,000.00	$ 400,000.07
Log (Sales Price)	XLOGPRICE	dollar/individual unit	$ 11.60	$ 0.66	$ 9.47	$ 12.90
Structural Characteristics (2004,2005)						
Housing Condition Excellent	DGEXC	binary/individual unit	0.00036985	0.0192286	0	1
Housing Condition Fair	DGFAIR	binary/individual unit	0.8161846	0.3873479	0	1
Housing Condition Good	DGGOOD	binary/individual unit	0.0574747	0.232756	0	1
Housing Condition Poor	DGPOOR	binary/individual unit	0.0434747	0.122756	0	1
Brick	XBRICK	binary/individual unit	0.7377765	0.4398598	0	1
Basement	XBASEMENT	binary/individual unit	0.9308381	0.2537387	0	1
Square Footage of Unit	XSQFTSTRC	feet/individual unit	1264.11	603.3997251	0	16920
Square Footage of Unit (squared)	XSQFTSTRC2	feet/individual unit	1962050.9	3241177.6	0	286286400
Age of Unit	XAGE	number/individual unit	77.4378282	23.4394005	1	215
Age of Unit (Squared)	XAGE2	number/individual unit	6545.98	3830.62	1	46225
Aircondition	XAIRCON	binary/individual unit	0.2574895	0.4372674	0	1
Half Bath	XHBTH	number/individual unit	0.2381093	0.4431362	0	3
Finished Basement	XBASEMFN	binary/individual unit	0.2748724	0.4464665	0	1
Garage	XATGR	binary/individual unit	0.0360973	0.1865393	0	1
Fireplace	XFIRE	binary/individual unit	0.1064428	0.3084149	0	1
Porch, Deck, Patio	XDECK_PRCH	binary/individual unit	0.748724	0.5570976	0	3
Rental Unit	XHSGRENT	binary/individual unit	0.0767069	0.2661356	0	1
Single Family Unit	XHSGRENT	binary/individual unit	0.1990532	0.3993029	0	1
Socio-Economic Characteristics (1990,2000)						
Average HH Income of Census Block	XINCOME	average/census blgrp	$ 34,625.31	$ 1.39	$ 6,875.00	$ 170,427.97
Log of average HH income in census block	XLOGINCOME	average/census blgrp	10.4523403	0.3263179	8.835647	12.046068
Percent African American HH	XPCTBLK	percentage/census blgrp	0.4773674	0.3759655	0	1
Commute Time	XCOMMUTE	rate/census blgrp	26.5527036	12.8990131	0	83
Neighborhood Characteristics (2005)						
Distance from Inner Harbor	XHARBOR	feet	7.4277811	0.7352478	3.714305	9.239885
Percentage of permits (permits greater than $5,000 exterior rehabs for housing units)	XPCTPERM	percentage/census blgrp	0.0155128	0.0128682	0	0.25
Percentage of foreclosed housing units	XPCTFOR	percentage/census blgrp	0.0211092	0.0270866	0	0.22
Percent of vacant housing units	XPCTVCT05	percentage/census blgrp	0.024347	0.0442405	0	0.42
Distance from vacant building	XVCBUILD	feet	5.3469915	2.3596861	-22.07034	8.562022
Rate of crime among all residents (number of crime per 1000 people in the city in 2005)	XPCTCHGCRM	percentage/census blgrp	2.5600172	17.0577263	0	262.42
Distance to commercial landuse	XCOMM	feet	6.287464	1.3183531	0	8.820729
Sold between January and March	XSALJANM	binary	0.0160515	0.1256782	0	1
Sold between April and June	XSALAPRJ	binary	0.3703676	0.482921	0	1
Sold between July and September	XSALJULS	binary	0.2627413	0.4401394	0	1
Sold between October and December	XSALOCTD	binary	0.0636142	0.2440734	0	1

Table 14: Summary statistics and definitions of all variables Investments (cont.)

Variable	Label	Unit of Measure/Analysis	Mean	Std Dev	Minimum	Maximum
HOME Partnership Investments (1994-2003)						
Distance to new construction investments	XNCONST	feet	8.2761871	0.6915716	4.142042	9.910031
Distance to rehab investments	XREHB	feet	7.6046753	0.8635933	1.885884	9.406079
Total Dollar of investment near sales	NEW150D	dollar/individual unit	160.7449804	13674.3	0	1562708
Total Dollar of investment near sales	NEW300D	dollar/individual unit	518.4005141	26465.86	0	2040000
Total Dollar of investment near sales	NEW500D	dollar/individual unit	61.3933649	5021.3	0	500000
Total Dollar of investment near sales	NEW1000D	dollar/individual unit	20013.85	149973.29	0	2040000
Total Dollar of investment near sales	NEW5000D	dollar/individual unit	29648.03	131145.92	0	1767250
Total Dollar of investment near sales	REHAB150D	dollar/individual unit	425.836806	15860.3	0	1500000
Distance to new investments of less than or equal to $29,999	XNEWCONS	feet	8.879908	0.7585754	4.518148	10.271508
Distance to new investments between $30,000 - 59,999	XNEWCONM	feet	9.3783688	0.5948643	4.142042	10.338305
Distance to new investments of greater than or equal to $60,000	XNEWCONL	feet	8.5502578	0.7237936	4.530159	10.276474
Distance to rehab investments of less than or equal to $29,999	XREHABS	feet	8.1264156	0.8933488	1.921561	9.867671
Distance to rehab investments between $30,000 - 59,999	XREHABM	feet	8.658741	0.8510464	1.885884	10.212023
Distance to rehab investments of greater than or equal to $60,000	XREHABL	feet	8.3590551	1.0266375	3.075742	10.045396

preliminary analyses did not return similar findings. In initial models, with only rehabilitation investments within 300 feet from sales were significant at the 95 percent measures based on the current literature, in which these measures have been deemed significant estimate outputs (Ding et al., 2001; and Ellen et al., 2000). However, preliminary analyses did not find similar findings. In initial models, with only rehabilitation investments within 300 feet from sales were significant at the 95 percent level in the model. Therefore, continuous variables with calculated distances to the nearest investment were used in this analysis.

METHODS

Three methods—the cluster analysis, transition matrix, and hedonic functions—were employed in this analysis. The first research question used the cluster analysis and transition matrix to identify which neighborhoods in Baltimore are more likely to experience change based on past trends. The cluster methodology is a statistical method that groups data into categories by housing similarities or dissimilarities. Geographic areas (e.g., census tracts) with similar housing and social and economic characteristics are placed into categories that define market types.

The cluster method used in this study is a non-hierarchical cluster technique called a k-means cluster. This cluster method uses Euclidean distances to cluster similar and dissimilar variables into distinctive categories. The k-means cluster is a commonly used method for neighborhood typologies because it is best suited for variables that are continuous or categorical (Turner et al., 2009). Before running the cluster analysis, data was standardized using z-scores to address different dimensions (e.g., housing sales, percentages, and number values) and units relative to city averages. Five categories were specified for this analysis to present a range of market types. Data were aggregated at the census tract level and categorized into these categories, ranked from stable (1) to distressed (5). Once all neighborhoods were included within a cluster category for each decennial period selected for this analysis, GIS was used to graphically display the concentration of clusters throughout the city.

Initially, a cluster method was used to evaluate neighborhood change. The purpose of this initial analysis was to provide a framework to determine which neighborhoods were more likely change over time. Specifically, the analysis observed distressed areas which have historically received a substantial portion of federal and local redevelopment dollars. A transition matrix method was used, which followed the process of clustering census tracts into market categories. This method is commonly used in empirical studies that explore racial and ethnic changes in neighborhoods over ten year periods. Transition matrices are simple methods used to track change status over time. The transition matrix method is based on discrete time Markov process analysis over two points in time. Using a cross-tabulation system, the matrix is able to provide categorical change counts from one stage to the next and show percent changes for forward and backward categorical flow proportion. For this analysis, historical and measured data was extracted from cluster analyses at the tract level. Census tracts were used as the unit of analysis because census data collected in earlier years for 1980 was only available at the census tract level. To determine the direction of tract changes over ten and 20-year periods, only forward categorical flow proportions were used to track neighborhood changes from Stage 1 to Stage 2. The forward method was used to determine if and how neighborhood improved in observation to subsequent years. Neighborhoods changes were examined for a ten-year timeframe (1980 to 1990 and 1990 to 2000), as well as a 20-year timeframe (1980 to 2000).

A second typology was developed using the same cluster method at the census block level. This level of analysis was chosen to provide neighborhood submarkets to test the effects of HOME investments across neighborhood markets.

Regression Models

The second and third research questions were explored using the hedonic regression method. This method was used to explain the sale price of a property as a function of its neighborhood characteristics, with the ability to factor in other mitigating factors such as scale and distance. The hedonic price regression method is a common technique used in the literature to determine the effects of neighborhood attributes on house prices. This method is used to determine the impact for housing attributes and public services and interventions. Hedonic models estimate property values based on structural variables, such as housing type, the number of bathrooms, heating units, and the existence of a garage or basement among other factors (Ding, 2000). Also included in these models are neighborhood variables, such as institutions, services, and public safety, and distance measures, like distance to the central business district, distance to employment centers, and distance to transportation nodes (Knapp and Ding, 2003; and Ding, 2000).

To address question 2, this study assumes that HOME investments will positively influence sale prices. This analysis required the use of GIS to measure distance variables and capture investments around housing sales. The basic model is expressed as:

P = f(S, N, IN, IR)

Where

P= sale price;
S = Structural characteristics;
N = Vector of socioeconomic neighborhood characteristics (including location variables);

IN = Vector of investment of new housing construction; and
IR = Vector of housing rehabilitation; and
e = error term

Thus, the model is:

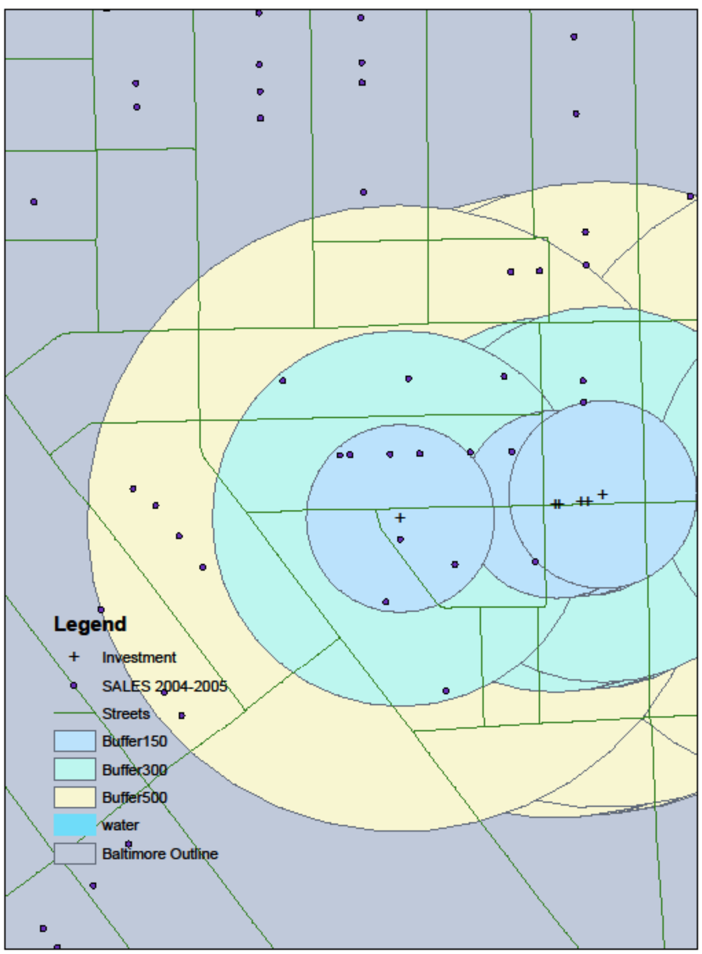
$$\ln P = \beta_0 + \beta_1 S + \beta_2 N + \beta_3 IN + \beta_4 IR + e \qquad (2.1)$$

Due to the non-linear form of prices and values, the dependent variable, sale price, will be used as a common form semi-log of housing sale price for this model. The structural attributes ($\beta_1 S$) and neighborhood characteristic variables ($\beta_2 N$) are control variables. $\beta_2 N$ represents a series of dummy variables indicating the quarter of the sale. Also included in this vector are neighborhood effects, such as percent of foreclosures or permit activity. Tables 12 and 13 above provide a list of variables included in the regression model.

New construction ($\beta_3 IN$) and rehabilitation variables ($\beta_4 IR$) represent distance measures to nearby sales. The GIS technique of “near distance” was used to calculate the distance between centroids for HOME investments sites and the location of sales transactions. Empirical studies use various distance measures (e.g., 150, 300, and 500 feet) to reflect the diminishing spatial effect of residential investments on nearby property values (Ding et al., 2000; and Ellen et al., 2001). These measures were not used in this analysis because HOME investments are located in the core of the city while most sales occur around the core and edges of the city as shown in Figures 14 and 15.

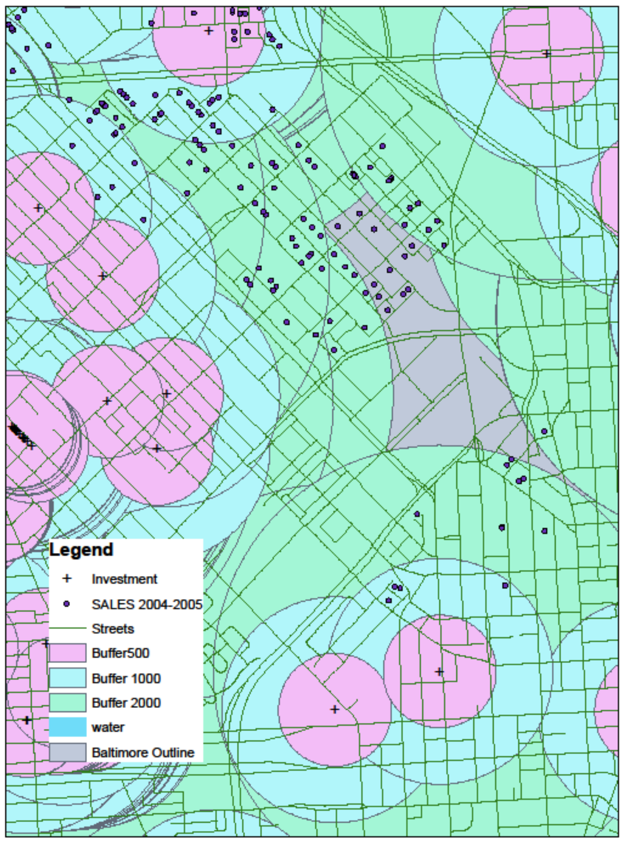
Figures 14 and 15 displays the distances between HOME investments and housing sale transactions. In this figure, HOME investments fall outside of the 150, 300, and 500 distances of sales transactions. Based on these figures, another analysis was completed to identify housing sales located within 500, 1,000, and 5,000 feet buffers from sales transactions. Distance dummy variables of distances which include binary variables of 0 or 1 if home sales were located within 1,000 and 5,000 feet buffers were analyzed and few dummy variables presented significant coefficients. For those that did present significant variables it was assumed based on other empirical studies that these findings were not unbiased (Galster et. al., 2006). Therefore, near distance measures were used to measure HOME impacts.

Figure 14: 150, 300, 500 Distance Buffers of HOME Investments



Note: Most housing sales fall outside of distance buffers which provide few significant variables in the initial regression models.

Figure 15: 500, 1000, 2000 Distance Buffers of HOME investments



Note: Housing sales in the city tend to occur within 1000 and 2000 distance bands.

Question 3 and its subparts assume the effect of HOME investments on nearby property value change based on scale, the concentration of units, and neighborhood housing market factors. This question is addressed with three separate models. This first model assumes that the effect of HOME investments on nearby property values will be positive if HOME investments represent large-scale efforts reflected by the dollar amount invested in the unit. The model for this hypothesis yields the following equation:

$P = f(S, N, IN_{30}, IR_{40}, IN_{31}, IR_{41})$

Where

P= sale price;
S = Structural characteristics;
N = Vector of socioeconomic neighborhood characteristics (including location variables);
IN = Vector of investment of new construction;
IR = Vector of rehabilitation;
IN_{30} = Vector of investment of new construction based on total value of investment; and
IR_{40} = Vector of rehabilitation based on total value of investment; and
e = error term

Thus the model is:

$$\ln P = \beta_0 + \beta_1 S + \beta_2 N + \beta_{30} IN + \beta_{40} IR + \beta_{31} IN + \beta_{41} IR + e \qquad (2.2)$$

New construction ($\beta_{31}NR$) and rehabilitation variables ($\beta_{41}IR$) represent distance measures of the sales based on the dollar value of the HOME investment project. Distance variables were calculated based the distance between centroids for HOME investments sites and the location of sales transactions. This calculation is the same for the total dollar value of the investments, which include small-value ($5,000 to $29,999), medium-value ($30,000 to $59,999), and large-value ($60,000 or more) investments. Each investment is separated by dollar amounts and the distance is calculated between the investment and the sale transaction. The general assumption is that greater impacts and increase neighborhood property values will occur with higher public investment (Ding et al., 2000; Ellen et al., 2001; and Galster et al., 2006).

The second model assumes that the effect of HOME investments on nearby property values will have a greater impact on properties located in less affluent neighborhoods based on average household income. This analysis was used in Ding et al.'s (2000) analysis in Cleveland. This analysis used equation 3.2 but estimated two separate models. Housing sales data was separated into two datasets, one for low-income neighborhoods, represented by the median household income at the census block level of household earning at or less than $29,999, and another dataset for more affluent neighborhoods, represented by households' median income of $30,000 or more.

While regressing housing sale prices with separate hedonic price functions for income may capture different impacts based on household affluence, this study goes further and regresses sale prices across neighborhood market clusters. Empirical studies indicate that the impact of investments is based on a number of neighborhood factors. A traditional hedonic equation which provides the magnitude of an attribute on sale prices in the disaggregate allows the researcher to understand which variables individually impact sale prices holding all else equal. However, a number of studies find that housing submarkets can also present similar results as traditional studies and provide discussion of how impacts vary based on the aggregate of housing and neighborhood quality variables in submarket clusters (Bourassa et al., 1999; Tu et al., 2007; and Fik et al., 2003).

To address question three subparts related to neighborhood housing markets, submarkets were identified using the cluster statistical methodology. Five clusters that exhibit a range of housing market types from stable to distress will be identified. Five clusters were specified in this study to provide a range of market types, but to allow for a small number of clusters for a meaningful analysis. Separate regression models will be analyzed for each cluster determined, therefore, a large number of cluster will sparse the dataset and present fewer observations in each analysis. Data included in the cluster analysis for this model will be collected for 2005 to correspond with the dependent variable: 2004 and 2005 sales data. The unit of analysis for this model will be census block groups to provide a granular level of data for analysis.

The cluster analysis output will be tested with the following regression model. This model assumes each cluster is statistically different from the next. This hypothesis yields the following equation (3.4):

P = f(S, N, CL)

Where

P= sale price;
S = Structural characteristics;
N = Vector of socioeconomic neighborhood characteristics (including location variables); and
CL = Neighborhood Housing Market clusters;
IN = Vector of investment of new construction;
IR = Vector of rehabilitation; and
e = error term

Thus the model is:

$$\ln P = \beta_0 + \beta_1 S + \beta_2 N + \beta_3 CL + \beta_{30} IN + \beta_{40} IR + e \qquad (2.3)$$

The additional Chow test analyzed to test the validity of the cluster variance. Based on the significant level of confidence, clusters are interpreted as separate submarkets. The Chow tests determine whether, among the regression equations, there is a significant difference between the clusters under the null hypothesis that there is a structural break in the data. The steps of estimating each cluster are similar to the models estimated for low-income versus more affluent neighborhoods. An understanding of changes across markets provide implications for the use of typologies and test the assumptions presented by Down (1980) and Mallach (2006) that a policy's effects are influenced by the stage of a given neighborhood within the context of its lifecycle, or more specifically, by the neighborhood's housing market type.

ANALYSIS

The analysis for this study is divided into three sections. The first part of the analysis examines the output of the cluster analysis and neighborhood change matrices among neighborhoods in Baltimore for 1980, 1990, and 2000. This analysis is based on census tracts cluster analyses. The second section examines the empirical findings of the impact of HOME Program investments on surrounding property values. The last section uses a 2005 cluster analysis based on census block groups and examines the empirical findings of the impacts of investments across housing market types.

Cluster 1 Results: Baltimore Census Tract Change 1980-2000

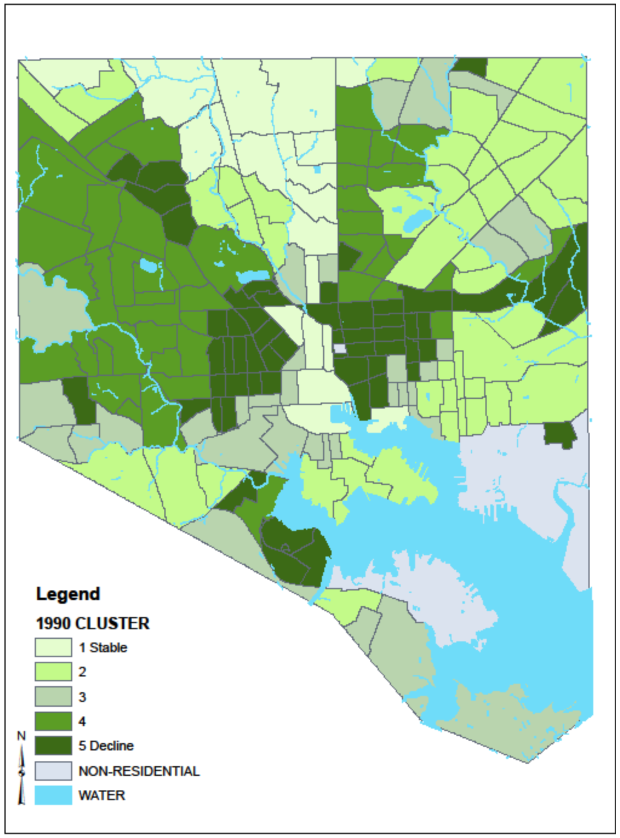
In this analysis, Baltimore neighborhoods were examined for 1980, 1990, and 2000. Neighborhoods were represented by census tracts. First, five clusters were identified for each time period, categorizing neighborhoods based on socioeconomic and housing decennial data. The same cluster method, using initial starts, was used to ensure neighborhoods fell into consistent clusters. Of 197 census tracts, 147 tracts were clustered into categories and then ranked from 1, which represented a stable neighborhood, to 5, which represented a distressed neighborhood. Neighborhoods classified into category 3 represent the midpoint between stable neighborhoods and distressed neighborhoods.

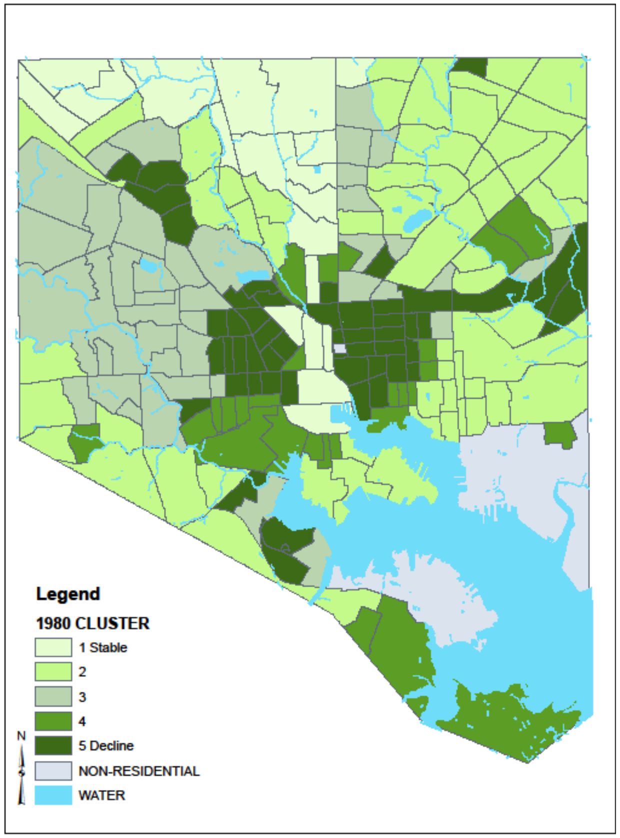
Figure 16 maps neighborhood clusters of housing and social and economic variables of census tracts for 1980, 1990, and 2000. In the cluster analysis for 1980, distressed clusters are located in the downtown core of the city, while stable areas (Categories 1 and 2) are along the edges of the city. This distribution of market types is common to the classic concentric ring pattern first identified by Burgess (1930), where older areas are located near the central core of the city and newer areas are along the outer parts of the city. The 1990 cluster presents a spread of decline from the central core, between two time periods, towards the western edge of the city. This area was previously Cluster 3. Further, distressed clusters spread farther north of the city along York Road according between 1990 and 2000. In addition, the number of tracts located along Baltimore's Harbor and labeled as distressed declined from 1990 to 2000. This decline may be due to commercial development around the Harbor and spillover effects into adjacent neighborhoods.

The neighborhood transition matrix method assists this analysis to track neighborhood changes between 1980, 1990, and 2000. Table 15 shows that between 1980 and 1990 few neighborhoods experienced significant changes. Approximately 90 percent of stable neighborhoods remained stable, and 73 percent of neighborhoods in Cluster 2 also remained constant. Significant changes occurred in Clusters 3 and 4. Ninety percent of neighborhoods in Cluster 3 switched to Cluster 4, a progressively more distressed cluster. Approximately 77 percent of neighborhoods in Cluster 2 moved to Cluster 3. As some neighborhoods declined mainly on the west side of the city, neighborhoods near the downtown improved. These improvements may be due to redevelopment along the Harbor in the early and mid-1990s, which revitalized by 2000.

Table 15 below presents neighborhood changes between 1990 and 2000. In this table, a larger percentage of neighborhoods moved across clusters between 1990 and

Figure 16: Cluster Maps for 1980, 1990, 2000





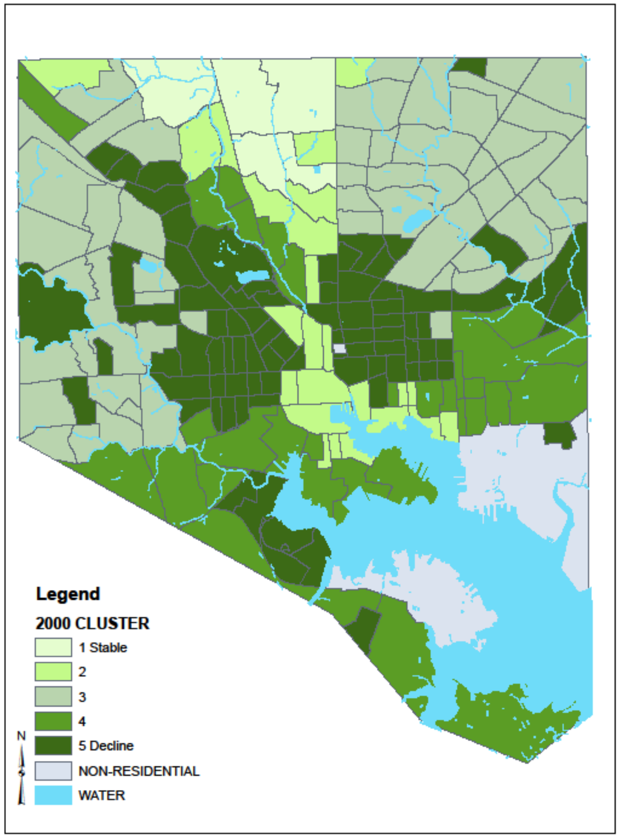
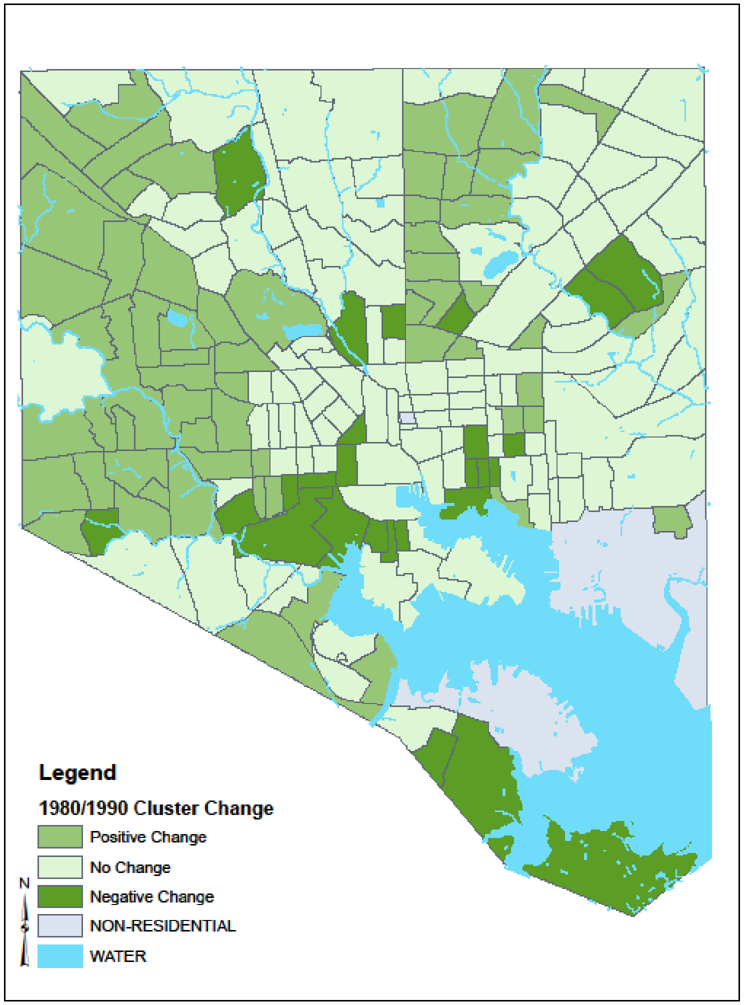


Figure 17: Cluster change maps for changes between 1980 and 1990, and 1990 and 2000



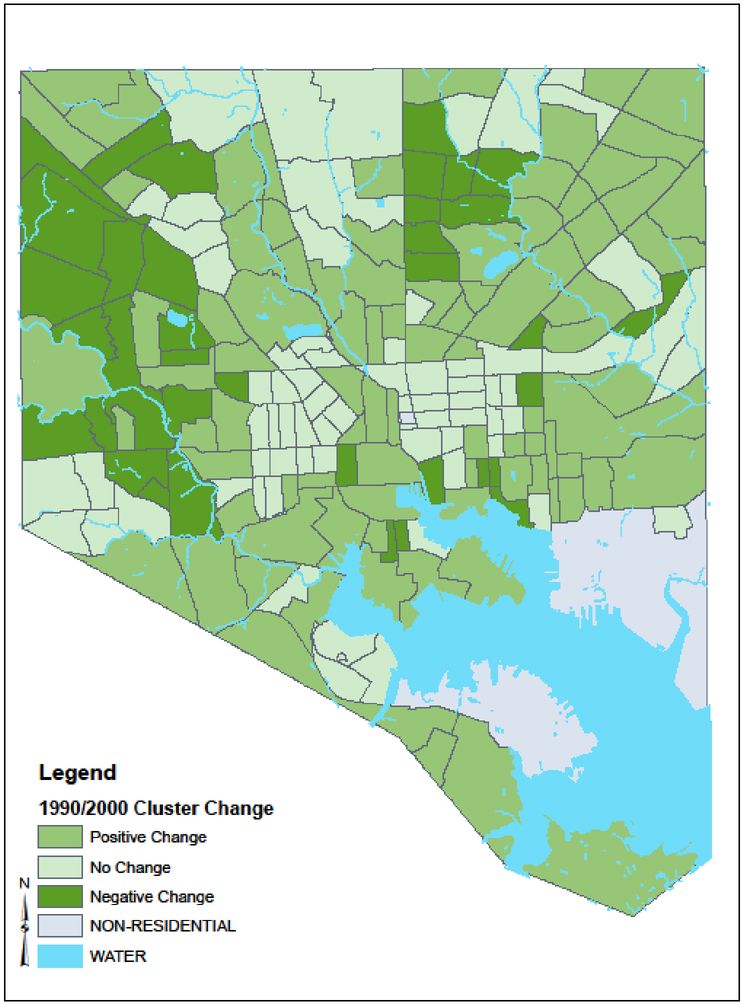


Table 15: Transition Matrices for neighborhood change from 1980 to 2000

Neighborhood Change Transition Matrix					
Year 1980	**Year 1990**				
Row Pct	**1 (Stable)**	**2**	**3**	**4**	**5 (Decline)**
1 (Stable)	89.47	10.53			
2	1.69	72.88	15.25	10.17	
3			2.33	**90.7**	6.98
4	3.85		**76.92**	0	19.23
5 (Decline)			4.0	2.0	94.0
Total Tracts	*19*	*45*	*32*	*46*	*55*

Neighborhood Change Transition Matrix					
Year 1990	**Year 2000**				
Row Pct	**1 (Stable)**	**2**	**3**	**4**	**5 (Decline)**
1 (Stable)	26.32	**73.68**			
2		6.67	**42.22**	**48.89**	2.22
3		18.75	25	25	**31.25**
4			**65.22**		**34.78**
5 (Decline)		1.82			98.18
Total Tracts	*5*	*24*	*57*	*30*	*81*

Neighborhood Change Transition Matrix					
Year 1980	**Year 2000**				
Row Pct	**1 (Stable)**	**2**	**3**	**4**	**5 (Decline)**
1 (Stable)	26.32	63.16	5.26	5.26	
2		8.47	**50.85**	37.29	3.39
3			55.81		**44.19**
4		19.23	7.69	26.92	**46.15**
5 (Decline)		4			96
Total Tracts	*5*	*24*	*57*	*30*	*81*

Note: Red and bold number are highlighted to show significant changes between clusters

2000 than during 1980 and 1990. Many stable neighborhoods, approximately 75.68 percent transitioned to Cluster 2, however, a large percent of neighborhoods in Cluster 4, approximately 65 percent, improved from Cluster 4 to Cluster 3. Many neighborhoods in Cluster 2 declined to either Cluster 3 or Cluster 4. Cluster 5 neighborhoods remained for both ten years observations, between 1980 and 1990, and 1990 and 2000.

In analysis of neighborhood change between 1980 and 2000, it appears that few neighborhoods experienced changes. Half of the neighborhoods in Clusters 3 and 4 move to Cluster 5. Another half of the neighborhoods in Cluster 2 transitioned to Clusters 3 and 4, and most of the neighborhoods in Cluster 1 moved to Cluster 2. Only 26 percent of stable neighborhoods remained stable from 1980 to 2000, while 96 percent of distressed neighborhoods remained the same. This analysis seems to follow Downs's (1980) model of neighborhood change, which proposes that neighborhoods at any stage can be stable, or improving or declining. However, reversing decline in more distressed markets appears more difficult than in markets in the earlier stages of decline.

A second step in this analysis was to include reinvestment zones. Reinvestment zones in Baltimore are located near the downtown. These areas include HNI, focused in neighborhoods with few disinvestments challenges for preservation and development; the Business target area, representative of economic development projects focused near the downtown; Enterprise Communities and Empowerment Zones, representative of business tax incentives focused in distressed areas; and Targeted Reinvestment Zones, representative of economic development, housing redevelopment and major commercial redevelopment projects in targeted areas. These zones were generally created at the federal and local levels between 1990 and 2000. HNI began in 2000 and was included in this analysis because most neighborhoods in this initiative had received HOME funds since 1994.

A survey sponsored by the Goldseker Foundation, the Baltimore Community Foundation, and the Baltimore Neighborhood Collaboration organization (ref), identify distressed clusters as neighborhoods where CDCs have worked to invest substantial resources to revitalize the surrounding areas. In examining neighborhood change among clusters in these zones, it appears that most zones have experienced positive changes, with zones near the central core experiencing no change. It can be assumed that sales within reinvestment zones are the same as sales outside of the investment zones. A paired difference test of the variance in log sale prices showed that sale prices within zones were statistically different from sale prices outside of zones.

The analyses of neighborhoods change in 1980, 1990, and 2000 and review of neighborhood change within reinvestment zones are important to this study. Distressed areas are the target of most reinvestment strategies and housing production programs. For Baltimore, these areas are less likely to change despite substantial attention and reinvestment resources based on the above cluster analysis. While minimal change may be present at the tract level, in general distressed neighborhoods remain constant. Additionally, middle neighborhoods represented by Cluster 3, despite locations in reinvestment zones, in most cases declined with very few improvements. Most improvements occurred in areas with significant private sector investments, such as in areas near the Inner Harbor. For the most part, in this cluster analysis, neighborhoods in Baltimore follow a common model of neighborhood change asserted by Downs in the 1980s. From 1980 to 2000, most neighborhoods in Clusters 3 and 4 continued to decline, while neighborhoods in Cluster 5 remained the same.

Cluster 2 Results: Baltimore Census Block Typology

For equation 3.4, an NHMT was constructed for Baltimore based on 2005 housing data. Housing data included the percent of permits, proportion of sales, percent of foreclosures, percent of vacant building and lots, proportion of subsidized homes, and proportion of commercial land uses. These data were aggregated to the census block group level for analysis. Additionally, average household income at the census block level for 2000 was also included in the cluster typology. A statistical cluster methodology was used to identify neighborhood clusters. Five clusters are determined using Euclidean distances based on the cluster center of initial cases using the non-hierarchical k-means method. The K-means methods based on the center of initial cases indicates that clusters are determined by Euclidean distances from the first set of cases in the dataset. In addition, the cluster analysis allowed for outliers to be removed providing more variation in cluster solutions. For each hedonic equation, the cluster results assigned a cluster for each record, provided distance as measured from the initial cases, and standard errors. Each record was placed in a cluster, numbered 1 to 5, and outliers were placed in cluster 0. In equation 3.4, cluster dummy variables created from the cluster analysis are included

Table 16 : Hedonic Regression for Clusters

Hedonic Regression on individual-unit sale price, 2005				
	R squared	*0.646*		
	b	std *b*	sig	sig
Intercept	4.90291	0.02875	***	<.0001
Structural Characteristics				
DGEXC	0.16885	0.02532	***	<.0001
DGFAIR	-0.09763	0.00591	***	<.0001
DGGOOD	0.05531	0.00763	***	<.0001
XBRICK	-0.06383	0.00393	***	<.0001
XBASEMENT	0.00734	0.006		0.2211
XSQFTSTRC	0.0001977	4.24E-06	***	<.0001
XSQFTSTRC2	-1.37E-08	7.31E-10	***	<.0001
XAGE	9.621E-05	8.641E-05		0.2656
XAGE2	-1.35E-08	4.17E-08		0.747
XAIRCON	0.07345	0.00411	***	<.0001
XHBTH	0.01403	0.00409		0.0006
XBASEMFN	0.03046	0.00411	***	<.0001
XATGR	0.04094	0.00901	***	<.0001
XFIRE	0.04875	0.00607	***	<.0001
XDECK_PRCH	0.00636	0.00303		0.0357
Clusters				
CL1	0.21325	0.02731	***	<.0001
CL2	0.20869	0.02653	***	<.0001
CL3	-0.09172	0.02651	**	0.0005
CL4	-0.16171	0.02676	***	<.0001
CL5	-0.22707	0.0309	***	<.0001
Note: *n* = 14291				

Table 17: 2005 Typology Summary Statistics

Neighborhood Indicator	Level of Data	Data Source	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Population Density (people per square miles)	Census block	US Census	10147.03	17490.95	14206.49	15525.25	13525.26
Percent change in population in 1990 and 2000	Census block	US Census	-0.77	-0.63	-0.21	-0.27	0.14
Percent of White Households	Census block	US Census	0.86	0.71	0.30	0.13	0.03
Percent change of White Households	Census block	US Census	0.09	-0.09	0.32	0.14	0.05
Percent of African American Households	Census block	US Census	0.09	0.20	0.66	0.83	0.94
Percent change of African American Households	Census block	US Census	-0.16	-0.54	-2.14	-0.57	-0.01
Percent unemployment	Census block	US Census	0.02	0.05	0.07	0.12	0.12
Percent change of unemployment	Census block	US Census	0.21	0.07	-0.24	-0.29	0.19
Average Household income	Census block	US Census	$ 88,794.05	$ 35,466.33	$ 36,740.33	$ 21,670.01	$ 19,075.55
Percent of owner occupied housing units	Census block	CPD	0.81	0.50	0.71	0.36	0.33
Percent of renter occupied housing units	Census block	CPD	0.19	0.49	0.29	0.63	0.65
Average age of housing units	Census block	MPV	56.23	54.13	52.59	50.90	51.24
Average values of housing unit (based on sale prices)	Census block	MPV	$ 434,505.05	$ 246,903.38	$ 95,487.19	$ 60,861.84	$ 37,850.78
Percent of foreclosed housing units	Census block	CPD	0.01	0.01	0.02	0.02	0.01
Percent of home sales	Census block	CPD	0.09	0.12	0.09	0.10	0.06
Percent of permits (permits greater than $5,000 exterior rehabs for housing units)	Census block	CPD	0.03	0.05	0.01	0.01	0.01
Rate of crime among all residents (number of violent crime per 1000 people in the city in 2005)	City district	CPD	0.69	1.54	1.51	4.09	3.79
Percent of vacant housing units	Census block	CPD	0.00	0.03	0.01	0.11	0.25
Percent of vacant lots	Census block	CPD	0.00	0.00	0.00	0.01	0.11
Proportion of commercial land (as a Percent of square miles of land uses)	Census block	CPD	0.07	0.13	0.09	0.12	0.22
Proportion of subsidize housing (including public housing projects)	Census block	CPD	0.00	0.00	0.00	0.02	0.02
**MPV: Maryland Property View Assessor Data							
**CPD: Baltimore City Planning Department							

in the model. Housing sales are regressed on the structural variables and cluster dummy. In Table 16, the clusters are significant at the 95 percent level and the clusters improved the model's R^2 from .42 to .55. A summary of clusters is included in Table 17. Cluster impacts on housing values also showed expected outcomes. Housing sales in Clusters 1 and 2 were valued at $22,000 and $26,000, respectively. Housing sales in Cluster 3 were discounted at $10,000 and sales in Clusters 4 and 5 were valued even lower at $15,000 and $19,000, respectively.

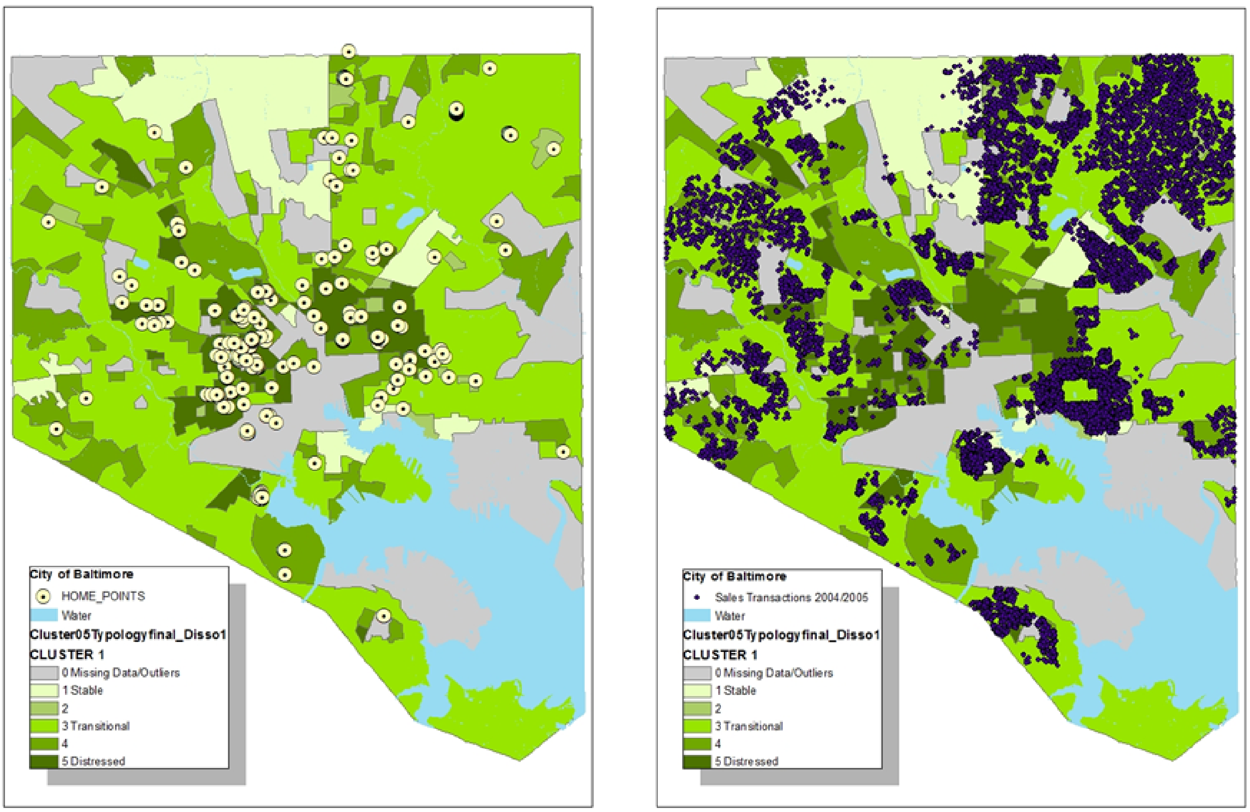
Based on 2005 typology, HOME investments are located in cluster 2-5 markets, with no investments in cluster 1 as shown in Table 18. Most HOME investments are located in clusters 4 and 5, which represent the most distressed clusters. Fewer HOME investments are located in the more stable and middle clusters 2 and 3. In review of home sales, Table 18 show that most sales occur in stable and middle clusters, 2, and 3. Cluster 4 contains the third highest number of sales, while cluster 5 contain the least. Based on this analysis, HOME investments are located in the most distressed clusters where fewer sales occur.

Table 18: HOME Investments (1993-2003) and Surrounding Sales in Baltimore (2004/2005)

NHMT Clusters	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
HOME Investments (N=446)	0	9	77	145	160
Sales (2004/2005) (N=13,519)	448	3261	7861	1745	125

The next section examines in more detail the impact of the HOME Program and is followed by an empirical analysis of effects within various neighborhood markets at the census block level. Special attention will be given to Clusters 3, 4, and 5, to determine whether investments in these areas positively affect surrounding property values given the historical trend towards decline or lack of improvement.

Figure 18: HOME Investments (1993-2003) and Surrounding Sales in Baltimore (2004/2005)



Note: Map on the left are HOME Reinvestments from 1993-2003 and the map on the right represent sale transactions in Baltimore for 2004 and 2005. Data for HOME reinvestment were obtained from the City of Baltimore Finance Department and sales transactions were obtained from Maryland Property View.

Empirical Results of HOME Partnership Impacts

Table 19 presents estimated results of regression outputs. Overall, the model fits well with 60 percent of the variation in the dependent variable explained by the independent variables. The model presents expected signs at various levels of significance. With the expectation of two variables, location in empowerment zones and presence of deck/porch, all other variables are significant at the five percent significance level. All variables, except the presence of brick and basement, carry the expected sign. In the context of Baltimore, it can be assumed that brick is a common material for homes, particularly for row homes, which represent over 60 percent of Baltimore's housing stock (Baltimore Housing Report, 2005-2010).

Structural variables provided a strong explanation for price differences in the model. Homes in excellent and good conditions sold for approximately $37,000 and $20,000 more than other homes, respectively. Homes in fair conditions were discounted by approximately $30,000. The higher the square footage of the property the lower the home valued by approximately $2.62 per additional square foot. Air conditioning and having a half bath also increased the value of the home by approximately $11,000 and $2,000 respectively. A finished basement adds $7,000 to the value of the home. Few homes contained detached garages and fireplaces, these amenities increased the value of the home by approximately $12,000 and $13,000 respectively. Seasonal variables, with the exception of winter months, are also significant. Homes sold in the spring and summer months increased the value of the home. All things being equal, homes sold in the winter months decreased the value by approximately $2,000; however, this estimate is not significant.

Social and economic variables, income, and race were all significant. Home values in neighborhoods with predominately African American households were discounted by approximately $20,000. Home values experienced a premium by approximately $19,000 the higher the income of householders in the neighborhood. Added commute time to work was also significant and decreased the home value by almost $200.

Neighborhood characteristics in terms of housing related variables also present major findings. All variables were significant at the 90 percent level except homes sold in empowerment zones. There were significant findings for homes sold in areas with high rates of foreclosure: increases in foreclosures discounted the home by approximately $6,000. Homes sold in neighborhoods with permit activities presented significant increases in home values. Crime rate is included in the analysis and measured as the count of violent crimes per person divided by the total population in the census block. Higher crime rates reduced home values by approximately $500, which is minimal and gives cause to question the impact of crime on home values. Similar to foreclosed units, increases in vacant buildings reduced the value of a home by approximately $4,000. An additional foot a sales transaction is from vacant buildings increases its home's value by $14,000. However, for every foot the unit was from the Inner Harbor, value dropped by $7,000. This demonstrates that the harbor is considered an amenity to homebuyers.

Initial models intended to test the impact of the investment on surrounding sale prices, distance measures of 150, 300, and 500 feet are included in the analyses. When these variables were included in the model, total dollars and the total number of projects are used to measure where scale and magnitude of the investments affect sale prices of surrounding properties. Due to the small number of HOME investments in Baltimore (approximately 400), impacts were difficult to determine. Most coefficients were not significant for any distance measures based on scale or magnitude of investments. Only coefficients for investments within 150 feet were significant; all other variables were insignificant. These results are based on the distance between HOME investments and sales as explained in the methods section. Secondly, dummy variables were created to represent binary variables based on whether a unit was in a 150-, 300-, or 500-foot buffer zone. This model also presented few significant variables; only homes sold within 150 feet of a new unit were significant. Table 17 above show that most homes sales are located approximately 2,000 to 5,000 feet from HOME investments. Therefore, an additional model was estimated for distances of 500, 1,000, and 5,000 feet from HOME investments. Results from this analysis yielded only three significant variables which included HOME new construction at 5,000 feet and rehab at 1,000 and 5,000 feet. Galster et al. (2006) analysis of Richmond Virginia presented similar findings when attempting to use distance thresholds. They concluded that there were insufficient sales observations within 1,000 feet of investments, no observable impact within 2,000 feet of investments, and too many confounding factors influencing impact within 5,000 feet to observe measurable effects. Galster et al. (2004) used continuous distance variables to measure impacts of investments.

Therefore, near distance measures were used in the model for a more granular analysis. These variables were significant at the 90 percent level. The sale price decreases by more than $3,000 the farther a unit is from the nearest HOME investment, and for a rehabilitation unit, the value decreases by almost $1,000.

Table 20 presents findings for the impact of HOME investments based on total dollar amounts. The total amounts of the investments are represented as distance variables to housing sales. First, HOME investments were divided into small-value

Table 19: Regression results for investments

Variables	Parameter Estimates				eβ with βs as coefficients from Full Model	Premium (at $114,000, City median)	
	R squared	*0.60*					
	b	std *b*	sig	sig			
Intercept	10.24926	0.16044	63.88	***			
Structural Characteristics							
XDGEXC	0.28591	0.188	1.52		1.330972662	$	37,730.88
XDGFAIR	-0.29228	0.0124	-23.57	***	0.74655947	$	(28,892.22)
XDGGOOD	0.16509	0.01879	8.79	***	1.179499269	$	20,462.92
XBRICK	0.00028672	0.00001335	21.48	***	1.000286761	$	32.69
XSQFTSTRC	-1.82E-08	1.86E-09	-9.77	***	0.999977034	$	(2.62)
XSQFTSTRC2	-0.00574	0.00056784	-10.11	***	0.994276442	$	(652.49)
XAGE	0.00004517	0.0000035	12.92	***	1.003503991	$	399.46
XAGE2	0.03462	0.01498	2.31	*	1.035226248	$	4,015.79
XAIRCON	0.09239	0.00918	10.07	***	1.096792488	$	11,034.34
XHBTH	0.0166	0.00733	2.26	*	1.016738546	$	1,908.19
XBASEMFN	0.06271	0.0091	6.89	***	1.064718026	$	7,377.85
XATGR	0.10211	0.01984	5.15	***	1.107505291	$	12,255.60
XFIRE	0.11416	0.01317	8.67	***	1.12093146	$	13,786.19
XDECK_PRCH	-0.00533	0.00737	-0.72		0.994684179	$	(606.00)
XELECTICHE	0.11503	0.01734	6.63	***	1.121907094	$	13,897.41
XHSGRENT	-0.02638	0.02368	-1.11		0.997978518	$	(230.45)
XHSGSINGF	0.21054	0.0159	13.24	***	1.042799226	$	4,879.11
XSALAPRJ	0.02434	0.00975	2.5	*	1.024638636	$	2,808.80
XSALJULS	0.11291	0.01052	10.73	***	1.119531171	$	13,626.55
XSALOCTD	-0.02045	0.01574	-1.3		0.979757683	$	(2,307.62)
Socio-Economic Characteristics							
XPCTBLK	-0.42429	0.0137	-30.97	***	0.816652008	$	(20,901.67)
XLOGINCOME	0.16055	0.01338	12	***	1.174156479	$	19,853.84
XCOMMUTE	-0.00348	0.00040442	-8.59	***	0.911737273	$	(10,061.95)
Neighborhood Characteristics							
XPCTFOR	-3.5368	0.3197	-11.06	***	0.946612297	$	(6,086.20)
XPCTPERM	5.47976	0.18705	29.3	***	1.122629105	$	13,979.72
XRTCRIME	-0.00175	0.00021462	-8.14	***	0.99552999	$	(509.58)
XPCTVCT05	-1.45296	0.11158	-13.02	***	0.965243173	$	(3,962.28)
XVCBUILD	0.02172	0.00188	11.56	***	1.123149346	$	14,039.03
XHARBOR	-0.00911	0.00546	-1.67		0.934571554	$	(7,458.84)
HOME Partnership Investments (1994-2003)							
XNCONST	-0.02771	0.00589	-4.71	***	0.795063618	$	(23,362.75)
XREHB	-0.00036041	0.00471	-0.08		0.997262952	$	(312.02)
Note: n= 13519							
***	*Significant at 99% Level*						
**	*Significant at 95% Level*						
*	*Significant at 90% Level*						

($5,000 to $29,999), medium-value ($30,000 to $59,999), and large-value ($60,000 or more) categories based on the total dollar value invested into the new construction or rehabilitation of the unit. In this model, all investment measures were significant except three.

The following investments were not significant in equation 3.2: distance to HOME new construction units with total invested dollars less than $30,000; HOME rehabilitation units with total dollars between $30,000 and $60,000. For significant variables, housing prices decreased by approximately $3,000 the farther the sale was from new construction greater than $30,000. Additionally, housing prices decreased by approximately $3,000 the farther the property was from a medium-scale rehabilitated unit investment. However, housing sales increased the farther the property was from a large-scale rehabilitation investment.

Table 21 provides results from equation 3.3 based on two separate datasets. One data set includes sales located in areas with poor households and the other includes sales in areas with non-poor households. This analysis tests the impacts of the concentration and scale of new construction and rehabilitation for housing units sold in census tracts with average household incomes greater than $26,000. The household income of $26,000 was selected based on HUD 2000 income limits for households represented as below poverty. Results in this analysis were compared to results in the analysis for housing units sold in census tracts with average household incomes less than $26,000. For housing units sold in census tracts greater than $26,000, with the exception of three investment variables, all other variables were significant. This differed considerably from the model with units in tracts with average housing values less than $26,000, where only one investment variable was not significant. These results reflect that lower income areas are greatly impacted by investments. Most investments with the exception of small scale new and rehab investments presented positive impacts on sale prices.

In areas with average household incomes greater than $26,000, only small-scale rehabilitation projects were significant and these presented negative impacts. Medium and large-scale new construction represented very small but positive impacts on units. Table 21 provides a review of separate estimated models for low-income versus more affluent households. Based on this review, the value of investments and impact of investments on surrounding property values presents varying effects. With the understanding that socioeconomic variables are not the only variables that make up housing submarkets, it is important to separately estimate neighborhood housing markets for this analysis.

For the next step, housing sales for each cluster in the 2005 typology were separated and a model was run for each cluster. Table 22 and 23 presents the estimated results of each cluster. For Cluster 1, only medium-scale rehabilitation investment projects are significant. Medium-scale projects have a positive effect on property values, increasing the property value by approximately $478.

For Cluster 2, only new construction medium- and large-scale investment projects are not significant in the model. In review of the units, small-scale projects and large rehabilitated projects have a positive impact while small- and medium-scale rehabilitation projects have a negative impact. This differs from Cluster 1, in which medium-scale projects produce positive impacts.

Table 20: Regression Results for Investments based on Scale of the Investment

Variables	Parameter Estimates				eβ with βs as coefficients from Full Model	Premium (at $114,000, City median)
	R squared	*0.60*				
	b	std b	sig			
Intercept	10.80872	0.17423	62.04	***		
Structural Characteristics						
XDGEXC	0.24277	0.187	1.3		1.274775392	$ 31,324.39
XDGFAIR	-0.29188	0.01235	-23.64	***	0.746858154	$ (28,858.17)
XDGGOOD	0.17609	0.0187	9.41	***	1.192545383	$ 21,950.17
XBRICK	0.00028012	0.0000133	21.06	***	1.000280159	$ 31.94
XSQFTSTRC	-1.76E-08	1.85E-09	-9.52	***	0.999977743	$ (2.54)
XSQFTSTRC2	-0.00555	0.00056632	-9.79	***	0.994465373	$ (630.95)
XAGE	0.00004297	0.00000348	12.34	***	1.003333046	$ 379.97
XAGE2	0.03589	0.01491	2.41	*	1.036541821	$ 4,165.77
XHBTH	0.08694	0.00916	9.49	***	1.090831228	$ 10,354.76
XFBTH	0.01994	0.00731	2.73	**		
XBASEMFN	0.05528	0.00911	6.07	***	1.056836487	$ 6,479.36
XATGR	0.09825	0.01978	4.97	***	1.10323856	$ 11,769.20
XFIRE	0.11756	0.01314	8.95	***	1.124749113	$ 14,221.40
XDECK_PRCH	-0.00465	0.00739	-0.63		0.995360795	$ (528.87)
XHSGRENT	-0.0136	0.02372	-0.57		0.986492062	$ (1,539.90)
XHSGSINGF	0.19901	0.0161	12.36	***		
XELECTICHE	0.11362	0.01726	6.58	***		
XSALAPRJ	0.02252	0.00969	2.32	*	1.022775489	$ 2,596.41
XSALJULS	0.10885	0.01047	10.4	***	1.114995089	$ 13,109.44
XSALOCTD	-0.02374	0.01566	-1.52		0.976539577	$ (2,674.49)
Socio-Economic Characteristics						
XPCTBLK	-0.45142	0.01438	-31.39	***	0.806143759	$ (22,099.61)
XLOGINCOME	0.14236	0.01347	10.57	***	4.428208786	$ 390,815.80
XCOMMUTE	-0.00356	0.00040293	-8.84	***	0.909802601	$ (10,282.50)
Neighborhood Characteristics						
XPCTFOR	-3.32338	0.32796	-10.13	***	0.949751479	$ (5,728.33)
XPCTPERM	5.21716	0.19165	27.22	***	1.116423279	$ 13,272.25
XRTCRIME	-0.00134	0.00021887	-6.12	***	0.996575454	$ (390.40)
XPCTVCT05	-1.26035	0.11278	-11.17	***	0.969780287	$ (3,445.05)
XVCBUILD	0.02087	0.00187	11.13	***	1.118056279	$ 13,458.42
XHARBOR	-0.0056	0.00547	-1.02		0.959257651	$ (4,644.63)
HOME Partnership Investments (1994-2003)						
XNCONST	0.02407	0.01442	1.67		1.231176126	$ 26,354.08
XREHB	-0.01736	0.00902	-1.93	*	0.873834709	$ (14,382.84)
XNEWCONS	0.01964	0.01169	1.68		1.191624037	$ 21,845.14
XNEWCONM	-0.04888	0.00892	-5.48	***	0.634647112	$ (41,650.23)
XNEWCONL	-0.05811	0.01308	-4.44	***	0.598937622	$ (45,721.11)
XREHABS	0.03246	0.00707	4.59	***	1.314308751	$ 35,831.20
XREHABM	-0.01159	0.00635	-1.83		0.902166589	$ (11,153.01)
XREHABL	-0.00655	0.00638	-1.03		0.948618459	$ (5,857.50)
Note: n= 13519						
***	*Significant at 99% Level*					
**	*Significant at 95% Level*					
*	*Significant at 90% Level*					

Table 21: Regression Results for Investment across Submarkets

	Full Model		Household Median Income				Submarkets Clusters									
			$26000 or more		$26000 or less		Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5	
XNCONST	0.02407		0.00714		0.01833		-0.0127		0.07966	**	0.0114		-0.0513		-0.0455	
	0.01442		*0.0152*		*0.01546*		*0.11691*		*0.02718*		*0.01819*		*0.04548*		*0.32169*	
XREHB	-0.01736	*	-0.0268	**	-0.0224	**	0.09635		-0.0438	**	0.01481		-0.0341		0.7096	**
	0.00902		*0.0094*		*0.0098*		*0.08312*		*0.01604*		*0.01106*		*0.03123*		*0.33575*	
XNEWCONS	0.01964		0.00532		0.0278	**	-0.0032		-0.1136	***	0.03841	**	0.0649		0.01858	
	0.01169		*0.0119*		*0.01259*		*0.08055*		*0.02096*		*0.01447*		*0.0435*		*0.28923*	
XNEWCONM	-0.04888	***	-0.0353	***	-0.0591	*	0.0026		0.02121		-0.0385	**	-0.0153		-0.5378	
	0.00892		*0.00924*		*0.00989*		*0.06124*		*0.01525*		*0.0113*		*0.02953*		*0.36264*	
XNEWCONL	-0.05811	***	-0.0406	**	-0.0486	**	0.10074		-0.0048		-0.0143		-0.0413		0.22801	
	0.01308		*0.01392*		*0.01385*		*0.07706*		*0.02349*		*0.01733*		*0.04197*		*0.26487*	
XREHABS	0.03246	***	0.03472	***	0.03337	*	-0.0163		0.05375	***	-0.0056		0.04078		-0.0251	
	0.00707		*0.00723*		*0.00791*		*0.06089*		*0.01239*		*0.00846*		*0.02602*		*0.16601*	
XREHABM	-0.01159		0.00913		-0.0156	**	-0.0957	*	0.0391	**	-0.0214	**	-0.0301		-0.195	
	0.00635		*0.00685*		*0.00684*		*0.05005*		*0.01275*		*0.00783*		*0.02395*		*0.16392*	
XREHABL	-0.00655		-0.0069		2.3E-05		-0.0819		-0.0301	*	0.00268		0.06138	**	-0.4653	
	0.00638		*0.00698*		*0.007*		*0.05428*		*0.01339*		*0.00821*		*0.01922*		*0.28689*	
Sample size	*13519*		*11685*		*1834*		*448*		*3261*		*7861*		*1745*		*125*	
R2	*0.6042*		*0.6176*		*0.6078*		*0.4075*		*0.4161*		*0.4801*		*0.4491*		*0.6382*	
Adjusted R2	*0.6031*		*0.6164*		*0.6065*		*0.3571*		*0.4096*		*0.4777*		*0.4371*		*0.5015*	
***	*Significant at 99% Level*															
**	*Significant at 95% Level*															
*	*Significant at 90% Level*															

Table 22: Implicit Prices of Coefficient Estimates for HOME Investments across Submarkets

	Submarkets Clusters														
	Cluster 1			Cluster 2			Cluster 3			Cluster 4			Cluster 5		
XNCONST	-0.0127			0.07966	**	398.3	0.0114			-0.0513			-0.0455		
XREHB	0.09635			-0.0438	**	-219.05	0.01481			-0.0341			0.7096	**	3548
XNEWCONS	-0.0032			-0.1136	***	-568.05	0.03841	**	192.05	0.0649			0.01858		
XNEWCONM	0.0026			0.02121			-0.0385	**	-192.7	-0.0153			-0.5378		
XNEWCONL	0.10074			-0.0048			-0.0143			-0.0413			0.22801		
XREHABS	-0.0163			0.05375	***	268.75	-0.0056			0.04078			-0.0251		
XREHABM	-0.0957	*	-478.5	0.0391	**	195.5	-0.0214	**	-107.15	-0.0301			-0.195		
XREHABL	-0.0819			-0.0301	*	-150.6	0.00268			0.06138	**	306.9	-0.4653		
			-478.5			-75.15			-107.8						3548
			$ 114,478.50			***$ 114,075.15***			***$ 114,107.80***			***$ 114,000.00***			***$ 110,452.00***
Sample size	*448*			*3261*			*7861*			*1745*			*125*		
R2	*0.4075*			*0.4161*			*0.4801*			*0.4491*			*0.6382*		
Adjusted R2	*0.3571*			*0.4096*			*0.4777*			*0.4371*			*0.5015*		
***	*Significant at 99% Level*														
**	*Significant at 95% Level*														
*	*Significant at 90% Level*														

Table 23: Implicit Prices of Coefficient Estimates for HOME Investments across Submarkets (continued)

	Full Model			Household Median Income					
				$26000 or more			$26000 or less		
Average Home Price in Baltimore		*$ 114,000.00*							
XNCONST	0.02407			0.00714			0.01833		
XREHB	-0.01736	-86.8	*	-0.0268	-134.15	**	-0.0224	-111.9	**
XNEWCONS	0.01964			0.00532			0.0278	139	**
XNEWCONM	-0.04888	-244.4	***	-0.0353	-176.25	***	-0.0591	-295.5	*
XNEWCONL	-0.05811	-290.55	***	-0.0406	-202.85	**	-0.0486	-242.95	**
XREHABS	0.03246	162.3	***	0.03472	173.6	***	0.03337	166.85	*
XREHABM	-0.01159			0.00913			-0.0156	-78.15	**
XREHABL	-0.00655			-0.0069			2.3E-05		
		-459.45			-339.65			-422.65	
		$ 114,459.45			***$ 114,339.65***			***$ 114,422.65***	
Sample size	*13519*			*11685*			*1834*		
R2	*0.6042*			*0.6176*			*0.6078*		
Adjusted R2	*0.6031*			*0.6164*			*0.6065*		
***	*Significant at 99% Level*								
**	*Significant at 95% Level*								
*	*Significant at 90% Level*								

In Cluster 3, only medium- and large scale new construction reinvestment projects, and medium scale rehabilitation projects are significant. For new construction, medium-scale new construction and rehabilitation projects had a positive impact on housing sales, while small-scale new construction projects presented a negative impact. In Cluster 4, only large scale rehabilitation projects presented impacts and these impacts were negative. For Cluster 5, no investments were significant. These findings present very different results from the other empirical studies which note that distressed areas present significant and positive impacts.

The analysis of clusters presents implications for how scholars measure and evaluate the impacts of investments on surrounding property values. As demonstrated in this research, impacts differ significantly in different neighborhood housing markets.

Comparison of other Empirical Studies with Baltimore's Analysis

To date, there are numerous studies that evaluate the impact of investments on surrounding property values (Ellen et al., 2006; Ding et al., 2000; Ellen, et al. 2003; and Galster, 2006). Studies find that investments must be in close proximity to home sales, generally within 150 to 300 feet. They further suggest that new construction investments in proximity to home sales will have a greater impact. Findings in this analysis do not support these observations. First, the initial cluster analyses of years 1980, 1990, and 2000 in Baltimore show that most distressed neighborhoods have not improved in the past 20 years. Neighborhoods which fell into distress categories remained distressed each decade with less than ten percent of neighborhoods which improved. Ding et al.'s (2000) analysis of Cleveland may provide some insight as to why the Baltimore results do not mirror other empirical studies.

Ding et al.’s (2000) analysis of Cleveland occurred in the mid-1990s during a time the city was experiencing an urban renaissance. In this study, a total of over 1,000 investments, represented by CDBG subsidized new construction and rehabilitated investments, were completed in the city within ten years. This study’s number of investments is significantly higher than Baltimore’s number of HOME investments. Baltimore’s HOME investments totaled to approximately 400 investments over approximately ten years. Also, in Ding et al.’s (2000) analysis, homes sales were fewer in comparison to Baltimore. Cleveland housing sales totaled approximately 7,000 housing units while Baltimore’s housing sales totaled approximately 13,000. For Cleveland, investments were approximately 14 percent of housing sales, while Baltimore investments represented approximately two percent of housing sales. In this manner, there were more investments in proximity to housing sales the city.

The scale of the investment is not the only difference between the Cleveland and Baltimore models. The size of the city and where investments are targeted may also present interesting findings. As shown in the initial decennial analysis of the city, much of Baltimore’s investments occurred within the downtown area. This section of the city is plagued with substantial disinvestment which scholars claim can impede the progress or effects of new investments or revitalization efforts (Galster et al., 2004). Therefore, few impacts were captured within 1,000 feet of investments because of the surrounding quality of the neighborhood. These findings were similar in Galster et al.’s (2006) study. This study finds that investments in Richmond, Virginia tend to occur more than 1,000 feet away from housing sales. At this distance, the authors concluded that the impact was difficult to determine but could better be explained using near distance measures.

Therefore, for Baltimore HOME investments to have an impact, the city must focus on the scale of the investment but also give attention to the location, or neighborhood quality where the investment is directed.

CONCLUSION

This study analyzes the effects of HOME Program investments on nearby property values. It evaluates the impacts of investments based on scale, concentration, and neighborhood effects. More specifically, it estimates whether the impact of housing sales differs across differ types of neighborhoods. The results of this analysis present similar findings to other empirical studies, which examine the effects of subsidized housing investments on nearby property values and provide additional implications for future studies.

In an initial analysis of neighborhood housing market change in Baltimore, findings indicate that neighborhoods that are either distressed or stable do not change substantially from one decennial period to the next. Much of this change tends to occur in neighborhoods that are borderline distressed or stable. While some Baltimore neighborhoods improved, a significant number of neighborhoods declined and moved from one market type to another over a 20-year period, from 1980 to 2000. The most distressed areas of the city received significant investments during this time, and yet market conditions remained distressed. Slight changes occurred in areas near major private sector investments, like the Inner Harbor. This provided implications for empirical analyses in this study. HOME investments tend to be located in distressed areas that presented little-to-no progress over 20 years; the hedonic models used in this study helped determine if positive effects of public investments occurred at a block level, and if so, which factors impacted those changes.

The significant empirical findings suggest that new construction and rehabilitation investments positively affect surrounding property values in Baltimore. However, these effects are based on the scale and concentration of housing investments. Small-scale HOME Program investment projects—meaning those projects in which only a small number of housing units are constructed or rehabilitated—were either not significant or presented negative impacts on surrounding housing values. This supports findings outlined in the relevant literature stating that large redevelopment projects tend to have positive impacts on surrounding property values.

This study also suggests that there are statistically significant differences between poor neighborhoods and non-poor neighborhoods. Coefficients in areas with average household income less than $26,000 showed few significant effects for housing investments. Only large-scale and concentrated investments were significant and presented positive effects on surrounding housing sales. In areas with average household incomes greater than $26,000, the effects were different. For these areas, small-scale projects had positive impacts, while medium- and large-scale projects presented negative impacts. These findings may demonstrate the results of neighborhood quality. Further analysis of market types revealed equally important findings.

Cluster analyses further aided this study. Housing investments in distressed market types were not significant, which may be due to external and neighborhood quality factors that overshadow the effects of investments. Too many vacant and foreclosed properties may limit the effect of new construction or rehabilitation projects.

Khadduri et al. (2002) suggest that investments should not be targeted to these areas unless there is a larger redevelopment plan. In less distress and transitional areas, small-scale investment projects had little-to-no impact, while medium- and large-scale investment projects presented positive impacts. These findings corroborate those of the existing literature in that larger investments have positive impacts on neighborhoods. However, this study differs from previous empirical findings because impacts for new construction and rehabilitation investment projects were similar.

Much of the literature states that new construction impacts will be greater than rehabilitation investments. These findings may be related to distance measures used in the other literature (i.e., 150, 300, and 500 feet). Distance buffers were not significant in this study. Based on near distance measures, this analysis finds that areas with higher income levels and higher home values, small-scale investment projects presented positive impacts, while large-scale investment projects presented negative impacts. This outcome is a product of neighborhood stability and indicates that larger investments may have negative implications by lowering home values in these market types.

In summary, this analysis of HOME Program investments in Baltimore shows that new construction and rehabilitation residential investment projects can have positive impacts on property values, but that the scale and concentration of investments are relevant. This study concludes that impacts differ based on neighborhood housing market types. Distressed neighborhoods are not appropriate for investment given that market conditions may overpower the potential for an investment to produce positive results. Transitional areas—those neighborhoods that are nearing a point of decline or stability—are more likely to change as a result of HOME Program investments, but the investments must be large-scale and highly concentrated. Finally, for more stable neighborhoods that may be experiencing destabilization due to rises in foreclosures and unforeseen population losses, small-scale investment projects are best. For these reasons, decision makers at the federal, state, and local levels must recognize that neighborhood market types are highly relevant and must be considered when making neighborhood investment decisions.

Still, further analysis is needed. Whereas market types reflect neighborhood conditions, it is important to understand whether other factors influence neighborhood change or the direction of investment impacts. Will neighborhood assets affect change? Specifically, if investments are located near a major transit stop or park, will these assets improve investment impacts on surrounding property values? Empirical studies that consider these factors are important and will help decision makers determine whether a distressed area is appropriate for housing program investments.

ESSAY THREE:
DO HOUSING MARKET TYPOLOGIES MATTER? SPATIAL ANALYSIS OF THE IMPACT OF URBAN AMENITIES IN BALTIMORE, MARYLAND

INTRODUCTION

Economic restructuring and the initial practices of urban renewal in the 1960s, downtown redevelopment in the 1980s, and reinvestment zones (e.g., Empowerment Zones) in the 1990s, have failed to assist American cities to address the conundrums of social and economic decline. Planners and policy makers continue to test various economic and housing development initiatives to no avail as both mid-sized and small cities still suffer from the continual out-migration of middle class urban dwellers to surrounding metropolitan areas. Today, even stable neighborhoods are at risk of abandonment and decline.

Scholars claim that the failures of past policies and strategies are based on policymakers' inability to address the magnitude of disinvestment in distressed areas. Neighborhood-wide revitalization programs and initiatives are unsuccessful in these neighborhoods (Katz, 2009). In review of place-based housing programs, scholars suggest that housing subsidy programs in isolation are not effective tools to revitalize urban neighborhoods (Khadduri and Rodda, 2004). For programs to be effective in distressed areas, they suggest that housing funds only be applied to areas that are part of a critical mass of resources that go beyond housing. These areas should be in proximity to neighborhood assets such as commercial redevelopment, excelling schools, or near urban amenities, such as parks and public transit (Khadduri and Rodda, 2004; and Mallach, 2005).

Within the past decade, influenced by place-based initiatives, urban amenities have become very important elements in the targeting of few and limited federal and local resources. Richmond, Virginia, Baltimore, Maryland, and other cities since 2000 have begun to focus housing reinvestment dollars towards areas located near urban amenities. These amenities differ in various cities but are commonly identified as transit nodes, green spaces, and neighborhood anchors (e.g. schools). Practitioners and policy makers espouse that targeting government programs near neighborhood amenities will lead to positive spillover effects and leverage government investment impacts. However, there is a need for more analysis.

Empirical studies which estimate the impact of urban amenities on surrounding housing prices find that proximity to transit, urban parks, commercial districts, high achieving schools, and unique housing stock show positive impacts (Straszheim, 1974; Anderson and West, 2003; Geoghegan et al., 2003; and Day et al., 2004a). These studies posit that homebuyers are willing to pay a premium for houses located near these amenities (Knaap and Sohn, 2004). However, many studies caveat that there are other external factors that may affect the impacts of urban amenities. These factors include noise, crime, and household socioeconomic characteristics (Chao et al., 2006; and Poudyal et al., 2009). These findings indicate that neighborhood quality influences the impact of urban amenities on nearby home sales and value. It further suggests that market forces will command different impacts of urban amenities and affect the additional amount or premium a homebuyer pays for a house located near an urban amenity.

The literature related to housing theory and market forces define housing as a differentiated good consisting of a variety of characteristics (Day, 2003). These characteristics include housing type, structural material, square footage, and location, which affect the price homebuyers are willing to pay for a housing unit. Additionally, housing is located within a neighborhood that contains a "bundle of spatially based attributes associated with clusters of residences" (Galster, in eds. O'Sullivan and Gibbs, 2003). These spatially based attributes include the quality of surrounding homes, the quality of neighborhood schools and services, and the socioeconomic characteristics of surrounding households. Similar spatial elements and housing structural characteristics tend to make up housing submarkets. With each submarket representing different characteristics, it can be assumed that different submarkets respond differently to the presence of urban amenities. This observation suggests that urban housing markets are made up of many separate submarkets that need to be separately estimated to determine the true impact of urban amenities given the conditions of the submarkets (Straszheim, 1974; Anderson and West, 2003; Geoghegan et al., 2003; and Day et al., 2004a). While scholars acknowledge that housing factors differ across housing submarkets, the gap in the literature related to urban amenities presents a limited understanding of how amenity impacts vary across neighborhood housing markets.

Therefore, it is instructive to first question whether urban amenities will impact neighborhood quality and identify what factors will influence the demand for these amenities in urban areas. Secondly, do the premiums of proximity to these amenities vary across neighborhood housing markets? This study extends the literature by examining the relationship between urban amenities and neighborhood housing markets, and uses housing data in Baltimore to estimate the impact of urban amenities on surrounding housing sale prices. The traditional hedonic model is used to calculate and estimate implicit prices of urban amenities. Spatial statistics are used to address spatial dependency among housing data.

LITERATURE REVIEW

The literature related to the benefits of environmental and urban amenities is extensive and has expanded within the past ten years with the introduction of new and improved methodology to measure the effects of and benefits of amenities and dis-amenities in both urban and suburban communities. Amenities, such as the proximity to transit stations and green space, waterfront real estate property, or dis-amenities, such as the proximity to brown fields and waste water treatment plants are evaluated in the literature. The general assumptions are that urban amenities will impact the price of surrounding sales transactions. Hedonic regression models are the commonly used statistical method. However, scholars have employed numerous modifications and refinements to improve their understanding of the willingness of households to pay for environmental and urban amenities. The two alternative methods used to explore the relationship between amenities and dis-amenities and nearby housing sales are spatial hedonic and two stage hedonic models.

The Hedonic Method

Hedonic modeling is the common tool used among housing analysts to capture the demand for housing and neighborhood characteristics sought by homebuyers. A hedonic model decomposes the expenditures of housing into measurable prices and quantities based on a bundle of housing characteristics, each containing its own implicit price. The theoretical foundation of hedonic price modeling is attributed to Rosen (1974), who provided a method by which housing prices could be predicted and compared based on different dwelling types or similar dwelling types in different places (Malpezzi in eds. O'Sullivan and Gibbs, 2003). Rosen (1974) suggested that the price of a house represents the sum of expenditures on a number of bundled housing characteristics. The bundle of housing characteristics may include structural attributes such as the square footage of the house, and structural amenities, such as the presence of a fire place or a finished basement, or the material of the housing unit, such as brick or aluminum siding. Additionally, neighborhood services and environmental amenities and dis-amenities are included as contributing factors that affect house prices. The equation for the hedonic price model is provided below.

$$y = \beta x + \varepsilon \tag{3.1}$$

In equation (4.1) y represents the actual sales price of a house, x is a vector of explanatory variables and ε is the error term.

Rosen (1974) further suggested that each expenditure carried its own implicit price or value for which households presented marginal willingness to pay for various structural elements and neighborhood characteristics. The marginal or implicit price of an attribute is:

$$\ln(P) = \beta 0 + \beta_i X_i + e \tag{3.2}$$

Equation 4.2 is calculated based on outputs from the hedonic estimates. Therefore, to estimate the value of the each bundle of characteristics and neighborhood quality on the sales price of a house, each component is decomposed or regressed on the price of a house P into the prices of individual attributes of the house and the neighborhood where the house is located (X_1, X_2, …….X_n). In the simplest form, the equation is computed with an ordinary least squares (OLS) regression of homes value or sales price on housing characteristics. The regression coefficients are transformed into estimates of the implicit price of the housing characteristics.

Empirical studies in the late 1990s and early 2000s, have given significant recognition to comparative analyses that evaluate environmental factors such as water hazards, landfills and brown fields, and views and access to neighborhood parks as contributing non-tangible factors that affect the price of housing (Boyle and Kiel, 2001; and Simons and Saginor, 2006). These scholars attempt to determine the demand for these goods. However, few techniques exist to measure the benefits of a unit of an environmental quality. Therefore, scholars have turned to housing markets to derive implicit prices and measure the demand for these goods (Brasington and Hite, 2003). Environmental and urban amenities are evaluated as factors that may be bundled into the housing purchase. As a non-tangible good, the value of the amenity is captured in the price of the residential property based on proximity to the property, holding all other independent variables equal (Carruthers et al., 2009). For example, home located near an urban park may be considered more desirable and households may be willing to pay a higher value for the house based on this particular location (Crompton, 2005). Numerous studies that evaluate environmental quality similar to the example of urban parks find that these amenities or dis-amenities influence housing values and sale prices.

Empirical studies that evaluate the benefits of the proximity to transit find that households are willing to pay a premium to be located near rail stations (Cervero and Duncan, 2002; and Cervero, 1994). Additional studies that estimate the impacts of housing sale prices near urban parks and water bodies suggests that these green spaces positively affect the prices of housing sales. They further posit that the size of these amenities such as large urban parks influences households' willingness to pay more to be located near a park (Chao et al., 2006; and Poudyal et al., 2009). Additional factors include the quality of area schools (Black, 1999; Brasington, 2003; and Cheshire and Sheppard, 2004), and air quality (Kiel and McClain, 1995; Chattopadhyay, 1999; Beron, Murdoch and Thayer, 2001; and Zabel and Kiel, 2000). In contrast, dis-amenities also affect sale prices by discounting housing sale prices based on proximity. Such dis-amenities include environmental hazards, brownfields, and distance to foreclosed properties (Boyle and Kiel, 2001; Kohlhase, 1991; Clack et al., 1997; Hite, 1998; Dale et al, 1999, Bae et al., 2007; Brasington and Hite, 2008; Lin et al., 2007; and Immergluck, 2005 and 2006).

Using the hedonic model, most studies that evaluate the benefits of amenities suggest that the impacts of amenities may be related to dis-amenities, such as crime and noise, or other factors such as commuting patterns (Bowes and Ihlanfeldt, 2001). In some cases, these impacts also vary based on the type of neighborhood. Song and Knaap (2003) study urban amenities in suburban communities and suggest that residents pay a premium for housing near commercial. In another study by Knaap and Ding (2003), the authors analyze the determinants of property values in Cleveland. The authors find that the number of business in the area discount home values based on proximity.

Further studies that estimate the impact of urban amenities on property values suggests that crime and socioeconomic conditions have greater impacts on sale prices (Bartik, et al., 1996; and Gibbons, 2004). Studies that analyze the relationship between social and economic conditions and urban amenities, find that individual household incomes, race and education are valid demand shifters to impact the effects of amenities on surrounding home values (Mahan, et al., 2000; and Brasington and Hite, 2005). These studies control for socioeconomic variables and find that urban amenities contain low explanatory powers to explain determinants of property values. These findings suggest that urban amenities in dissimilar housing submarkets will show different effects. In review of these studies, there are limited empirical analyses that attempt to estimate the impacts of urban amenities across neighborhood submarkets.

Methods of Measuring Spatial Effects

To understand the impacts of environmental and urban amenities, a number of scholars have begun to employ spatial hedonic models to better capture the effects of these factors on housing sale prices. Spatial dependency among housing data is a key element that scholars attempt to control. In a hedonic price function, the dependency of spatial data assumes that property sale prices are not independent of selling prices of surrounding properties (Day, 2003). Properties located in proximity to each other or within the same geographic boundary will share similar features including neighborhood attributes, housing type and structure, and in most cases socioeconomic characteristics of households. In a classic hedonic regression model the challenge of spatial dependence is not only linked to the supply side related to the similarities in adjacent homes but also on the demand side, where homebuyers may emulate one another’s behavior and tend to select similar homes based on structural and neighborhood amenities (Carruthers et al., 2010).

Scholars claim that traditional hedonic models are ineffective tools to address these factors because this model assumes that houses are purchased in isolation of characteristics of nearby homes, neighborhood quality, or even homebuyer behaviors. To the contrary, scholars suggest that buyers make purchases based on the quality and characteristics and quality of adjacent homes. In the past ten years, empirical studies have attempted to model these observations with the use of the geographically or locally weighted regression (GWR) and other spatial models to analyze spatial impacts of environmental amenities among neighborhood level data.

Initial techniques used by scholars to capture non-fixed spatial variables and neighborhood effects of factors based on locational housing markets led to the phenomenon of spatial drift of coefficients (Can 1990 and 1992; and Ding, 2000). Spatial drift of coefficients attempt to capture neighborhood effects by using interaction terms, a concept built upon by the interaction of Cartesian coordinates with housing attributes to generate unique location values (Fik et al., 2003). However, spatial interaction terms and diffusion methods used within an OLS regression model remained insufficient to capture spatial dependence in housing markets. Therefore, scholars turned to spatial hedonic regression models to correct the inadequacies of traditional OLS models and model spatial drifts in linear model coefficients.

Spatial hedonic regression models developed by Anselin (1988 and 1990) are used to investigate spatial non-stationary estimates, and capture variability in the quality of amenities, which is limited in the conventional hedonic model using OLS. The ability of these models to capture housing market spatial dependence are generally found in studies valuing the quality of the environment. They apply GWR models to estimate the marginally implicit price and a series of implicit demand functions to describe the relationship between the price of distance from environmental amenities and dis-amenities (Carruthers and Clark, 2009; and Cho et al., 2006).

Spatial statistics used in environmental studies address spatial dependency in two distinct models: spatial lag models or spatial error models (Geoghegan et al., 1997; Gawande and Jenkins-Smith, 2001; Leggett and Bockstael, 2000; and Boackstael and Bell, 1999). For the spatial lag model, an additional weighted regressor in the form of a spatially lagged dependent variable (Wy) is included in the traditional model to assess the existence and strength of spatial dependency or interaction. The model is represented as:

$$y = \rho Wy + X\beta + \varepsilon \qquad (3.3)$$

where ρ is a spatial autoregressive coefficient, ε is a vector of error terms, and Wy is the weighted spatially lagged variable, calculated as an n by n spatial weight matrix.. The spatial lag term W in this model picks up on unobserved factors that affect the composed housing value (Brasington and Hite, 2008).

In Equation (4.3), the ρ is the spatial autoregressive parameter to be estimated. It measures the degree of spatial dependence between the sale prices of nearby houses in the sample. The spatial weight matrix W summarizes the spatial configuration of the sample based on k nearest neighborhood weight matrix. Next, X is the explanatory variable, and α is the parameter associated with the spatial lag of the explanatory variables. The Wy term in (4.3) captures the extent to which house prices in one neighborhood are affected by the price of houses in an adjacent neighborhood.

The spatial lag model assumes that events that occur in one place can predict an increased likelihood of similar events in neighboring places. This assumption implies that sales of nearby homes will influence each other and the weight matrix allows the spatially lagged weighted dependent variable to be endogenous to the spatial lag variable. The spatial error model is represented by a spatially lagged variable in the error structure, therefore, in equation (4.3) above and equation (4.4) below the lagged variables are used to address immeasurable factors correlated with the dependent variable. The model is represented as:

$$y = \rho Wy + X\beta + WX\alpha + \varepsilon \tag{3.4}$$

this is the spatial lag model with an additional set of spatially lagged exogenous variables (WX). This model assumes that omitted variables are likely to induce spatial dependence among the error terms. This model attempts to address the spatial interaction among market participants.

Empirical studies that compare the traditional hedonic regression model with a spatial model show that spatial models improve the predictive ability and capacity of the model to address highly correlated variables due to spatial dependence (Chao et al., 2006; and Poudyal et al., 2009). GWR models or spatial lag models are not constrained by rigid boundaries and may inform policymakers on the spatial impact of investments. However, the spatial lag and other spatial models still present limitations to address the estimation problem of endogenity. Scholars point out that the distance to urban amenities, even when spatial dependency is addressed, is still impacted by endogenous factors such as housing price (Brasington, 2001). This incident occurs when there is a contemporaneous correlation between the regressor (price) and the error term. The error term contain omitted variables which are correlated with the regressor which cause the regressor to be endogenous and yield biased and inconsistent parameter estimates (Brasington, 2001). Therefore, there is a need to control for this challenge.

An alternative to the spatial regressive models is the spatial two stage least squares (2SLS) regression. This model is used in analyses to address and effectively estimate spatial dependency. In the past ten years, the 2SLS method has become more common in analyses that explore the value of urban amenities (Chattopadhyay, 1999; Zabel and Kiel, 2000; Black 1999; and Brasington, 2000 and 2003). While the spatial lag model addresses the spatial interaction among market participants, the weighted dependent variable is endogenous and cannot properly be estimated using OLS. This is based on the fact that on the supply side, adjacent houses contain similar characteristics and buyers may purchase homes based on the demand for these characteristics. One the demand side, scholars suggests that homebuyers emulate each other's behaviors (Carruthers et al.,2007. This results in spatial interaction among homebuyers participating in the market. Therefore, Kelejian and Prucha (1998) developed an alternative spatial two stage least squares (2SLS) estimator by which the spatially lagged variables or weighted price variable is regressed on all the regressors plus spatial lag regressors of those same variables. This hedonic model is used to produce predicted variables that are then used to replace the actual variables in the spatial lag model. The predicted variables allow the 2SLS model to produce efficient unbiased parameter estimates despite the presence of the spatial error dependence not corrected in the spatial lag model (Carruthers et al.,2007 and Das et al., 2003).

In summary, the evaluation of urban amenities with spatial statistical models has become common as researchers attempt to capture the spatial effects and values of urban amenities during sales transaction. Implications from these studies will present significant findings for researchers and practitioners developing policy related to where to target local and federal housing amenities. The general gaps in the literature are based on differing effects among housing markets and statistical spatial modeling to estimate impacts.

STUDY AREA AND RESEARCH QUESTIONS

The city of Baltimore will be the case study for this analysis. This study will observe home transactions and the impacts of the following amenities: the proximity to universities, the proximity to green spaces including trails and parks, and the proximity to transit, including light rail and subway. Housing sales transactions for 2004 and 2005 will be examined to estimate the impact of urban amenities on sale prices. Approximately 13,000 homes were sold in the city between 2004 and 2005, most homes are located between 600 to 8,000 feet from urban amenities as presented in table 24. This study will address the gaps in the existing literature through three related questions:

(1) Do urban amenities affect the sale price of nearby homes?

(2) Will effects of amenities change across neighborhood sub-markets?

(3) In the context of local and spatial effects of proximate housing sales, will spatial models improve and better explain the effects of urban amenities on housing sales when socioeconomic variables are controlled in the model?

DATA

This analysis will include the following variables: housing structural, locational, neighborhood characteristics/quality, reinvestment, and urban amenity data. The structural data for sale prices of single-family units were obtained from the Maryland Property View database, which collects data from assessors' offices throughout the State. Structural variables include building age, house style, date of the sale, garage presence, and size, square footage of the house, and types of utilities. Housing data were obtained from the city of Baltimore and Maryland Property View. Neighborhood quality include: percentage permits, proportion of sales, percent of foreclosures, percent of vacant building and vacant lots, proportion of subsidized homes, and the proportion of commercial land uses. These data were collected from city of Baltimore Planning Department for 2005 at the census block level. Additional data include social and economic data such as the percent of African American households in a census block group and average household income collected from the 2000 census at the census block level. Other socioeconomic variables included median household income, commute, and commute time.

Single-family houses and rental units sold in 2004 and 2005 were selected for this study. Records with missing data, arms-length transactions, and outliers were deleted from the data. Sales of more than $400,000 and less than $10,000 were also excluded from the analysis based on box plots analyses that showed the maximum and low points in the data spread. Additionally homes more than 5,000 feet from urban amenities were excluded from the analysis based on the assumption that the impact of the amenities will decline the further the housing sales transaction is from the amenity. Rental properties were included in the analysis. The total data set included 13,519 sales for 2004 and 2005. The data set also include spatial lags of each variable used in this analysis. Spatial lags were created with the spatial weight matrix (Wij) commonly presented in equation 4.2) to match each transaction to its four nearest neighbors. Once this matrix was generated, it was used to calculate spatial lags of all the variables in listed in Table 24 below. This table lists descriptive analysis for only non-lagged variables included in this analysis.

Descriptive statistics show that a typical unit sold in Baltimore for $109,000, and contained approximately 1,200 square feet of living space. Most units were built in the mid 1920's as common for housing located in post-industrial cities. Units generally were brick, with porches, but few contained fireplaces, half-baths, and garages. This is based on the row house building type in Baltimore.

GIS was used to calculate distance measures between amenities and property sales centroids. Amenities included in this analysis were: (i) transit nodes, which include distance to light rail and subway stations; (ii) green spaces, which included parks and urban trails; (iii) major universities; and (v) commercial land uses. Figures 19-21 provide the location of urban amenities in the city.

Table 24: Summary Statistics of all variables included for the Amenities Model

Summary Statistics						
Variable	**Label**	**Unit of Measure/Analysis**	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Sales Price	PRICE	dollar/individual unit	$ 109,362.74	$ 1.93	$ 13,000.00	$ 400,000.07
Log (Sales Price)	XLOGPRICE	dollar/individual unit	11.6024255	0.6584033	9.472705	12.89922
Structural Characteristics (2004,2005)						
Housing Condition Excellent	DGEXC	binary/individual unit	0.00036985	0.0192286	0	1
Housing Condition Fair	DGFAIR	binary/individual unit	0.8161846	0.3873479	0	1
Housing Condition Good	DGGOOD	binary/individual unit	0.0574747	0.232756	0	1
Brick	XBRICK	binary/individual unit	0.7377765	0.4398598	0	1
Basement	XBASEMENT	binary/individual unit	0.9308381	0.2537387	0	1
Square Footage of Unit	XSQFTSTRC	feet/individual unit	1264.11	603.3997251	0	16920
Square Footage of Unit (squared)	XSQFTSTRC2	feet/individual unit	1962050.9	3241177.6	0	286286400
Age of Unit	XAGE	number/individual unit	77.4378282	23.4394005	1	215
Age of Unit (Squared)	XAGE2	number/individual unit	6545.98	3830.62	1	46225
Aircondition	XAIRCON	binary/individual unit	0.2574895	0.4372674	0	1
Half Bath	XHBTH	number/individual unit	0.2381093	0.4431362	0	3
Finished Basement	XBASEMFN	binary/individual unit	0.2748724	0.4464665	0	1
Garage	XATGR	binary/individual unit	0.0360973	0.1865393	0	1
Fireplace	XFIRE	binary/individual unit	0.1064428	0.3084149	0	1
Porch, Deck, Patio	XDECK_PRCH	binary/individual unit	0.748724	0.5570976	0	3
Rental Unit	XHSGRENT	feet/individual unit	0.0767069	0.2661356	0	1
Socio-Economic Characteristics (1990,2000)						
Average Income of Census Block	XINCOME	average/census blgrp	$ 34,625.31	$ 1.39	$ 6,875.00	$ 170,427.97
Log of average income in census block	XLOGINCOME	average/census blgrp	10.4523403	0.3263179	8.835647	12.046068
Percent of African American	XPCTBLK	percentage/census blgrp	0.4773674	0.3759655	0	1
Commute Time	XCOMMUTE	rate/census blgrp	26.5527036	12.8990131	0	83
Neighborhood Characteristics (2005)						
Distance from Inner Harbor	XHARBOR	feet	1682	0.7	41	10300
Percentage of permits (permits greater than $5,000 exterior rehabs for housing units)	XPCTPERM	percentage/census blgrp	0.0211092	0.0270866	0	0.22
Percentage of foreclosed housing units	XPCTFOR	percentage/census blgrp	0.0155128	0.0128682	0	0.25
Percent of vacant housing units	XPCTVCT05	percentage/census blgrp	0.024347	0.0442405	0	0.42
Distance from vacant building	XVCBUILD	feet	209.975635	2.3596861	2.6E-10	5229.244021
Rate of crime among all residents (number of crime per 1000 people in the city in 2005)	XRTCRIME	percentage/census blgrp	2.5600172	17.0577263	0	262.42
Distance to commercial landuse	XCOMM	feet	538	1.32	0	6773
Sold between January and March	XSALJANM	binary	0.0160515	0.1256782	0	1
Sold between April and June	XSALAPRJ	binary	0.3703676	0.482921	0	1
Sold between July and September	XSALJULS	binary	0.2627413	0.4401394	0	1
Sold between October and December	XSALOCTD	binary	0.0636142	0.2440734	0	1

Figure 19: Green Space Amenities in Baltimore

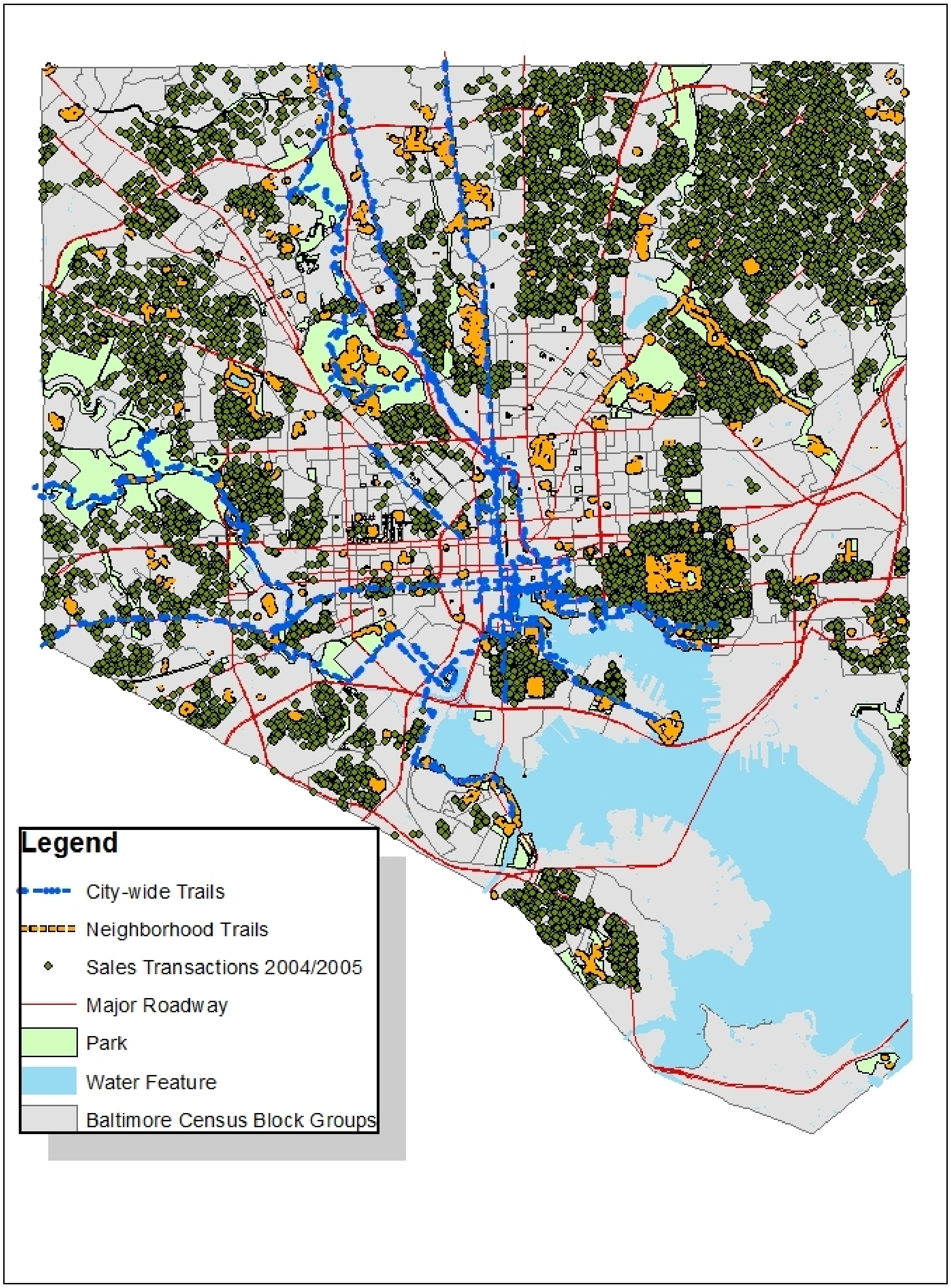


Figure 20: Transit Amenities in Baltimore

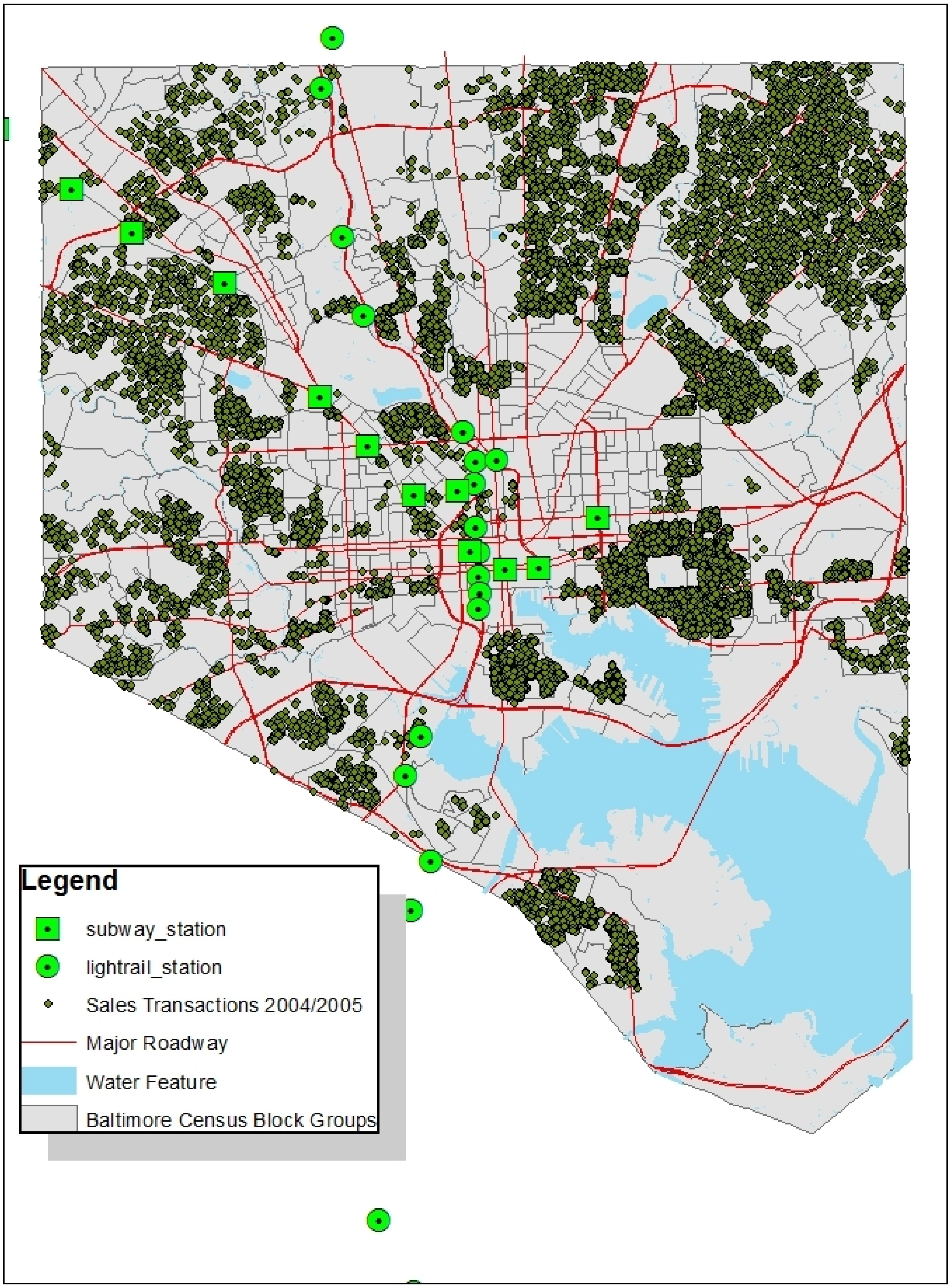
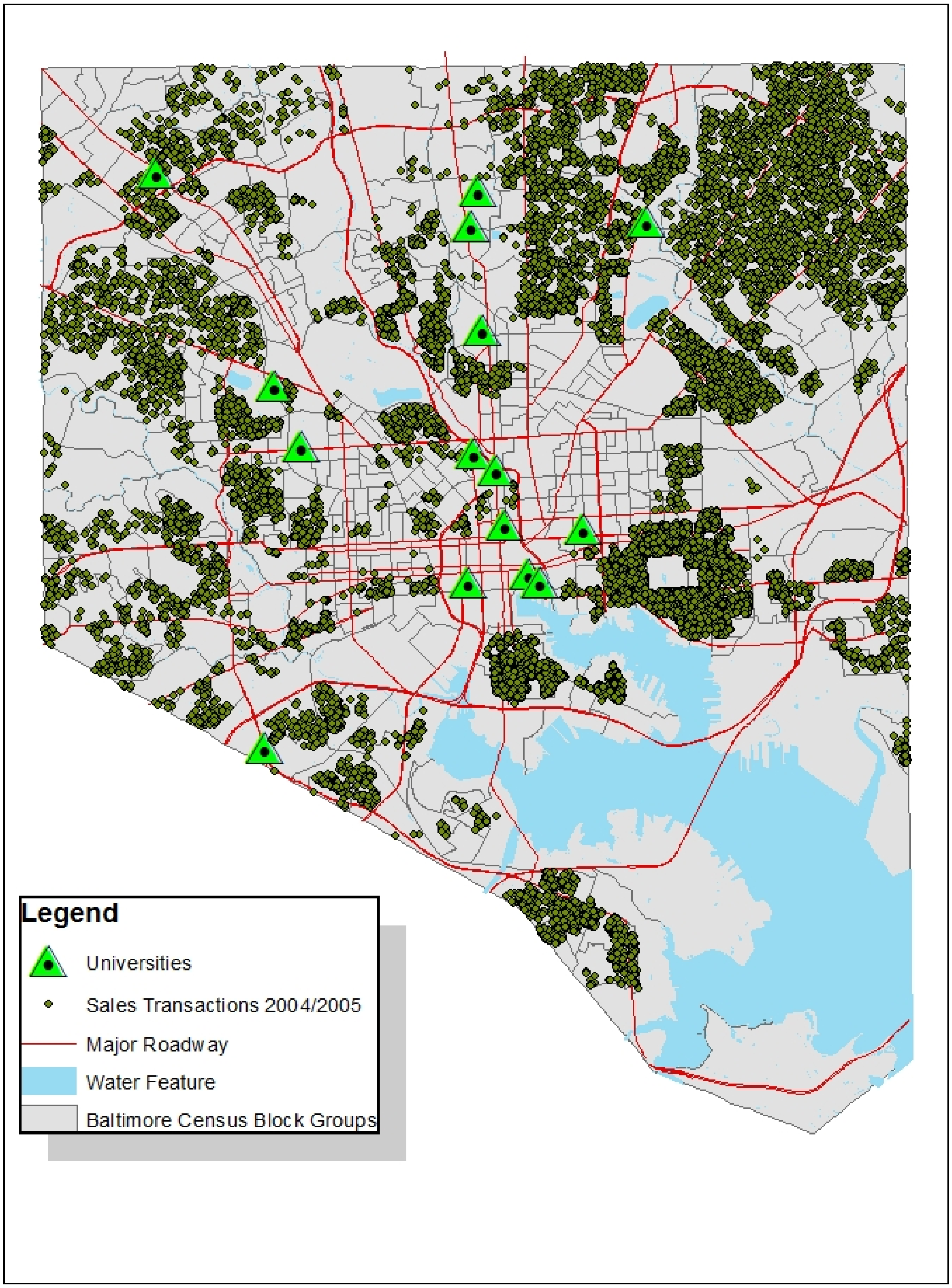


Figure 21: Community Anchor Amenities (Universities) in Baltimore



METHODS

The first research question attempts to determine if neighborhood amenities influence housing sales, controlling for other structural and locational variables. To address this question, a multivariate regression model is used to explain the sales price of a property as a function of neighborhood amenities. The basic model is expressed as:

P = f(S, N, T, U)

Where

P= sale price;
S = Structural characteristics;
N = Vector of socioeconomic neighborhood characteristics (including location variables);
T = Time (Season of Sale);
U = Urban Amenities; and
e = error term

Thus the model is:

$$\ln P = \beta_0 + \beta_1 S + \beta_2 N + \beta_3 T + \beta_4 u + e \qquad (3.5)$$

Due to the non-linear form of prices and values, the dependent variable, sales price, will be used as a common form natural log of housing sales price for this model. The structural attributes ($\beta_1 S$) and neighborhood characteristic variables ($\beta_2 N$) are control variables. $\beta_2 N$ include race, ethnicity and income variables and represent a series of dummy variables indicating the quarter of the sale. This vector also includes neighborhood characteristic variables such as the percent of foreclosures and permits activity, and distance measures to vacant buildings. Socioeconomic factors capture the quality of the neighborhoods. $B_3 T$ represent time variables in the model as dummy variables for homes sold in three month time periods for January through March, April through July, and October through December. August through September is the baseline dummy variable not included in the model.

Urban amenities ($\beta_6 U$) include continuous distance measures to the nearest sales transaction. For example, the distance to the nearest park it measured in proximity to the housing transaction. These distance measures were completed for distance to transit, green space, community anchors and commercial land uses. The first stage hedonic price function for sale transactions for years 2004 and 2005 is used to address question 1.

Question 2 is addressed by estimating separate models for housing submarket clusters. The cluster statistical method and hedonic regression equation are used in this analysis to define clusters. The cluster method is a statistical method that groups similar data into categories, based the non-hierarchical cluster technique. This methods uses Euclidean distances to group similar and dissimilar variables into distinct categories. Each observation in the data set is assigned to the nearest cluster. The k-means cluster is a commonly used method in neighborhood typologies because it is best suited for large datasets in which variables are continuous or categorical (Coulton, Theodos, and Turner, 2009). Clusters were developed in a previous study. These clusters were tested to determine their statistical validity Before running the cluster analysis, data are standardized using z-scores so different dimensions (e.g., housing sales, percentages, and number values) become common units that are relative to city averages for the analysis. The number of clusters was determined by analyzing cluster trees, looking for the maximum value of the pseudo-F statistic and the minimum of the R^2 (Finch, 2005).

Five clusters were determined in the study and tested based on the following hedonic price function:

$$\ln (P) = (\beta_0 + \beta_1 S_{1i} + \beta_2 C_{2i} + e_i) \qquad (3.6)$$

Where:
P= sale price;

S = Structural characteristics;
C = Clusters (1 through 5); and
e = error term

Upon determining significant clusters, an additional Chow test was used to verify clusters were statistically significant. Next, a separate regression model was estimated for each of the five clusters in equation 3.7. These models were compared to determine the varying effects of urban amenities across submarkets.

The last question uses the Moran I statistic to determine the spatial dependency in the data (Anselin, 1995). The Moran I statistic is computed based on z-scores to identify spatial outliers and clusters. The calculation of Moran I is:

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j\neq i}^{n} w_{i,j}(x_i - \bar{X}) \tag{3.7}$$

Where x_i is an attribute for feature i, X is the mean of the corresponding attributes, $w_{e,\,j}$ is the spatial weight between feature i and j. This analysis will be followed with a Durbin Watson test to test for autocorrelation. A spatial lag model was used to estimate the results of the explanatory variables on sale prices. The basic model is expressed as:

P = f(Wy(P), S, N, T, U)

Where
P= sale price;
Wy(P) = Spatial lag of sales price;
S = Structural characteristics;
N = Vector of socioeconomic neighborhood characteristics (including location variables);
T = Time (Season of sale);
U = Urban Amenities; and
e = error term

Thus the model is:

$$\ln (P) = (\beta_0 + Wy(P) + \beta_1 S + \beta_2 N + \beta_3 T + \beta_5 U + e) \tag{3.8}$$

The limitations of the spatial lag model are its inability to address endogenity of house prices. Therefore, a 2SLS was estimated to address endogenity. This process required two steps. First a first stage regression model was estimated including a spatial lag and an intercept for the z vector to explain sales price of housing in Baltimore as presented in equation 4.7.

Second, parameters from the first stage model were used to calculate the marginal implicit price of distance to urban amenities. Upon calculating these prices, dollars are adjusted for 2010 dollars. It is assumed that due to spatial dependency, the price estimates will vary across geographic scale. This is due to the model's non linear-form. The geographic variation is based on the fact that different consumers will pay different marginally implicit prices for different values based on distances variation. Carruthers et al. (2007 identify diminishing marginal utility to explain how each incremental distance away from an urban amenity is valued greater than the inth increment.

ANALYSIS

Table 25 presents the hedonic regression model estimated based on equation 4.1 without the inclusion of urban amenities variables. The explanatory variables explain .58 percent of the model. All signs were expected based on the factors included in the model that affect sale prices and was consistent with housing literature. Older homes were discounted along with homes that identified as fair quality. As the average median income of an area increased, housing sale prices were positively impacted. A higher percent of African Americans households and higher commute time negatively show impacts sale prices. Neighborhood characteristics present the expected signs. Higher percent of foreclosures in a census block show negative values, which was similar to increases in vacant properties and crime rates. For distance variables, property values increased every one additional foot a housing unit is from a vacant building.

Results of Estimates for Urban Amenities

Table 25 present regression results. Proximity to the Harbor is considered an urban amenity, but the negative sign in this model indicates that housing is not valued the same as housing farther from the Harbor. Therefore, disinvestment in this area may affect the negative value of the distance to the Harbor. Time variables included homes sold in spring, summer, and winter months. Houses sold in winter months were discounted; however, this variable was not significant in the model. Houses sold during the summer and springs carried positive signs.

In Model 2, urban amenity variables were included in the model. These additional variables improved the model R^2 of .58 to .63. Estimates in this model showed that housing sales in proximity to universities, parks, trails, and subway stations would sell for higher prices based on their locations. However, estimates for commercial land and Baltimore's light rail present the opposite effect. For both amenities, home prices decrease for every foot the unit is closer to commercial land and Baltimore's light rail. Findings from this model were similar to Knaap and Ding (2000)'s analysis of Cleveland. The authors find that for each additional mile away from commercial land uses housing values increased. Increases in home prices with each mile from light rail stations may be based on commuting patterns and the use of public transit in Baltimore. Figures 19-21 show urban amenities in the city in relation to housing sales. Few homes are located near light rail stops, and additionally, if households are not dependent on the MARC train or transit, there are limited advantages to locate near these transit stops.

Table 25: OLS Coefficient Outputs without Amenities

	Equation 1				eβ with βs as coefficients from Full Model	Premium (at 114,000, City median)
OLS	*R squared*	*0.58*				
	b	sig	std *b*			
Intercept	10.20684	0.15955	63.97	<.0001		
Structural Characteristics						
XDGEXC	0.28957	0.18707	1.55	0.1217	$ 1.336	$ 38,287.24
XDGFAIR	-0.25682	0.0126	-20.39	<.0001	$ 0.774	$ (25,820.15)
XDGGOOD	0.14241	0.0186	7.66	<.0001	$ 1.153	$ 17,447.62
XBRICK	0.02757	0.0149	1.85	0.0643	$ 1.028	$ 3,186.71
XBASEMENT	0.00682	0.01539	0.44	0.6575	$ 1.007	$ 780.14
XSQFTSTRC	0.0003135	0.00001248	25.13	<.0001	$ 1.000	$ 35.74
XSQFTSTRC2	-1.95E-08	1.84E-09	-10.6	<.0001	$ 1.000	$ (0.00)
XAGE	-0.00419	0.00058499	-7.17	<.0001	$ 0.723	$ (31,587.76)
XAGE2	0.00003831	0.00000356	10.76	<.0001	$ 1.000	$ 4.37
XAIRCON	0.12972	0.0095	13.66	<.0001	$ 1.139	$ 15,790.09
XHBTH	0.07975	0.00912	8.75	<.0001	$ 1.083	$ 9,463.86
XBASEMFN	0.05969	0.00906	6.59	<.0001	$ 1.062	$ 7,011.85
XATGR	0.11326	0.0198	5.72	<.0001	$ 1.120	$ 13,671.23
XFIRE	0.11388	0.0131	8.69	<.0001	$ 1.121	$ 13,750.41
XDECK_PRCH	-0.00875	0.00736	-1.19	0.2344	$ 0.991	$ (993.15)
XHSGRENT	0.00108	0.0235	0.05	0.9635	$ 1.000	$ 9.44
Socio-Economic Characteristics						
XPCTBLK	-0.41155	0.01363	-30.2	<.0001	$ 0.822	$ (20,333.75)
XLOGINCOME	0.15649	0.01331	11.76	<.0001	$ 1.169	$ 19,311.49
XCOMMUTE	-0.00464	0.00035517	-13.06	<.0001	$ 0.884	$ (13,214.56)
Neighborhood Characteristics						
XPCTFOR	-3.50264	0.31795	-11.02	<.0001	$ 0.947	$ (6,029.00)
XPCTPERM	5.19868	0.18633	27.9	<.0001	$ 1.116	$ 13,222.61
XRTCRIME	-0.00169	0.00021364	-7.91	<.0001	$ 0.996	$ (492.15)
XPCTVCT05	-1.35489	0.11132	-12.17	<.0001	$ 0.968	$ (3,699.23)
XVCBUILD	0.02031	0.00187	10.88	<.0001	$ 1.021	$ 2,339.01
XHARBOR	-0.00974	0.00544	-1.79	0.0734	$ 0.990	$ (1,104.97)
XSALAPRJ	0.01594	0.00961	1.66	0.0973	$ 1.016	$ 1,831.72
XSALJULS	0.10523	0.01038	10.13	<.0001	$ 1.111	$ 12,650.14
XSALOCTD	-0.02649	0.01562	-1.7	0.09	$ 0.974	$ (2,980.21)
Note: n= 13,519						
***	*Significant at 99% Level*					
**	*Significant at 95% Level*					
*	*Significant at 90% Level*					

Table 26: OLS Coefficient Outputs with Amenities

	Model 2 (Include Urban Amenities)				eβ with βs as coefficients from Full Model	Premium (at 114,000, City median)
OLS	*R squared*	*0.63*				
	b	sig	std *b*			
Intercept	11.2684	0.1775	63.48	<.0001		
		Structural Characteristics				
XDGEXC	0.31986	0.18164	1.76	0.0783	$ 1.377	$ 42,970.59
XDGFAIR	-0.21639	0.01246	-17.37	<.0001	$ 0.805	$ (22,181.99)
XDGGOOD	0.13896	0.01807	7.69	<.0001	$ 1.149	$ 16,994.91
XBRICK	-0.00315	0.01451	-0.22	0.8281	*$ 0.997*	*$ (358.54)*
XBASEMENT	0.04448	0.01507	2.95	0.0032	*$ 1.045*	*$ 5,185.18*
XSQFTSTRC	0.00029539	0.0000122	24.22	<.0001	$ 1.000	$ 33.68
XSQFTSTRC2	-1.67E-08	1.79E-09	-9.33	<.0001	$ 1.000	$ (0.00)
XAGE	-0.00438	0.00057141	-7.67	<.0001	$ 1.000	$ -
XAGE2	0.00003073	0.00000349	8.81	<.0001	$ 1.000	$ 3.50
XAIRCON	0.12792	0.00927	13.79	<.0001	$ 1.136	$ 15,556.68
XHBTH	0.06708	0.00887	7.56	<.0001	$ 1.069	$ 7,909.44
XBASEMFN	0.06733	0.00885	7.61	<.0001	$ 1.070	$ 7,939.92
XATGR	0.10303	0.01925	5.35	<.0001	$ 1.109	$ 12,371.81
XFIRE	0.09023	0.01276	7.07	<.0001	$ 1.094	$ 10,764.56
XDECK_PRCH	0.01245	0.00723	1.72	0.0851	$ 1.013	$ 1,428.17
XHSGRENT	0.00644	0.02301	0.28	0.7797	$ 1.000	$ -
		Socio-Economic Characteristics				
XPCTBLK	-0.58235	0.01526	-38.16	<.0001	$ 0.757	$ (27,667.72)
XLOGINCOME	0.13349	0.01352	9.87	<.0001	$ 1.143	$ 16,280.32
XCOMMUTE	-0.00133	0.0004065	-3.28	0.001	$ 0.965	$ (3,955.66)
		Neighborhood Characteristics				
XPCTFOR	-1.88751	0.31565	-5.98	<.0001	$ 0.971	$ (3,289.59)
XPCTPERM	4.01071	0.18683	21.47	<.0001	$ 1.088	$ 10,071.91
XRTCRIME	-0.00141	0.00020868	-6.74	<.0001	$ 0.996	$ (410.76)
XPCTVCT05	-1.51586	0.10883	-13.93	<.0001	$ 0.964	$ (4,130.66)
XVCBUILD	0.02471	0.00183	13.5	<.0001	$ 1.025	$ 2,852.03
XHARBOR	0.00812	0.00551	1.47	0.1405	$ 1.008	$ 929.45
XHSGRENT	0.00644	0.02301	0.28	0.7797	$ 1.000	$ -
XSALAPRJ	0.03595	0.00944	3.81	0.0001	$ 1.037	$ 4,172.86
XSALJULS	0.12137	0.01019	11.91	<.0001	$ 1.129	$ 14,710.85
XSALOCTD	-0.01193	0.0152	-0.78	0.4326	$ 0.988	$ (1,351.94)
XHSGRENT	0.00644	0.02301	0.28	0.7797	$ 1.000	$ -
		Urban Amenities				
XUNIV	-0.08623	0.00844	-10.21	<.0001	$ 0.917	$ (9,418.31)
XPARKS	-0.01647	0.00434	-3.79	0.0001	$ 0.984	$ (1,862.20)
XTRAIL	-0.06946	0.00426	-16.32	<.0001	$ 0.933	$ (7,649.69)
XLTRAIL	0.10506	0.0084	12.51	<.0001	$ 1.111	$ 12,628.61
XSUB	-0.08444	0.00768	-10.99	<.0001	$ 0.919	$ (9,230.95)
XCOMM	0.03325	0.00295	11.27	<.0001	$ 1.034	$ 3,854.22
Note: n= 13,519						
***	*Significant at 99% Level*					
**	*Significant at 95% Level*					
*	*Significant at 90% Level*					

Results of Estimates for Urban Amenities for each Market Type

Second, Table 27 below presents coefficient estimates for each housing market type developed to examine how impacts change across neighborhood markets. In review of Tables 27-28, each foot closer to universities positively influenced sale prices for Clusters 3 (middle market neighborhoods) while universities present negative impacts on homes sales in Cluster 2 (stable neighborhoods). These outputs may be influenced by household decisions. Universities and redevelopment around these facilities may present positive impacts for transitioning neighborhoods while more stable neighborhoods may

Table 27: Estimates for Clusters

Variables	Full Model		Submarkets Clusters									
2SLS			Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5	
XUNIV	-0.0391	***	-0.0219		0.18597	***	-0.0399	***	-0.0226		-0.5393	
	0.00758		*0.06048*		*0.0316*		*0.00911*		*0.03099*		*0.65914*	
XHARBOR	0.01776	**	0.00233		-0.0376	**	0.03384	***	0.04422	*	0.54392	
	0.00492		*0.02564*		*0.01192*		*0.00616*		*0.02137*		*0.47943*	
XPARKS	-0.0178	***	0.0293		0.00422		-0.011	**	-0.0457	**	-0.2298	*
	0.00388		*0.02317*		*0.00798*		*0.0049*		*0.01516*		*0.11293*	
XTRAIL	-0.0243	***	-0.0437	*	-0.0337	***	-0.002		0.00127		0.31337	
	0.00385		*0.02267*		*0.0088*		*0.00602*		*0.01377*		*0.18287*	
XLTRAIL	0.04499	***	0.0671		-0.0554	**	0.02424	*	0.00879		-0.9656	
	0.00758		*0.06863*		*0.02099*		*0.012*		*0.01948*		*0.50615*	
XSUB	-0.0432	***	-0.1458		-0.1501	***	0.00137		-0.0521	**	0.46931	
	0.00691		*0.09625*		*0.02754*		*0.00911*		*0.02263*		*0.27791*	
XCOMM	0.0126	***	0.04946	**	0.01105		0.01243	***	0.01994	*	-0.0951	
	0.00266		*0.0179*		*0.00605*		*0.00327*		*0.01*		*0.10988*	
Sample Size	*N=13519*		*n= 448*		*n= 3261*		*n= 7681*		*n= 1745*		*n= 125*	
R2	*0.7*		*0.43*		*0.48*		*0.54*		*0.56*		*0.66*	
Adjusted R2	*0.69*		*0.38*		*0.47*		*0.54*		*0.55*		*0.52*	
***	*Significant at 99% Level*											
**	*Significant at 95% Level*											
*	*Significant at 90% Level*											

consider their presence a nuisance due to student housing and accommodations. For the more distressed and least distressed clusters (5 and 1) proximity to universities was not significant. In general, the discount of the house price near the university is $2,000. Distances near the Harbor also showed findings that differed across neighborhood clusters. The most distressed and least distressed markets did not show significant coefficients related to distances to the Harbor. For Clusters 3 and 4, distance to the harbor carries a negative value. This may be the result of more distressed neighborhoods located adjacent to the Harbor. Cluster 2, representative of stable neighborhoods, shows positive impacts based on distance to the Harbor. These findings may be linked to surrounding redevelopment near the Harbor.

Urban green space and parks showed different results across neighborhood market types. The locations of housing near parks were only significant in transitional and distressed clusters (3, 4, and 5), while housing prices in stable clusters (1 and 2) were not affected by the presence of parks. Proximity to trails presented an opposite effect. Housing prices in proximity to trails were only significant in stable clusters (1 and 2), but not significant for distressed clusters. Location near trails positively influenced housing sales for the more stable housing market types. Transit including Baltimore's light rail and subway were only significant in Clusters 2, 3, and 4. House prices in close proximity to subways were not significant in cluster 3. For these clusters, proximity to light rail carries a negative value in Cluster 3 but shows that each foot a unit is closer to the light rail station in Cluster 2 will positively affects sales value. These estimates may be influenced by Cluster 2 households in close proximity to transit stations.

Table 28: Implicit Prices for Clusters

2SLS	Full Model				Submarkets Clusters: Cluster 1				Cluster 2			
Variable	Estimates	eβ with βs as coefficients from Full	Premium (at 114,000, City median)		Estimates	eβ with βs as coefficients from Full Model	Premium (at 114,000, City median)		Estimates	eβ with βs as coefficient	Premium (at 114,000, City median)	
XUNIV	-0.03908	0.961673772	$ (4,369.19)	***	-0.02188	$ 0.978			0.18597	$ 1.204	$ 23,300.02	***
XHARBOR	0.01776	1.017918647	$ 2,042.73	***	0.00233	$ 1.002			-0.0376	$ 0.963	$ (4,206.82)	**
XPARKS	-0.01782	0.982337837	$ (2,013.49)	***	0.0293	$ 1.030			0.00422	$ 1.004		
XTRAIL	-0.01159	0.988476905	$ (1,313.63)	***	-0.04372	$ 0.957			-0.03366	$ 0.967	$ (3,773.38)	***
XLTRAIL	0.04499	1.0460174	$ 5,245.98	***	0.0671	$ 1.069	$ 7,911.88	*	-0.05542	$ 0.946	$ (6,146.00)	**
XSUB	-0.04321	0.95771025	$ (4,821.03)	***	-0.14583	$ 0.864			-0.15011	$ 0.861	$ (15,890.08)	***
XCOMM	0.0126	1.012679714	$ 1,445.49	***	0.04946	$ 1.051	$ 5,780.21	**	0.01105	$ 1.011		
			$ (3,783.14)				$ 13,692.08				$ (6,716.26)	
			$ 110,216.86				***$ 127,692.08***				***$ 107,283.74***	
Sample size	*13519*				*448*				*3261*			
R 2	*0.6042*				*0.4075*				*0.4161*			
Adjusted R 2	*0.6031*				*0.3571*				*0.4096*			
***	*Significant at 99% Level*											
**	*Significant at 95% Level*											
*	*Significant at 90% Level*											
Average Home Price		*$ 114,000.00*										

2SLS	Submarkets Clusters: Cluster 3				Cluster 4				Cluster 5			
Variable	Estimates	eβ with βs as coefficient	Premium (at 114,000, City median)		Estimates	eβ with βs as coefficient	Premium (at 114,000, City median)		Estimates	eβ with βs as coefficients from Full Model	Premium (at 114,000, City median)	
XUNIV	-0.03986	$ 0.961	$ (4,454.67)	***	-0.02257	$ 0.978			-0.53927	0.583173814		
XHARBOR	0.03384	$ 1.034	$ 3,923.78	***	0.04422	$ 1.045	$ 5,154.20	**	0.54392	1.722746811		
XPARKS	-0.01099	$ 0.989	$ (1,246.00)	**	-0.0457	$ 0.955	$ (5,092.55)	*	-0.2298	0.794692525	$ (23,405.052)	*
XTRAIL	-0.00196	$ 0.998	$ (223.22)		0.00127	$ 1.001			0.31337	1.368027608		
XLTRAIL	0.02424	$ 1.025	$ 2,797.12	*	0.00879	$ 1.009			-0.96556	0.380769909		
XSUB	0.00137	$ 1.001			-0.05209	$ 0.949	$ (5,786.25)	**	0.46931	1.598890578		
XCOMM	0.01243	$ 1.013	$ 1,425.86	***	0.01994	$ 1.020	$ 2,295.97	*	-0.09508	0.909300188		
			$ 2,446.09				$ (3,428.62)				$ (23,405.05)	
			$ 116,446.09				***$ 110,571.38***				***$ 90,594.95***	
Sample size	*7861*				*1745*				*125*			
R 2	*0.4801*				*0.4491*				*0.6382*			
Adjusted R 2	*0.4777*				*0.4371*				*0.5015*			

Lastly, commercial land was only significant in Clusters 1, 3, and 4. Within these clusters sales, prices are negatively impacted by distances to commercial land. This impact may be influenced by the condition of the commercial or location of commercial land near major roadways.

Though estimates in the model contain expected signs and all amenities are significant at the five percent significance level, the Moran I analysis in Figure 22 show high levels of spatial features with attribute values similar in magnitude to demonstration spatial dependency in the data (Anselin, 1995). Moran I was computed for the regression model and presented clustering in the data set based on the results in Table 29. The Moran's I score of 0.26 is highly significant, indicating strong autocorrelation of the residuals. Given the z-score of 37.84, there is a less than 1 percent likelihood that this clustered pattern could be the result of random chance.

Table 29: Global Moran's I and Durbin Watson Test

Global Moran's I Summary	
Moran's Index:	0.268302
Expected Index:	-0.001534
Variance:	0.000051
z-score:	37.836682
p-value:	0

Durbin-Watson D	1.987
Number of Observations	13519
1st Order Autocorrelation	0.007

This analysis was supported by the Durbin Watson test used in the hedonic literature test for autocorrelation with the assumption that the errors associated with one observation are not correlated with the errors of other observations. This test is used to analyze correlated residuals. The Durbin Watson test statics around or higher than two demonstrates spatial autocorrelation. Additionally the Breusch-Pagan test was computed with the spatial lag model and a likelihood ratio test to examine for heteroskedasticity and spatial dependence. The Breusch -Pagan test was not significant, however the likelihood ratio test of spatial lag dependence was significant. These results led to conclusions that although the spatial lag term improved the model fit, it did not diminish the spatial effects. Table 29 shows the results of the tests for spatial dependence and demonstrates significant clustering of the data and spatial autocorrelation.

Moran I's statistics are used to map spatial clusters. Positive values for Moran I's indicate that the feature, sale price, has neighboring features with similarly high or low attribute values. This analysis implies that the feature is a part of a cluster. Low values of I indicate that a feature has neighboring features with dissimilar values, which represents an outlier. For spatial clustering to be significant, p-values must be small. In Figure 22, (HH) indicate high values, (LL) indicate low values, (HL) indicate high values surrounded by low values, and (LH) indicate low values surrounding by high values. The spatial model follows that of the typology created using 2005 housing data. Dependency clusters are located in areas near the harbor and in neighborhoods with high densities, such as Patterson Park. Due to significant spatial dependency exhibited in the analysis, a spatial model was estimated.

To address spatial autocorrelation in the model, a spatial lag model was estimated. This model was compared to the first step of an alternative 2SLS estimator to estimate the impact of urban amenities. The spatial lag model was estimated based on equation 4.2. The spatial lag model improved estimates with an R^2 of .68. The 2SLS model was estimated based on equation 4.3. For the 2SLS model, spatially lagged price variables are regressed on explanatory variables and regression on spatial lags of those variables to produce predicted values. The predicted values are used in place of the actual equation to yield unbiased parameter estimates to correct for spatial dependence. The spatial models improve estimates from the spatial lag model of .68 to .70.

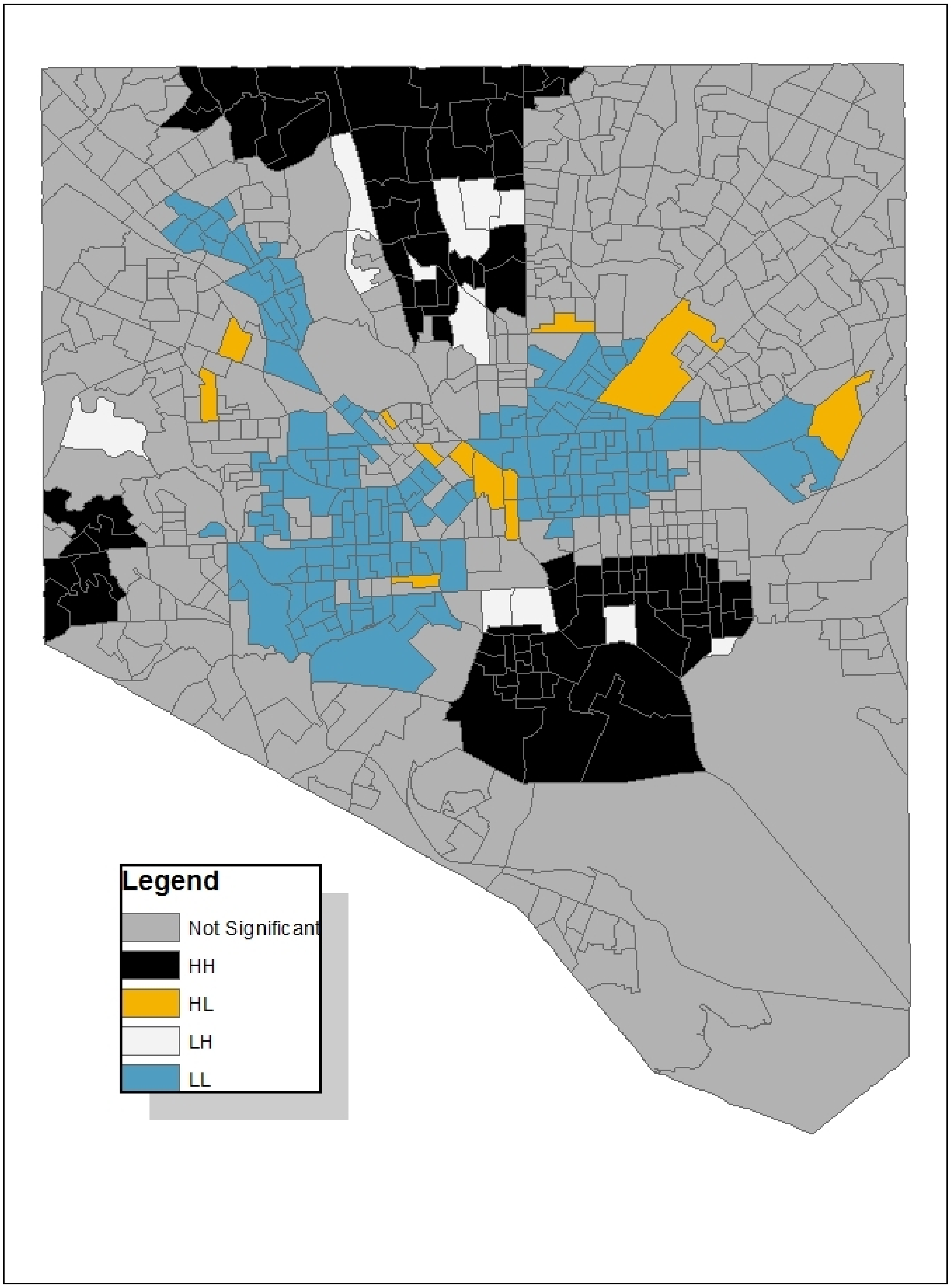
This model's coefficient suggests that each foot a unit is closer to a commercial land use the sales price will increase. The spatial lag model also provides improved estimates for sign for rental property is a concern because rental properties tend to be valued lower and thus should carry a negative sign in a regression. In the spatial lag model, the variable age is not significant and permits do not carry the same magnitude as the OLS model. The light rail coefficient remains negative in this model.

The 2SLS provides an improvement to the estimates. In this model, the sign of commercial land is negative and the sign of rental properties remains positive. Though the R-squared has improved, the results of the coefficients may indicate that there are still some unobserved influences affecting the model. The estimated coefficients are not significantly different from the spatial lag model for the urban amenities. However, for other factors there are significant differences in the estimate results. To interpret the coefficients and the value of amenities on sales price, the explanatory variables were converted to dollars using the following equation. Below, these values represent the implicit price homebuyers are willing to pay for an additional quantity of the amenity:

$$\ln(sale\_price) = \beta 0 + \beta_i x_i + e \qquad (3.8)$$

Impacts of sale prices were computed as change in sale prices from one-unit change in one of the explanatory independent variables holding all other variables constant. For

Figure 22: Moran's I Cluster Analysis



Note: (HH) indicate high values, (LL) indicate low values, (HL) indicate high values surrounded by low values, and (LH) indicate low values surrounding by high values.

example, in Table 28 above, the coefficients are interpreted by the exponent of the spatial regression estimates. The premium or willingness of the homebuyer to pay a higher sale prices, from changing independent (x1) to (x1-1) while holding all other explanatory variables constant is computed as the average sale price in the city multiplied by the exponent of the coefficient minus one. This value is computed for all significant independent variables.[6]

Table 30 provides the output from the spatial 2SLS model and the premium of explanatory variables on sale prices. Table 31 provides the premium for OLS, spatial lag and first stage of 2SLS models. Distinct differences among models are highlighted in red. Properties with excellent conditions are sold for approximately $74,000 more than houses in good conditions ($12,000) compared to poor rated houses. Properties rated as fair condition are discounted for approximately $11,000. Properties with structural and housing amenities such as air conditioning, finished basements, detached garage and half baths are sold for a range of $2,000 to 12,000 more. A rental property sold for approximately $500 less than owned properties. A higher percentage of African American households reduce the sale price by approximately $13,000. However, higher incomes aggregated at the census block level add to the value of the house by approximately $4,000. Areas with higher commute rates discount housing values by approximately $7,000.

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[6] An example of the computation of column 6 in table is as follows. To determine the willingness or premium for a house in proximity to a park, the coefficient estimate is -.01782 of the original house price. If the distance to the park increases by one feet, holding all other variables constant at an average price of $114,000, the potential homebuyer is willing to pay $2,013 more for the house.

Neighborhood characteristic variables also showed interesting findings. Higher rates of foreclosures discounted the value of housing by approximately $1,500, while increased activities through permits adds to the value of the house by approximately $3,000. Homes closer to vacant buildings discount the value of the house by $1,500 and higher percentages of vacant properties reduce the price of the house by $1,800. Each additional mile closer to the Harbor discounted housing sale prices by approximately $2,000. Based on the coefficient estimates, the best time to sell a home in Baltimore is during summer months of July to September.

Estimates for urban amenities show that housing prices increase by more than $4,000 for each additional mile the sales transaction is in proximity to Baltimore universities. Additionally, distances to parks and trails increased home values by approximately $2,000 each. The distance of houses from the subway added to the value of the home by approximately $5,000. However, each additional mile to Baltimore light rail stations discounted home values. This was the same for additional commercial. The closer the housing sale is to the light rail discounts the prices by approximately $5,000 while proximity to commercial land discounts prices by approximately $1,400.

Table 30: OLS and Spatial Hedonic Regression Models

(OLS Model)	*R squared*	*0.63*		
	b	sig	std *b*	
Intercept	11.2684	0.1775	63.48	<.0001
	Structural Characteristics			
XDGEXC	0.31986	0.18164	1.76	0.0783
XDGFAIR	-0.21639	0.01246	-17.37	<.0001
XDGGOOD	0.13896	0.01807	7.69	<.0001
XBRICK	-0.00315	0.01451	-0.22	0.8281
XBASEMENT	0.04448	0.01507	2.95	0.0032
XSQFTSTRC	0.00029539	0.0000122	24.22	<.0001
XSQFTSTRC2	-1.67E-08	1.79E-09	-9.33	<.0001
XAGE	-0.00438	0.00057141	-7.67	<.0001
XAGE2	0.00003073	0.00000349	8.81	<.0001
XAIRCON	0.12792	0.00927	13.79	<.0001
XHBTH	0.06708	0.00887	7.56	<.0001
XBASEMFN	0.06733	0.00885	7.61	<.0001
XATGR	0.10303	0.01925	5.35	<.0001
XFIRE	0.09023	0.01276	7.07	<.0001
XDECK_PRCH	0.01245	0.00723	1.72	0.0851
XHSGRENT	0.00644	0.02301	0.28	0.7797
	Socio-Economic Characteristics			
XPCTBLK	-0.58235	0.01526	-38.16	<.0001
XLOGINCOME	0.13349	0.01352	9.87	<.0001
XCOMMUTE	-0.00133	0.0004065	-3.28	0.001
	Neighborhood Characteristics			
XPCTFOR	-1.88751	0.31565	-5.98	<.0001
XPCTPERM	4.01071	0.18683	21.47	<.0001
XRTCRIME	-0.00141	0.00020868	-6.74	<.0001
XPCTVCT05	-1.51586	0.10883	-13.93	<.0001
XVCBUILD	0.02471	0.00183	13.5	<.0001
XHARBOR	0.00812	0.00551	1.47	0.1405
XSALAPRJ	0.03595	0.00944	3.81	0.0001
XSALJULS	0.12137	0.01019	11.91	<.0001
XSALOCTD	-0.01193	0.0152	-0.78	0.4326
	Urban Amenities			
XUNIV	-0.08623	0.00844	-10.21	<.0001
XPARKS	-0.01647	0.00434	-3.79	0.0001
XTRAIL	-0.06946	0.00426	-16.32	<.0001
XLTRAIL	0.10506	0.0084	12.51	<.0001
XSUB	-0.08444	0.00768	-10.99	<.0001
XCOMM	0.03325	0.00295	11.27	<.0001
Note: n= 13,519				
***	*Significant at 99% Level*			
**	*Significant at 95% Level*			
*	*Significant at 90% Level*			

(Spatial Lag)	*R squared*	*0.687*		
	b	sig	std *b*	
Intercept	1.909412	0.07051509	27.0781	<.0001
	Structural Characteristics			
WLOGPRICE	-0.00273154	0.001246057	-2.1921	0.02837
XDGEXC	0.215044	0.03213989	6.69088	<.0001
XDGFAIR	-0.04190151	0.004586064	-9.1367	<.0001
XDGGOOD	0.04308832	0.006749347	6.38407	<.0001
XBRICK	-0.03035172	0.003703591	-8.1952	<.0001
XBASEMENT	0.002990896	0.004952248	0.60395	0.54588
XSQFTSTRC	9.69E-05	4.56E-06	21.2668	<.0001
XSQFTSTRC2	-6.59E-09	7.00E-10	-9.4104	<.0001
XAGE	8.99E-05	7.57E-05	1.18637	0.23548
XAGE2	-4.56E-08	3.66E-08	-1.2441	0.21348
XAIRCON	0.04157979	0.003335371	12.4663	<.0001
XHBTH	0.0133949	0.003238808	4.13575	<.0001
XBASEMFN	0.02307948	0.003245332	7.11159	<.0001
XATGR	0.02659504	0.00707074	3.76128	0.00017
XFIRE	0.02634948	0.004635863	5.68383	<.0001
XDECK_PRCH	0.009089366	0.002617636	3.47236	0.00052
XHSGRENT	0.04001206	0.007894206	5.06854	<.0001
	Socio-Economic Characteristics			
XPCTBLK	-0.09067401	0.005625179	-16.119	<.0001
XLOGINCOME	0.04765859	0.01112607	4.28351	<.0001
XCOMMUTE	-0.00118672	0.000149696	-7.9275	<.0001
	Neighborhood Characteristics			
XPCTFOR	-0.4585195	0.1188441	-3.8582	0.00011
XPCTPERM	0.5869112	0.06582343	8.91645	<.0001
XRTCRIME	-0.00021173	8.31E-05	-2.5482	0.01083
XPCTVCT05	-0.2517832	0.0381904	-6.5928	<.0001
XVCBUILD	0.0114786	0.001333607	8.60718	<.0001
XHARBOR	0.01597274	0.004555456	3.50629	0.00045
XSALAPRJ	0.01189709	0.003455065	3.44338	0.00057
XSALJULS	0.04303869	0.003743984	11.4954	<.0001
XSALOCTD	-0.01812935	0.005512005	-3.2891	0.00101
	Urban Amenities			
XUNIV	-0.02254954	0.006668609	-3.3814	<.0001
XPARKS	-0.01992214	0.003573555	-5.5749	<.0001
XTRAIL	-0.01999945	0.003572811	-5.5977	<.0001
XLTRAIL	0.04298369	0.006844252	6.28026	<.0001
XSUB	-0.04641642	0.006431285	-7.2173	<.0001
XCOMM	-0.01364018	0.004906906	-2.7798	0.00544
Note: n= 13,519				
***	*Significant at 99% Level*			
**	*Significant at 95% Level*			
*	*Significant at 90% Level*			

(2SLS)	*R squared*	*0.70*		
	b	sig	std *b*	
Intercept	4.91151	0.18781	26.15	<.0001
	Structural Characteristics			
WLOGPRICE	0.57731	0.00956	60.36	<.0001
XDGEXC	0.50319	0.16251	3.1	0.002
XDGFAIR	-0.10193	0.01131	-9.01	<.0001
XDGGOOD	0.10455	0.01613	6.48	<.0001
XBRICK	-0.08141	0.00925	-8.8	<.0001
XBASEMENT	0.04986	0.01348	3.7	0.0002
XSQFTSTRC	0.00022507	0.00001089	20.67	<.0001
XSQFTSTRC2	-1.45E-08	1.60E-09	-9.05	<.0001
XAGE	-0.00151	0.00050801	-2.98	0.0029
XAGE2	0.0000107	0.00000311	3.44	0.0006
XAIRCON	0.09677	0.00831	11.64	<.0001
XHBTH	0.03476	0.00795	4.37	<.0001
XBASEMFN	0.04999	0.00792	6.32	<.0001
XATGR	0.05801	0.01722	3.37	0.0008
XFIRE	0.06159	0.01121	5.49	<.0001
XDECK_PRCH	0.02108	0.00647	3.26	0.0011
XHSGRENT	0.06291	0.01982	3.17	0.0015
	Socio-Economic Characteristics			
XPCTBLK	-0.2645	0.01469	-18	<.0001
XLOGINCOME	0.03916	0.0122	3.21	0.0013
XCOMMUTE	-0.0024	0.00036249	-6.62	<.0001
	Neighborhood Characteristics			
XPCTFOR	-0.82651	0.28289	-2.92	0.0035
XPCTPERM	1.29736	0.17229	7.53	<.0001
XRTCRIME	-0.00052873	0.00018727	-2.82	0.0048
XPCTVCT05	-0.64701	0.09844	-6.57	<.0001
XVCBUILD	0.01372	0.00165	8.33	<.0001
XHARBOR	0.01776	0.00492	3.61	0.0003
XSALAPRJ	0.03017	0.00844	3.58	0.0004
XSALJULS	0.10649	0.00912	11.68	<.0001
XSALOCTD	-0.0266	0.0136	-1.96	0.0505
	Urban Amenities			
XUNIV	-0.03908	0.00758	-5.15	<.0001
XPARKS	-0.01782	0.00388	-4.59	<.0001
XTRAIL	-0.02427	0.00385	-6.31	<.0001
XLTRAIL	0.04499	0.00758	5.93	<.0001
XSUB	-0.04321	0.00691	-6.25	<.0001
XCOMM	0.0126	0.00266	4.74	<.0001
Note: n= 13,519				
***	*Significant at 99% Level*			
**	*Significant at 95% Level*			
*	*Significant at 90% Level*			

Table 31: OLS and Spatial Hedonic Regression Implicit Prices

(OLS Model)	*R squared* *0.63*		
	b	sig	Premium (at 114,000, City median)
Intercept	11.2684	***	
Structural Characteristics			
XDGEXC	0.31986		$42,970.59
XDGFAIR	-0.21639	***	($22,181.99)
XDGGOOD	0.13896	***	$16,994.91
XBRICK	-0.00315		($358.54)
XBASEMENT	0.04448	**	$5,185.18
XSQFTSTRC	0.00029539	***	$33.68
XSQFTSTRC2	-1.67E-08	***	$0.00
XAGE	-0.00438	***	($498.23)
XAGE2	0.00003073	***	$3.50
XAIRCON	0.12792	***	$15,556.68
XHBTH	0.06708	***	$7,909.44
XBASEMFN	0.06733	***	$7,939.92
XATGR	0.10303	***	$12,371.81
XFIRE	0.09023	***	$10,764.56
XDECK_PRCH	0.01245		$1,428.17
XHSGRENT	0.00644		$736.53
Socio-Economic Characteristics			
XPCTBLK	-0.58235	***	($50,321.41)
XLOGINCOME	0.13349	***	$16,280.32
XCOMMUTE	-0.00133	***	($151.52)
Neighborhood Characteristics			
XPCTFOR	-1.88751	***	($96,734.88)
XPCTPERM	4.01071	***	$6,177,208.42
XRTCRIME	-0.00141	***	($160.63)
XPCTVCT05	-1.51586	***	($88,963.41)
XVCBUILD	0.02471	***	$2,852.03
XHARBOR	0.00812		$929.45
XSALAPRJ	0.03595	***	$4,172.86
XSALJULS	0.12137	***	$14,710.85
XSALOCTD	-0.01193		($1,351.94)
Urban Amenities			
XUNIV	-0.08623	***	($9,418.31)
XPARKS	-0.01647	***	($1,862.20)
XTRAIL	-0.06946	***	($7,649.69)
XLTRAIL	0.10506	***	$12,628.61
XSUB	-0.08444	***	($9,230.95)
XCOMM	0.03325	***	$3,854.22
Note: n= 13,519			
***	*Significant at 99% Level*		
**	*Significant at 95% Level*		
*	*Significant at 90% Level*		

(Spatial Lag)	*R squared* *0.687*		
	b	sig	Premium (at 114,000, City median)
Intercept	1.909412		
Structural Characteristics			
WLOGPRICE	-0.00273154		
XDGEXC	0.215044	***	$27,350.48
XDGFAIR	-0.04190151	***	($4,678.08)
XDGGOOD	0.04308832	***	$5,019.43
XBRICK	-0.03035172	***	($3,408.11)
XBASEMENT	0.002990896		$341.47
XSQFTSTRC	9.69E-05	***	$11.05
XSQFTSTRC2	-6.59E-09	***	$0.00
XAGE	8.99E-05		$10.24
XAGE2	-4.56E-08		($0.01)
XAIRCON	0.04157979	***	$4,840.02
XHBTH	0.0133949	***	$1,537.29
XBASEMFN	0.02307948	***	$2,661.66
XATGR	0.02659504	***	$3,072.51
XFIRE	0.02634948	***	$3,043.77
XDECK_PRCH	0.009089366	***	$1,040.91
XHSGRENT	0.04001206	***	$4,653.86
Socio-Economic Characteristics			
XPCTBLK	-0.09067401	***	($9,882.05)
XLOGINCOME	0.04765859	***	$5,564.63
XCOMMUTE	-0.001186717	***	($135.21)
Neighborhood Characteristics			
XPCTFOR	-0.4585195	***	($41,927.04)
XPCTPERM	0.5869112	***	$91,020.43
XRTCRIME	-0.00021173	*	($24.13)
XPCTVCT05	-0.2517832	***	($25,374.89)
XVCBUILD	0.0114786	***	$1,316.10
XHARBOR	0.01597274	***	$1,835.51
XSALAPRJ	0.01189709	***	$1,364.37
XSALJULS	0.04303869	***	$5,013.52
XSALOCTD	-0.01812935	***	($2,048.12)
Urban Amenities			
XUNIV	-0.02254954	***	($2,541.88)
XPARKS	-0.01992214	***	($2,248.65)
XTRAIL	-0.01999945	***	($2,257.29)
XLTRAIL	0.04298369	***	$5,006.98
XSUB	-0.04641642	***	($5,170.54)
XCOMM	-0.01364018	**	($1,544.42)
Note: n= 13,519			
***	*Significant at 99% Level*		
**	*Significant at 95% Level*		
*	*Significant at 90% Level*		

(2SLS)	*R squared* *0.70*	
	b	Premium (at 114,000, City median)
Intercept	4.91151	
Structural Characteristics		
WLOGPRICE	0.57731	
XDGEXC	0.50319	$74,554.76
XDGFAIR	-0.10193	($11,047.42)
XDGGOOD	0.10455	$12,564.04
XBRICK	-0.08141	($8,913.01)
XBASEMENT	0.04986	$5,828.13
XSQFTSTRC	0.00022507	$25.66
XSQFTSTRC2	-1.45E-08	$0.00
XAGE	-0.00151	($172.01)
XAGE2	0.0000107	$1.22
XAIRCON	0.09677	$11,583.20
XHBTH	0.03476	$4,032.32
XBASEMFN	0.04999	$5,843.71
XATGR	0.05801	$6,808.72
XFIRE	0.06159	$7,241.99
XDECK_PRCH	0.02108	$2,428.63
XHSGRENT	0.06291	$7,402.13
Socio-Economic Characteristics		
XPCTBLK	-0.2645	($26,494.78)
XLOGINCOME	0.03916	$4,552.80
XCOMMUTE	-0.0024	($273.27)
Neighborhood Characteristics		
XPCTFOR	-0.82651	($64,116.59)
XPCTPERM	1.29736	$303,196.96
XRTCRIME	-0.00052873	($60.26)
XPCTVCT05	-0.64701	($54,308.57)
XVCBUILD	0.01372	$1,574.86
XHARBOR	0.01776	$2,042.73
XSALAPRJ	0.03017	$3,491.79
XSALJULS	0.10649	$12,809.82
XSALOCTD	-0.0266	($2,992.42)
Urban Amenities		
XUNIV	-0.03908	($4,369.19)
XPARKS	-0.01782	($2,013.49)
XTRAIL	-0.02427	($2,733.48)
XLTRAIL	0.04499	$5,245.98
XSUB	-0.04321	($4,821.03)
XCOMM	0.0126	$1,445.49
Note: n= 13,519		
***	*Significant at 99% Level*	
**	*Significant at 95% Level*	
*	*Significant at 90% Level*	

Premium dollar amounts highlighted in red show differences in comparison to the traditional and spatial models.

CONCLUSIONS

In this study, the relationship between urban amenities and sales transactions in the City of Baltimore were analyzed for sales that occurred in 2004 and 2005. This analysis used an OLS hedonic regression, which was complemented by spatial statistics to address the spatial effects demonstrated in the data. In addition, this analysis estimated separate hedonic price functions for identified NHMs to determine if and how estimates differed across markets. While it is evident that urban amenities affect surrounding home values, the additional spatial models and separately estimated submarkets provided interesting conclusions.

The OLS hedonic regressions suggest that the urban amenities slightly improved the prediction of housing sale prices. What was more telling was that the effects of the amenities. Each mile closer to commercial land and light rail negatively influenced sale prices, while all other amenities (distance to parks, trails, universities, and subway stations) presented positive impacts.

The presence of significant spatial effects in the hedonic regression model suggests that surrounding homes and other unexplained neighborhood effects influenced sale prices. Therefore, spatial hedonic regression models were used to improve the OLS model and present more efficient estimates. The spatial lag model appeared to improve this OLS model but still present a level of spatial autocorrelation based on the limitations of the spatial lag model to address correlation in the error term.

The 2SLS appeared to improve the model with inclusion of spatial weights regressed on variables plus the spatial lag of the variable. In this model, variables carried similar signs as the OLS model. However, there was improvement in the model with more significant variables. This model was complemented with separately estimated models reflective of housing submarkets.

The 2SLS cluster models show that the effect of urban amenities varied based on neighborhood housing market conditions. On two extremes among the NHMs, urban amenities do not affect sale prices in stable and distressed markets. Other unobserved factors may be at work in these market types that cause the effects to not exist or to appear minimal. In less affluent and transitional submarkets, urban amenity coefficients were significant but took on different signs. Parks presented positive impacts in all NHMs where they were significant; however, other amenities presented conflicting effects when NHMs were compared. Light rail in the general model negatively affected sale prices, but in Cluster 2, a more stable housing market, an additional mile closer to light rail presented positive impacts on sale prices. The magnitude of the amenity estimates also varied across markets even when they carried similar signs.

As cities begin to target urban amenities for economic revitalization, it is important to question the varying effects of amenities given the quality of the neighborhood. Federal governmental agencies support targeted housing and economic development investments near urban amenities for added benefits to leverage resources. Current studies assert that urban amenities will positively affect surrounding sale prices; however, this study cautions agencies to rethink how amenities are used to leverage resources and guide targeted strategies.

The estimates in this study suggest that urban amenity effects differ across submarkets. Therefore, policy makers must reexamine planning strategies and question the validity of NHM differences. The location of investments near urban parks in distressed neighborhood may present significantly different findings versus investments in more affluent areas. This study finds that sales transactions in distressed neighborhoods increase by approximately $23,000 with each mile closer to an urban park. This price increase is significantly higher than if the sales transaction was located in a transitional housing market. In this submarket, parks only increase sale prices by approximately $1,200.

Additionally, factors considered as urban amenities may in fact represent dis-amenities in the context of the city of Baltimore, or take on conflicting effects across submarkets. Proximity to a university in a more stable market discounts sale prices, as seen in this analysis where sales transactions near universities located in Cluster 2 are discounted by $23,000. In a more distressed or transitional submarket, this effect is the opposite. For each additional mile a housing sale is from a university in Cluster 3, the price increases by approximately $4,000. These findings are important as city resources flow to transitional areas to tackle impending decline and disinvestment.

Further research is still needed. A third step in a 2SLS regression consisted of estimating the demand for urban amenities. This technique allows scholars to address omitted variable bias or other unknown factors that may affect housing sale prices given the significant spatial effects presented in both hedonic models. The demand regression model employed in a 2SLS will assist researchers to understand what demand shifters affect urban amenities to identify substitutes among the variables. For example, what would happen when an urban amenity is compared to a federal or local housing investment? Are these goods purchased together, are they substitutes, or non-related goods? Is there a relationship between the location of urban amenities and reinvestments?

Do both factors have equal effects on housing sale prices? These questions should be considered as local governments look to target limited investments near urban amenities. Additionally, urban amenities may not be consistent across cities. The Baltimore model may differ from another model in a city where public transportation is more widely used, or may contain high property values and markets. These factors should be considered and applied to other cities.

GENERAL CONCLUSIONS AND FUTURE RESEARCH

In this dissertation, I focused on Baltimore, Maryland, and examined the usefulness of NHMTs. I used traditional OLS and spatial econometric models to determine if NHMTs matter in examination of government housing investments or the targeting of investments near urban amenities. In general, the literature on hedonic price functions tends to ignore the spatial nature and make up on NHMs. When predicting the effects of housing and neighborhood characteristics on sale prices, models lean on socioeconomic factors to represent markets. However, seminal work by Day (2003) suggests that estimation techniques should explicitly analyze separate submarkets for scholars to understand the spatial relations between properties and neighborhood characteristics. This analysis supports these observations.

In review of the conceptual foundations of NHMTs in essay 1, this analysis finds that numerous cities employ various techniques to graphically portray their neighborhoods and provide strategies to intervene to effect change. The purpose of these typologies is to guide decisions of how and where to invest in neighborhoods. Federal investments are designed to provide suitable housing to disadvantaged households, but today, the U.S. Department of Housing and Urban Development is encouraging stakeholder to target investments to improve “place.” Therefore, in this context housing-related (e.g., sale prices) and neighborhood characteristics variables (e.g., percentage of foreclosed properties in a census block) are more effective to define neighborhood markets. However, socioeconomic variables may be important to explain the status of neighborhoods, as household socioeconomic characteristics influence where they live, and help cities understand why some neighborhoods are distressed or stable. Socioeconomic factors may be important to assist cities to recognize the direction or pattern of neighborhood change Socioeconomic changes may affect housing values, and neighborhood characteristics (e.g., permit activity).

Further analysis is necessary. The cluster method remains questionable among scholars who attempt to validate whether meaningful housing submarkets are created using the cluster methodology. This method is not based on theory but a technical process of separating dis-similar geographic areas based on quantitative data. Qualitative analyses are excluded in this process. Few questions are asked, such as whether strong neighborhood associations or community support and initiatives are valuable factors to assess or determine the ability of these submarkets to improve. Additionally, neighborhood assets such as the proximity to parks, neighborhood anchors, and other factors are not included in this typology. Cities only have a static image of neighborhood conditions and little information about positive factors, such as increases in home values or decreases in percent of vacant properties in a neighborhood, to effect change.

Additionally, census designated boundaries such as block groups may not be sufficient boundaries to capture submarkets. Reinvestment and neighborhood progress may be occurring at the neighborhood block level and not captured in the aggregate analysis. Smaller submarkets may exist within census block groups, and this challenge discounts the presence of smaller affluent areas surrounded by disinvested neighborhoods. These factors and challenges must be addressed.

Moreover, in essay 2, this study finds that despite on-going reinvestment efforts and initiatives in the city of Baltimore, distressed neighborhoods have not changed. This study shows that in 1980, neighborhoods in distressed clusters remained in this status in 1990 and 2000, with less than 10 percent of neighborhoods having improved. NHMTs matters, and this is evident in this study. In review of HOME investments and the impact of investments on surrounding housing sale prices, findings suggest that the impact of HOME investments varies across market type. In Baltimore’s more distressed neighborhoods, the impact of investments on nearby sale prices is significant and positive when investments are large scale. In transitional markets, both medium and large-scale investments show positive impacts for each additional mile an investment is to a sales price. And in more stable areas, investments tend to have little effect or negative impacts. Therefore, NHMs matter and cities must understand the impact of investments in such markets to appropriately plan strategies for the greatest impact.

Future studies are needed. Baltimore’s analysis is not a one size fits all. Prior to HNI in 2000, Baltimore had not been strategic in its investment of HOME dollars. Moreover, HNI efforts were not large enough to measure the impact of the Program. Results from this analysis conclude that investments in the city are not concentrated enough to provide significant results or impacts, even when investments were measured across submarkets. More qualitative analyses or case studies may be more appropriate at a neighborhood level. This analysis may also be a replication to compare other cities using HOME dollars. In empirical studies of Cleveland, Ohio (Ding et al., 2000) and Richmond, Virginia (Galster et al., 2006), it appears that the total dollar amount of investments were larger or more concentrated at the block level than Baltimore’s investments.

Comparative analysis and case studies may also be necessary to understand the impact of urban amenities in neighborhoods as discussed in essay 3. This study suggests that the impact of urban amenities changes across neighborhood housing markets, therefore typologies matter. In more stable neighborhoods, urban amenities are not determining factors to predict housing sale prices. In distressed neighborhoods, adjacent parks are the only amenities that present significant and positive impacts. In transitional neighborhoods, it appears that urban amenities are significant, but the level of significance depends on the exact amenity. In one neighborhood type, proximity to a university may present positive impacts, while in another less distressed market, the impact may be negative. Therefore, what proves to be an amenity in one case may in fact represent a dis-amenity in another. Understanding NHMTs is important as cities are encouraged to target investments near urban amenities to leverage resources.

In addition, the spatial nature of markets matter. This analysis estimated separate markets to determine the different impacts of amenities. Even using this method, spatial autocorrelation existed within the data; therefore, spatial modeling is important to assess neighborhoods. Because neighborhood sale prices are influenced by other sale prices and neighborhood quality, which may not have been captured within census designated boundaries, spatial hedonic regression models were considered to present efficient and un-biased estimates. This analysis suggests that spatial models better explained the impact of amenities across NHMs. However, more analyses are needed to complement this study.

The additional two-stage demand model used by scholars to examine the impact of environmental amenities and quality in communities would contribute to the findings in this essay. The second stage of this technique will be useful to understand how the demand for urban amenities changes in different neighborhoods, and which factors impact that demand, whether it is the race and ethnicity or median income of householders in the neighborhood. Additionally, this method allows researchers to determine other factors not explained or unknown through omitted variable bias. The next step in this analysis would be to determine the demand for proximity to parks, universities, and transit. Determining how this demand differs in various markets would be of great interest to policy makers as they encourage cities to invest around neighborhood assets. For example, it would be futile to invest around parks if households within that market type do not see parks as an asset.

Another factor not considered in essay 3, which is important to the research, is the quality of parks, subway stations and even universities. Other studies analyze the size of parks to determine levels of significance and impacts. While this study controls for other neighborhood factors based on market types, it does not estimate impacts based on the size and quality of amenities. Therefore, these factors must be considered and will provide benefit to the discussion.

Overall, this study in three interrelated essays demonstrated that NHMTs matter in cities. Most cities in the U.S. continue to invest in their more distressed markets; however, as they expand to areas hard hit by foreclosures and persistent disinvestments, they must understand the dynamics of neighborhood market conditions and how these markets respond differently to reinvestment strategies. In general, these essays find the NHMTs matter and can be useful vehicles to guide cities in how they invest in specific neighborhoods to leverage limited resources or in an attempt to improve neighborhood conditions. While most scholars suggest that government investments and amenities will not revitalize neighborhoods, practitioners should understand what strategies and within which markets these efforts will have the greatest impact to stabilize area conditions. However, practitioners and scholars must take caution in using NHMTs as a tool; they should only serve as a base for neighborhood analyses. Additional qualitative analyses are necessary to clearly understand the conditions and direction of neighborhoods.

Bibliography

"Baltimore, Maryland: A Neighborhood Investment Strategy Paying Off" (National League of Cities, October 2005)

Abelson, Peter. "Properties Prices and the Value of Amenities," *Journal of Environmental Economics and Management,* 6 (1979): 11-28

Abelson, Peter. "Property Prices and the Value of Amenities," *Journal of Environmental. Economics and Management*. 6(1979): 11-28.

Abravanel, Martin D., Nancy M. Pindus, and Brett Theodos. Evaluating Community and Economic Development Programs: A Literature Review to Inform Evaluation of the New Markets Tax Credit Program: Final Report, September 2010

Abt Associates Inc. Development and Analysis of the National Low Income Housing Tax Credit Database: Final Report, Summer 1999

Accordino, John and Gary Johnson. "Addressing the Vacant and Abandonment Property Problem," *Journal of Urban Affairs* 22 (2000): 301-315.

Aldenderfer, Mark, and Roger Blashfield. *Cluster Analysis.* London, Series/Number 07-044: Sage University Paper, 1984.

Anselin Luc (1988) *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers, Boston, MA.

Anselin Luc, Bera AK (1998) *Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics.* In Ullah A, Giles DAE (eds.) Handbook of Applied Economic Statistics. Marcel Dekker, New York, NY.

Anselin, Luc. "Spatial econometrics in RSUE: Retrospect and prospect," *Regional Science and Urban Economics*, 37 (2007): 450-456

Baltimore City Consolidated Plan. July 2005, July 2010. Retrieved at: http://www.baltimorehousing.org/inside_plansandreports.asp

Benson, Earl D. et al. "Pricing Residential Amenities: The Value of a View," *Journal of Real Estate Finance and Economics,* 16 (1998): 1, 55-73.

Board of Governors of the Federal Reserve System. *Putting Data to Work: Data-Driven Approaches to Strengthening Neighborhoods*. Richmond, Virginia: December 2011

Bourassa, Steven, Eva Cantoni and Martin Hoesli. "Spatial dependence, housing submarkets, and house prices," *Journal of Real Estate Finance and Economics* 35 (2002): 143-160

Bourassa, Steven, Martin Hoesli and Vincent Peng. "Do housing submarkets really matter?" *Journal of Urban Economics* 12 (2002): 12-28

Bourassa, Steven, Martin Hoeslim, Foort Hamelink, Bryan MacGregor. "Defining housing submarkets" *Journal of Housing Economics*, 8 (1999): 160-183

Bowes, David R. "Identifying the Impacts of Rail Transit Stations on Residential Property Values," *Journal of Urban Economics* 50(2001): 1-25

Boyle, Melissa and Katherine Kiel. "A Survey of House Price Hedonic Studies of the Impact of Environmental Externalities," *Journal of Real Estate Literature*, 9(2001): 117 – 144.

Brasington, David and Diane Hite. "A Mixed Index Approach to Identifying Hedonic Price Models," *Regional Science and Urban Economics,* 38(2008): 271 – 284.

Brasington, David and Diane Hite. “Demand for Environmental Quality: A Spatial Hedonic Analysis” *Regional Science and Urban Economics*, 35(2005): 57 – 82.

Brasington, David and Diane Hite. “Demand For Environmental Quality: A Spatial Hedonic Analysis,” *Regional Science and Urban Economics* 35(1) (2005): 57-82

Brasington, David. “Demand and Supply of Public School Quality on Metropolitan Areas: TheRole of Private Schools,” *Journal of Regional Science*, 40(2000): 583 – 605.

Briggs, Xavier de Souza, Joe T. Darden, and Angela Aidala. “In the Wake of Desegregation: Early Impacts of Scattered-Site Public Housing on Neighborhoods in Yonkers, New York.” *American Planning Association Journal* 65 (1999): 27-49

Brown, Prudence. “Comprehensive Neighborhood-based Initiatives,” *Cityscape Journal of Policy Development and Research* 2 (1996): 161-173

Bruce, Grady D. and Robert E. Witt. “Developing Empirically Derived City Typologies: An Application of Cluster Analysis” *The Sociological Quarterly* 12 (1971): 238-246

Bruch, Elizabeth E. “Neighborhood Choice and Neighborhood Change,” *American Journal of Sociology*. 112 (3) (2006): 667–709.

Can, Ayse. “Specification and Estimation of Hedonic Housing Price Models,” *Regional Science and Urban Economics*, 22(1992): 453 – 474.

Can, Ayse. “The Measurement of Neighborhood Dynamics in Urban House Prices,” *Economic Geography*, 66(1990): 254 – 272.

Carmon, Naomi. “Neighborhood Regeneration: The State of the Art,” *Journal of Planning Education and Research* 17, (1997): 131-144

Chattopadhyay, Sudip “Estimating the Demand for air Quality: New Evidence Based on the Chicago Housing Market,” *Land Economics*, 75(1999): 22 – 38.

Clay, Philip and Robert Hollister. *Neighborhood Policy and Planning*. Lexington, Massachusetts: D.C. Heath and Company, 1983.

Clay, Phillip. *Neighborhood Renewal.* Lexington, Massachusetts: D.C. Heath and Company, 1979.

Cohen, James. “Abandoned Housing: Exploring Lessons from Baltimore” *Housing Policy Debate* 12, (2001): 415-448.

Cortes, Alvaro. “Estimating the Impacts of Urban Universities on Neighborhood Housing Markets: An Empirical Analysis” *Urban Affairs Review* 39, (2004): 342-375

Crystal, Ruth., Survey of Nonprofit Groups in Baltimore prepared for the Baltimore Neighborhood Collaborative, retrieved: December 2011

Day, Brett, (2003). “Submarket Identification In Property Markets: A Hedonic Housing Price Model For Glasgow,” Report to EU Working Group on Noise, CSERGE, University College London, UK.

Ding, Chengri, and Knaap, Gerrit-Jan. “Property Values in Inner City Neighborhoods: The effects of Home ownership, Housing Investment, and Economic Development,” *Housing Policy Debate* 13(2003):701-727.

Ding,Chengri, Robert Simons, and Esmail Baku . “The Effect of Residential Investment on Nearby Property Values: Evidence from Cleveland, Ohio,” *Journal of Real Estate Research ½*, 19 (2000): pp. 25-48

Downs, Anthony. *Neighborhoods and Urban Development*. Washington: The Brookings Institution, 1981.

Ellen, Ingrid Gould, Michael Schill, Scott Susin, and Amy Schwartz. "Building Homes, Reviving Neighborhoods: Spillovers from Subsidized Construction of Owner-Occupied Housing in New York City," *Journal of Housing Research*, 12, (2001): 185-216.

Engberg, Rodney A. and Susan W. Friedman "State Enterprise Zones and Local Housing Markets," *Journal of Housing Research* 10 (1999):163-187

Fik, Timothy, David Ling, Gordon Mulligan "Modeling Spatial Variation in Housing Prices: A Variable Interaction Approach," *Real Estate Economics*.31 (2003): 623–646

Frankel, David M. and Andy Pauzner. "Expectations and the Timing of Neighborhood Change. Journal of Urban Economics," 51 (2002): 295-314.

Fulbright-Anderson, K., Anne C Kubisch and James P. Connell (Eds.). *New Approaches to Evaluating Community Initiatives*, Vol. 2: Theory, Measurement, and Analysis. Washington, D.C.: The Aspen Institute, 1998.

Galster, Galster, Kathryn Pettit, Anna Santiago, Sandra Newman and Peter Tatian. "The Impact Of Supportive Housing On Neighborhood Crime Rates," *Journal of Urban Affairs*, 24(2002),: 289–315. doi: 10.1111/1467-9906.00128

Galster, George and Ronald B. Mincy. "Understanding the Changing Fortunes of Metropolitan Neighborhoods, 1980 to 1990." *Housing Policy Debate*, 3 (1998): 303-352.

Galster, George C. 2002. *A Review of Existing Research on the Effects of Federally Assisted Housing Programs on Neighboring Residential Property Values*, Report to the National Association of Realtors, September.

Galster, George C. *An Econometric Model of the Urban Opportunity Structure: Cumulative Causation among City Markets, Social Problems, and Underserved Areas*. Washington, DC: Fannie Mae Foundation. 1998.

Galster, George, Anna M. Santiago, Robin E. Smith, and Peter A. Tatian. 1999. *Assessing Property Value Impacts of Dispersed Housing Subsidy Programs, HUD.* Washington, DC: Department of Housing and Urban Development. May 1999.

Galster, George, Chris Walker, Chris Hayes and Patrick Boxall. “Measuring the Impact of CDBG Spending on Urban Neighborhoods,” *Housing Policy Debate* 15 (2004): 903-934

Galster, George, Ken Temkin, Chris Walker and Noah Sawyer. “Measuring the Impacts of Community Development Initiiatives,” *Evaluation Review* 28, (2004): 1-38.

Galster, George, Peter Tatian, and John Accordino. “ Targeting Investments for Neighborhood Revitalization,” *Journal of the American Planning Association* 72 (2006): 457-467.

Galster, George, Peter Tatian, Robin Smith. “The Impact of Neighbors Who Use Section 8 Certificates on Property Values,” *Housing Policy Debate*, 10 (1999):879-917.

Galster, George, Roberto G. Quercia, and Alvaro Cortes. “ Identifying Neighborhood Thresholds: An Empirical Exploration.” *Housing Policy Debate*, 3 (2000): 701-732.

Galster, George. “Are Neighborhoods Self-Stabilizing? Exploring Endogenous Dynamics,” *Urban Studies* 44 (2007): 167-185.

Gibb, Kenneth, and Tony O’Sullivan. *Housing Economics and Public Policy*. Malden, Massachusetts: Blackwell Science Ltd, 2003.

Goodman, Allen C. “Hedonic Prices, Price Indices, and Housing Markets,” *Journal of Urban Economics*, 7(1978): 471-84.

Goodman, Allen C. and Thomas G. Thibodeau. “Housing Market Segmentation,” *Journal of Urban Economics*, 5(1998): 121-143

Goodman, Allen C. and Thomas G. Thibodeau. “Housing Market Segmentation and Hedonic Prediction Accuracy,” *Journal of Urban Economics*, 12(2003): 181-201

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

Greenbaum, Robert and John Engberg.. “An Evaluation of State Enterprise Zone Policies.” *Policy Studies* Review 17 (2000):29-46.

Grigsby,W. and M. Baratz, G. Galster, and D. Maclennan. “Dynamics of Neighborhood and Decline.” *Progress in Planning* 28 (1987): 1-76

Grogan, Paul S. and Tony Proscio. *Comeback Cities.* Boulder, Colorado: Westview Press, 2000.

Gyourko, Joseph and Albert Saiz, "Reinvestment in the Housing Stock: The Role of Construction and Supply Side Costs," *Journal of Urban Economics*, (2004): 238-256.

Gyourko, Joseph E. and Saiz, Albert, *Urban Decline and Housing Reinvestment: The Role of Construction Costs and the Supply Side* (May 2003). Federal Reserve Bank of Philadelphia Working Paper No. 03-9. Available at SSRN: http://ssrn.com/abstract=570323

Hays, R. Allen, "Housing Markets and Submarkets," in The Federal Government and Urban Housing: Ideology and Change in Public Policy. Second edition. (Albany: State University of New York Press, 1995), 57-81

Helms, A.C.. "Understanding Gentrification: An Empirical Analysis of the Determinants of Urban Housing Renovation," *Journal of Urban Economics* 54 (2003): 474-498.

Hillier, Amy and Dennis Culhane. "Abandoned Housing: Exploring Lessons from Baltimore." *Housing Policy Debate* 12 (2001):449-448.

Hite, Diane, Wen Chern, Fred Hitzhuzen, and Alan Randall. "Property Value Impacts of an EnvironmentalDisamenity: The Case of Landfills," *Journal of Real Estate Finance and Economics*, 22(2001): 185 – 202.

Johnson, Jeffrey, and Bryan Bednarz. 2002. Neighborhood Effects of the Low Income Housing Tax Credit Program: Final Report, Washington, D.C.: U.S. Department of Housing and Urban Development.

Jud, G. Donald and James Watts. "Schools and Housing Values," *Land Economics*, 57 (1981): 459-470.

Kain, John F. and John M. Quigley, "Measuring the Value of Housing Quality," *Journal of the American Statistical Association*, 65 (1970): 532-548.

Kain, John F., and William Apgar,. *Housing and Neighborhood Dynamics: A Simulation Study*. Cambridge, Massachusetts: Harvard University, 1985.

Kasarda, John D. “Inner-City Concentrated Poverty and Neighborhood Distress: 1970 to 1990,” *Housing Policy Debate* 4 (1993):253–302.

Keating, W, Norman Krumholz, and Philip Star. *Revitalizing Urban Neighborhoods.* Lawrence, Kansas: University Press of Kansas, 1996.

Keating, W., and Norman Krumholz. *Rebuilding Urban Neighborhoods.* Thousand Oaks, California: Sage Publications, 1999.

Kelejian Harry, Prucha Ingmar “A Generalized Spatial Two Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances,” Journal of Real Estate Finance and Economics, 17(1998): 99 – 121.

Khadduri, Jill and David Rhodda. *Using Your HOME Dollars for Rental Production: A Planning Paper for Local Policy Makers* prepared for the Department of Housing and Urban Development, Office of Policy Development and Research, C-OPC-21895, Washington, DC:March 2004

Kolodny, Robert. *Some Policy Implications of Theories of Neighborhood Change,* p. 93–110.In Neighborhood Policy and Planning, ed. Phillip L. Clay and Robert M. Hollister Lexington, MA: Heath, 1983

Krupka, Douglas J. and Noonan, Douglas S."Neighborhood Dynamics and the Housing Price Effects of Spatially Targeted Economic Development Policy," IZA Discussion Papers 4308, Institute for the Study of Labor (IZA), 2009

Kuhn, Randall and Dennis P. Culhane. “Applying Cluster Analysis to Test a Typology of Homelessness by Pattern of Shelter Utilization: Results from the Analysis of

Administrative Data," *American Journal of Community Psychology*, 26 (1998): 207-232

Lang, Robert. "Did Neighborhood Life-Cycle Theory Cause Urban Decline?" *Housing Policy Debate*, 11(2000):1-6.

Lee, Chang-Moo, Dennis P. Culhane, and Susan M. Wachter. "The Differential Impacts of Federally Assisted Housing Programs on Nearby Property Values: A Philadelphia Case Study," *Housing Policy Debate*, 10(1999): 75-93

Leggett, Christopher. and Nancy Bockstael. "Evidence of the Effects of Water Quality on Residential Land Prices," *Journal of Environmental Economics and Management,* 39(2000): 121-144.

Little, James T. "Residential preferences, neighborhood filtering and neighborhood change," *Journal of Urban Economics*, 3(1976): 68-81.

Lynch, Allen, and David Rasmussen. "Measuring the Impact of Crime on House Prices," *Applied Economics*, 33 (2001): 1981-1989.

Lyons, Robert F. and Scott Loveridge.. "An Hedonic Estimation of the Effect of Federally Subsidized Housing on Nearby Residential Property Values." Staff Paper P93-6, Paper provided by University of Minnesota, Department of Applied Economics in its series Staff Papers with number 13377 (1993)

Maclennan D, Tu Y, 1996, ``Economic perspectives on the structure of local housing systems," *Housing Studies*. 11(1996): 387-406

Mallach, Alan, *Bringing Buildings Back: From Abandoned Properties to Community Assets.* National Housing Institute and Rutgers University Press (2006): 75-85.

Mallach, Allan. “From Abandonment to Reuse: Issues and Policies in Urban Abandonment.” Prepared for seminar hosted by Fannie Mae Foundation, 5 November 2001.

Megbolugbe, Isaac, Linneman, Peter D., Hoek-Smit, Marja. “Understanding Neighborhood Dynamics: A Review of the Contributions of William G. Grisby,” *Urban Studies*, 33 (1996): 1779-1795.

Metzger, John T. “Planned Abandonment:The Neighborhood Life-Cycle Theory and National Urban Policy,” *Housing Policy Debate*, 11 (2000): 7-40.

Morancho, Aurelia Bengochea. “A hedonic valuation of urban green area” *Landscape and Urban Planning* 66(2003): 35-41

Nguyen, Mai Thi “Does Affordable Housing Detrimentally Affect Property Values? A Review of the Literature,” *Journal of Planning Literature*, 20(2005): 15-26.

Oakley, Deirdre, and Tsao Hui-Shein. “Socioeconomic gains and spillover effects of geographical targeted initiatives to combat economic distress: An examination of Chicago’s Empowerment Zone,” *Cities* 24(2007):43-59.

Oakley, Deirdre, and Tsao Hui-Shien, “A New Way of Revitalizing Distressed Urban Communities? Assessing the Impact of The Federal Empowerment Zone Program,” *Journal of Urban Affairs* 28 (2006):443-471.

Ottensmann, John R. “Positive Discrimination, Spatial Targeting, and Urban Policy,” *Journal of Planning Literature*, 2 (1987): 243-253

Palmquist, Raymond B. “Valuing Localized Externalities.” *Journal of Urban Economics* 31(1992.): 59-67

Pollock, Marcus, and Ed Rutkowski, *The Urban Transition Zone: A Place Worth A Fight.* J.H Furst Co.Inc, 1998

Quercia,Roberto, and George Galster. “Threshold Effects and Neighborhood Change,” *Journal of Planning Education and Research*, 20(2000):146-435.

Rapaport,, C. "Housing Demand and Community Choice: An Empirical Analysis,” *Journal of Urban Economics*, 42, No. 2 (1997): 243-260.

Redburn, F., and Terry Buss,. *Public Policies for Distressed Communities.* Lexington, Massachusetts: D.C. Heath and Company, 1982.

Reid, Carolina. “Neighborhoods in Bloom: Measuring the Impact of Targeted Community Investments” in Community Investments (Winter 2006): 24

Rohe, William, Stewart, Leslie. “Home Ownership and Neighborhood Stability,” *Housing Policy Debate*, 7(1996): 37-81.

Roni, Peter. “Evaluating Community Development Interventions.” In: Urban Problems and Community Development, edited by Ronald Ferguson and William Dickens. Washington, D.C.: Brooking Institution Press(1999): 521-559; 565-567

Rosenthal, Stuart. “Old homes, externalities, and poor neighborhoods. A model of urban decline and renewal,” *Journal of Urban Economics*, 63, (2008): 816-840.

Rothenberg, Jerome, George C. Galster, Richard V. Butler and John Pitkin, *The Maze Of Urban Housing Markets: Theory, Evidence, and Policy*. Chicago: The University of Chicago Press, 1991

Rusk, David. *Baltimore Unbound: A Strategy for Regional Renewal.* The Abell Foundation, Baltimore, Maryland,1996.

Ryzin, Van, Gregg G. and Andrew Genn. "Neighborhood Change and the City of New York's Ten-Year Housing Plan" *Housing Policy Debate,* 10 (1999): 799-838.

Sawicki, David S. and Patrice Flynn. "Neighborhood Indicators: A Review of the Literature and an Assessment of Conceptual and Methodological Issues," *Journal of Urban Economics,* 3(1976):146-166

Schill, Michael H., Ingrid Gould Ellen, Amy Ellen Schwartz, and Ioan Voicu. "Revitalizing Inner-City Neighborhoods: New York City's Ten-Year Plan," *Housing Policy Debate,* 13 (2002): 529-566.

Schilling, Joseph and Naomi Friedman. "The Revitalization of Vacant Properties: Richmond Virginia Case Study" Prepared for the International City/County Management Association (Washington DC, 2002).

Schnare, Ann; and Raymond J. Struyk. "Segmentaion in urban housing markets," *Housing Policy Debate,* 13 (2002): 529-566.

Schwab, William A. "The Predictive Value of Three Ecological Models: A Test of the Life-Cycle, Arbitrage, and Composition Models of Neighborhood Change," *Urban Affairs Review*, 23(1987):295-308

Schwartz, Alex. "New York City and Subsidized Housing: Impacts and Lessons of the City's $5 Billion Capital Budget Housing Plan," *Housing Policy Debate*, 10 (1999): 839-877.

Schwirian, Kent. "Models of Neighborhood Change." *Annual Review of Sociology* 19(1983):83-102.

Shephard, Stephen, "Hedonic Analysis of Housing Markets," in Handbook of Regional and Urban Economics, Cheshire and Mills (eds.), Vol. 3(1999): 1595-1635.

Shevky, E. & Bell, W., *Social Area Analysis*, Greenwood Press, Connecticut. 1955

Simons, R. and J. Saginor. 2006. “The Value Impact of New Residential Construction and Neighborhood Disinvestment on Residential Sales Price” *Journal of Real Estate Research ½*, 15 (1998): 147-161.

Song, Yan and Gerrit-Jan Knaap. “Measuring Urban Form: Is Portland winning the war on sprawl?” *Journal of the American Planning Association* 70 (2004): 210-225

Song, Yan, and Gerrit-Jan Knaap. “Measuring the effects of mixed land uses on housing values,” *Regional Science and Urban Economics* 34(2004): 663-680

Straszheim, Mahlon. An Econometric Analysis of the Urban Housing Market. NBER, 1975.

Temkin, Kenneth and William Rohe. “Neighborhood Change and Urban Policy,” *Journal of Planning Education and Research*, 15(1996): 159 - 170.

Turnham, Jennifer, Bonjorni, Jessica. “Review of Neighborhood Revitalization Initiatives.” Prepared for the Neighborhood Reinvestment Corporation by Abt Associates (Washington DC), 2002.

U.S. Department of Housing and Urban Development Office of Community Planning and Development. *Home and Neighborhoods: A Guide to Comprehensive Revitalization Techniques prepared for the Department of Housing and Urban Development*, Washington, DC: 2004

Urban Institute. *Impllementing Block Grants for Housing: An Evaluation of the First Year of HOME* prepared for the Department of Housing and Urban Development, Office of Policy Development and Research, HC-5898, Washington, DC: November 1995

Vaughan, Roger J. and Mary E. Vogel. The Urban Impacts of Federal Policies. Vol. 2. Economic Development. Santa Monica, CA: RAND Corporation, 1977

Wachter, Susan and Kevin Gillen. “Public Investment Strategies: How They Matter for Neighborhoods in Philadelphia: Identification and Analysis” For the William Penn Foundation (October 2006).

Walker, Chris, Chris Hayes, George Galster, Patrick Boxall, and Jennifer Johnson. The Impact of CDBG Spending on Urban Neighborhoods. Washington DC: The Urban Institute, (October 2002).

Weicher, John and Thomas Thibodeau, “Filtering and Housing Markets: An Empirical Analysis,” *Journal of Urban Economics,* 23 (1988): 21-40.

Whalley, Diane. “Neighborhood Variations in Moderate Housing Rehabilitation Program Impacts: An Accounting Model of Housing Quality Change,” *Economic Geography,* 64 (1988): 45-61.

Whitehead, Christine M. E., "Urban Housing Markets: Theory and Policy," in Paul Cheshire and Edwin S. Mills, eds., Handbook of Urban and Regional Economics, 3 North Holland, 1999: 1560-1594.

Wishart, David. *ClustanGraphics Primer: A Guide to Cluster Anlaysis.* Edinburgh and St. Andrews, Scotland: Allstar Services, Ltd, 2006.

Wu, J. Richard M. Adams, and Andrew J. Plantinga “Amenities in an Urban Equilibrium Model: Residential Development in Portland, Oregon,” *Land Economics,* 80,: (2004)19-22

Yannis M. Iaonnides and Jeffrey E. Zabel. "Neighborhood Effects and Housing Demand." *Journal of Applied Econometrics,* 18 (2002):563-584.