SPATIAL TEMPORAL DYNAMICS OF NEIGHBORHOOD QUALITY OF LIFE: CHARLOTTE, NC

by

Elizabeth Catherine Delmelle

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Approved by:

____
Dr. Jean-Claude Thill

____
Dr. Harrison Campbell

____
Dr. Owen Furuseth

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Dr. Claudia Flowers

ABSTRACT

ELIZABETH CATHERINE DELMELLE. Spatial temporal dynamics of neighborhood quality of life: Charlotte, NC. (Under direction of DR. JEAN-CLAUDE THILL)

Quality of life (QoL) is an encompassing measure of a neighborhood's condition, describing the well-being an individual may expect by residing in a particular place. Over time, some or all of these conditions will change for the better or worse, yet the driving forces behind the dynamics of neighborhood-level QoL are not well understood. The purpose of this dissertation is to gain a better comprehension of the patterns, trajectories, and explanatory factors of change across the multidimensional QoL conditions of neighborhoods. Utilizing neighborhoods in Charlotte, NC over the course of the 2000-2010 decade as a case study, this dissertation employs three complementary analytical approaches to examine spatial, multidimensional dynamics: Markov Chains, self-organizing maps, and a set of cross-lagged panel models.

Results highlight the role of spatial spillovers in shaping the change process; a neighborhood's mobility in terms of QoL is not independent of its immediate surroundings. Geographically, older, inner-ring suburban neighborhoods are shown to be most vulnerable to declines across multiple QoL dimensions; middle-age housing further proves to be a significant explanatory predictor of changes in crime concentrations, relative economic status, youth social indicators, and homeownership rates, thus supporting economic filtering theories of neighborhood change. Neighborhoods characterized by the highest QoL attributes are the most stable through time. Lower-income neighborhoods are found to be heterogeneous in terms of their corresponding social problems, and a temporal, reciprocal relationship between crime and youth-related problems is revealed. Improvements to the lowest QoL neighborhoods were heightened at the peak of the housing and economic boom in the city, but following the great recession, many of these neighborhoods reverted back to their conditions earlier in the decade, illuminating the shifting dynamics before, during, and after the recent, great recession. Policy implications of results are discussed.

DEDICATION

To all who have, and continue to enhance the quality of my life

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CHAPTER 1: INTRODUCTION

Neighborhood quality of life (QoL) is a multidimensional concept describing the overall livability of a neighborhood. Crime rates, school quality, walkability, employment accessibility, available amenities, and environmental quality are all factors, among many others, that may contribute either positively or negatively to a neighborhood's overall QoL. Over time, a neighborhood's quality of life may improve or decline due to any number of factors such as public or social policy initiatives, the construction of new suburban neighborhoods, gentrification, or population in-migration, to name a few.

Understanding the dynamics of these changes is critical for planners and policy makers for several reasons. From an economic viewpoint, QoL serves as an indicator of the overall competitiveness or desirability of a place as it feeds into individual, business, and developer location decisions (Rogerson, 1999). At the metropolitan and state level, QoL has become an important concept for the study of city and regional competitiveness and economic growth (Gabriel et al., 2003; Jensen and Leven, 1997; Rogerson, 1999; Royuela et al., 2010; Wong, 2001), however, at the neighborhood level, the subject, especially in relation to change over time, has received much less attention.

Second, from a planning and policy making perspective, a common interest amongst city leaders is to help create neighborhoods that are able to provide their residents a high quality of life. Although the extent to which and how this occurs is in debate, the literature suggests that there is reason to believe that neighborhoods are capable of shaping the lives of their residents. For example, they dictate the quality of local services such as schools, medical care, or after school programs, form the environment in which social networks and peer influences may be created, and determine the proximity to urban opportunities including employment (Ellen and Turner, 1997).

Given that neighborhood QoL conditions factor into location and relocation decisions of individuals or businesses, and that the resulting, aggregate level conditions of a neighborhood change with these decisions, quality of life can be considered both a cause and a consequence of neighborhood change. To date, empirical, longitudinal studies on the way in which neighborhoods evolve and change over time with respect to quality of life have been limited (Galster et al., 2007; Sampson et al., 2002), or linked to one particular dimension of change such as economic (income or housing prices), social conditions, racial composition, or crime, although from a policy or planning standpoint, the ways in which neighborhoods evolve across each of these dimensions is important, and presumably interrelated. In a recent review and research agenda proposal for urban neighborhoods, Ellen and O'Regan (2010) specify that the causes of neighborhood change remain a puzzle, acknowledging that "virtually all the papers on neighborhood change call for additional analysis on the dynamics of neighborhood composition (Ellen and O'Regan, 2010, pg 367)".

1.1. Statement of Research

The purpose of this research is to contribute to the understanding of neighborhood dynamics in relation to the multidimensional concept of quality of life. Utilizing a unique dataset that has traced QoL indicators at two year time increments over the course of the 2000 to 2010 decade for the city of Charlotte, NC as a case study, this dissertation seeks to identify patterns, trajectories, and explanatory factors related to temporal changes of these spatially situated neighborhoods.

This research has three major objectives aimed at contributing to the understanding of multidimensional quality of life dynamics at an intra-urban scale. The first objective is to explore the decennial evolution of a consistently collected QoL index, at two year time periods. In this section, pattern-based processes of change are examined through the use of a Markov Chain Modeling approach. Tests on the assumptions of Markov processes enable several specific questions to be answered including: whether or not the process of change differed before, during, and after the economic downturn (time homogeneity), the role of spatial dependence or spatial spillovers in influencing transition probabilities (spatial independence), and to what extent past conditions play in determining future QoL conditions (time independence). For the spatial dependence question, aside from the standard spatial Markov framework used in the literature where the mean value of neighbors are used, this study expands upon that concept to explore alternate neighborhood specification to include the value of the most frequent neighbor (mode), the median, and the upper and lower quartile to further explore the role of spatial dependency. Finally, transition probabilities are used in a predictive framework to test the utility of these pattern-based estimates in forecasting neighborhood status, and to identify characteristics of neighborhoods that deviate from their most probable future state.

The second objective of this dissertation is to identify neighborhood trajectories of change across multidimensional attribute space. Very few studies have explored neighborhood changes across multiple dimensions at multiple periods of time. Given the complexities involved in distinguishing patterns or trends is such datasets, a combined geocomputational and visualization approach based on the self-organizing map is utilized. This methodology enables the unique trajectories of change across the attribute space that each neighborhood has followed to be identified. The trajectories followed by neighborhoods with similar characteristics are then compared to help distinguish the magnitude, direction, and paths taken by various types of neighborhoods. In addition, these trajectories are linked with the spatial location of neighborhoods to identify which neighborhoods have become more similar in their QoL characteristics over time.

Finally, the third component of this research seeks to identify explanatory or predictive factors of the decennial trends of four QoL dimensions. This final part will utilize a cross-lagged panel model within a structural equation modeling framework aid in disentangling some of the causes and consequences behind decennial change trends. By bridging economic, sociological, and geographic notions and theories of neighborhood change, this methodology is able to test whether certain hypothesized variables play a role in explaining change across several QoL dimensions. Particular emphasis is placed on the hypothesized reciprocal relationships between these dimensions over time. Finally, this analytical approach will examine change according to 2, 4, 8, and 10 year time lags over the course of the 2000-2010 decade. Aside from providing insight into the length of time for neighborhood changes to manifest themselves, these models also illuminate dynamics in the rapidly transforming metropolis featuring population growth, suburbanization, downtown skyscraper construction, and neighborhood revitalization.

Together these three objectives will contribute to the understanding of how neighborhoods change over time at a small temporal and spatial resolution and they approach the subject of neighborhood change in a manner that is multidisciplinary and multidimensional. The theoretical basis draws from a number of research traditions that have separately developed theories or models regarding the causes and consequences of change, while the empirical work capitalizes upon methodological advances in geographic information systems (GIS), spatial analysis and statistical approaches to bridge these disciplines in a comprehensive study. Collectively, these research objectives will offer insight into the both the spatial and temporal dimensions of change, including the role of spatial spillovers in shaping the change process, the influence of the transforming spatial structure of the city on driving neighborhood trajectories of QoL change, and the process of change throughout a decade marked by rapid growth for the initial seven years, followed by an economic recession and housing market bust.

1.2. Structure of the dissertation

The dissertation will be structured as follows: Section 2 provides a literature review on quality of life research, theories of neighborhood change, empirical research on neighborhood change, and finally, on methodologies available for analyzing spatial-temporal and multidimensional data. Next, in Section 3, the specific research questions are stated and discussed. A description of the study area, data, and methodologies are presented in Section 4, results in Section 5, and conclusions in Section 6. Finally, limitations of the study are summarized in Section 7.

CHAPTER 2: LITERATURE REVIEW

2.1. Quality of Life

2.1.1. Defining Quality of Life

'Quality of Life' is a challenging concept to define, but at its most basic, it refers to the overall satisfaction of people's lives. Research in this area spans multiple disciplines including economics, psychology, political science, sociology, geography, and planning, and as an applied subject, generally connotes research aimed at shaping policy outcomes (Schuessler and Fisher, 1985). The literature is largely in agreement that an individual's quality of life is shaped by both objective, or exogeneous factors, and subjective, or endogenous, perceptions of these factors and of him or herself. Quality of life research therefore attempts to understand, measure, or describe both of these objective and subjective components (Dissart and Deller, 2000). Research performed in the fields of geography, planning, and economics, which do not directly study the personal, subjective factors associated with individual well-being, happiness, or life satisfaction as examined by psychologists, rests on the assumption that the social and physical environment of an area is capable of influencing the well-being of residents (Lambiri et al., 2006). Empirical studies on this relationship have examined the mediating factors through which communities or neighborhoods impact individual life satisfaction. For example, Sirgy and Cornwell (2002) find supportive evidence that the social features of a neighborhood contribute to community satisfaction, which in turn translates to life satisfaction, and found that satisfaction with the economic conditions of a neighborhood influences satisfaction of one's house and home, which then feeds into life satisfaction.

To geographers, the objective meaning of QoL refers to the conditions of a particular place at a period in time, and forms the environment within which people seek happiness (Helburn, 1982). This view provides a policy relevant framework for improving places and performing applied urban research. Pacione (2003) has placed QoL research on a spectrum within the broader field of urban geography where work at the intra-urban scale has often focused on the disadvantaged end, mapping and seeking explanatory reasons behind multiple indicators of deprivation (health, wealth, housing, education, crime, environment, polarization, etc.). He argues that poverty is a central element linking the multidimensional problem of deprivation where individual challenges are compounded, establishing a situation of multiple deprivations. The major contribution of geographers to this field is through the incorporation of spatial considerations, by for example, mapping deprivation indicators (Longley and Tobón, 2004), comparing QoL between spatial areas (or urban vs. non-urban), or by performing spatial statistical analyses to identify clusters of areas with similar QoL values (Campanera and Higgins, 2011).

2.1.2. Measuring Quality of Life

Given that quality of life research encompasses a number of disciplines covering both individual, subjective factors regarding the quality of one's life, and the more objective factors that may affect a person's life, the mechanisms for measuring QoL vary by research domain and objective. Because QoL itself is not directly measurable, QoL measurements are often referred to as indicators (Schuessler and Fisher, 1985). Myers

(1998) categorized four approaches to measuring, or building knowledge about QoL: livability comparisons, wage differentials, personal well-being, and community trends.

Falling within the geographic tradition are livability comparisons which are measured with objective characteristics of communities derived from secondary data sources such as education levels, local income levels, housing prices, health care, cultural amenities, or crime. These variables are typically combined through an additive weighting strategy to derive an overall indicator of quality of life, which can then be used to rank places that are better or worse off (Boyer and Savageau, 1981; Cutter, 1985; Liu, 1975). Motivated by the notion that QoL plays an important role in location and migration decisions of businesses and residents, and that places (cities, neighborhoods, or larger regions) can be characterized, and therefore distinguished from one another by a unique set of attributes regarding their physical and social environments, indices based on this methodology have been adopted by cities as a means for advertizing or promoting economic development (Rogerson, 1999). Place ratings developed in line with this methodology eventually worked their way into popular culture and magazines with city ranking guides published annually by Money Magazine, Fortune Magazine, and appearing in a *Places Rated Almanac*, available to businesses and citizens wishing to make location decisions. While high rankings in these guides are often used by city officials to advertise or attract businesses (Rogerson, 1999), low rankings effectively serve to damage a local economy, potentially deterring individual or business location decisions (Pacione, 2003).

Critics of this objective indicator approach contend that variables comprising an overall QoL index can be arbitrarily selected, or data-driven, lacking theoretical concerns and that the weighting methods used to combine variables is also arbitrarily selected. Finally, others suggest that relying solely on objectively measurable factors does not consider how residents of a city perceive their local environment (Myers, 1998). In order to overcome this latter limitation, the integration of both subjective and objective indicators has also been proposed to develop indices (Randall and Morton, 2003).

Within the urban economic tradition, QoL represents non-marketable goods such as climate, local amenities, public services, or crime rates, for example, and, according to Myers's (1998) categorization, is based on the notion of wage differentials or disamenity compensation where places that offer lower quality of life must offer higher salaries to effectively compete for and attract skilled workers. More broadly, however, the urban economic research tradition utilizes a revealed preference approach to estimate, rather than measure quality of life. Operating under an assumption of spatial equilibrium, and a theory of household supply and demand, if a household migrates to a new location in order to improve its QoL, then increased demand should result in price changes to locally traded goods such as housing or wages (Lambiri et al., 2006). Hedonic price analysis is used to capture the value of QoL capitalized in these goods (Jensen and Leven, 1997; Roback, 1982; Rosen, 1974). Aside from wages and housing, population levels or growth provide an alternative for estimating the demand of an urban areas and its amenities or QoL (Rappaport, 2009). These measures aid in determining where the cost of doing business are highest (Myers, 1998), or to rank cities, and are arguably more theoretically grounded than the use of composite indicators, however, they are limited in their reliance on a state of spatial equilibrium and complicated estimation techniques (Lambiri et al., 2006).

Moving away from the quantitative approaches of measuring the quality of places, psychologists and some branches of sociology tend to focus on the personal well-being of individuals, relying upon qualitative personal interviews to understand what factors contribute to individual happiness or satisfaction. These subjective indicators attempt to measure such concepts as personal feelings, attitudes, preferences, opinions, judgments, or beliefs. Regression analyses may be used to estimate the contribution of various factors on the overall satisfaction of individual lives. These studies have generally revealed that life satisfaction is largely shaped by personal factors of which local governments have no control over, and are therefore of little use to policy makers or planners (Myers, 1998; Schuessler and Fisher, 1985).

Finally, the fourth approach identified by Myers is the suggested methodology for urban planners where objective indicators are traced over time and supplemented with citizen assessment and feedback of factors. In this case, the emphasis is on community trends over time, and encourages public participation in discussing which factors to monitor or measure. Planners are most concerned with QoL change over time, especially considering feedback effects that may arise from changes in QoL. For example, rising QoL may encourage local economic development, which may then undermine some of the characteristics that led a neighborhood or region to become an attractive destination (Myers, 1998). This dissertation will exploit a dataset developed in line with this last conceptualization of QoL indicators, that traces a consistently set of variables across time, and was developed and is shared with the local community.

Given that the purpose of this dissertation is to explore the temporal dynamics of neighborhood quality of life, the next two sub-sections focus on the neighborhood change literature – first by providing an overview of theories and models of neighborhood change followed by empirical studies of change related to various QoL dimensions.

2.2. Theories of Neighborhood Change

Theories of neighborhood change have been developed since the earliest part of the 1900s, and represent a basis for empirically examining change in specific urban settings. Beginning with an ecologically-based view of cities with the Chicago School where change was envisioned as part of an invasion\succession processes, to more economically grounded theories of house filtering and neighborhood life cycle models, the review of these models is intended to capture their major ideas, themes, and critiques; not to provide an exhaustive review of the literature on each model.

2.2.1. Invasion\Succession Models

The earliest formal models of neighborhood change date back to the early 1900s and the Chicago School of sociology. Sociologists in the Chicago School viewed cities as 'natural areas' analogous to adaptive, evolving, and equilibrium-seeking ecological systems where change is an inevitable outcome of time (Temkin and Rohe, 1996). This human ecological perspective of urban areas gave rise to a spatial and geometric ordering of urban spaces where competition for space resulted in concentric rings or zones as outlined in Burgess's (1925) concentric zone model. Dynamics in this model occur through a process of invasion and succession, terms borrowed from plant and animal ecology, where one category or group of individuals or land use type moves into a neighborhood previously occupied by another type, and eventually becomes the dominant group of individuals or land use type. Presented in terms such as competition, conflict, and accommodation (Schwirian, 1982), the process of neighborhood change was

Darwinian in nature owing to its ecological theoretical roots. Invasion/succession theory became a popular framework for describing racial change occurring within urban neighborhoods as one race began to move into a neighborhood, making current residents uncomfortable and prompting an exodus of the previously dominant race out of the neighborhood. The major critique of this theory lies within its plant ecology roots devoid of the economic realities of cities (Temkin and Rohe, 1996).

2.2.2. Filtering and Neighborhood Life-Cycle Models

Conceptually, the filtering model is very similar to the invasion/succession model, but couched in economic terms. Initially developed by Hoyt (1933), the filtering model describes a process of neighborhood decline as a function of housing age. As newer housing is built along the urban fringe, it attracts wealthier residents, leaving older housing stock to low income residents. Contrary to the concentric ring pattern proposed by ecological theorists, Hoyt envisioned urban growth patterns to occur in sectors or wedges, with new housing construction occurring on the fringes of these wedges. The process of filtering was presented as a result of an increase in housing demand attributed to rising incomes, and the depreciation of dwelling units with increasing age (Leven et al., 1976).

William Grigsby and colleagues (1987) expanded upon these ideas to describe the filtering processes, not as an inevitable outcome of age, but as a function of the structural quality of properties. As housing stock ages, the price of maintaining a particular quality increases, which leads to a decrease in investment and upkeep of these properties on the part of landlords. Further, Grigsby introduced a spatial element to these ideas by suggesting that spatial concentrations of disinvestment may occur when a landlord fears that an investment in property upkeep will become worthless if his neighborhoods do not follow suit; thus producing entire neighborhoods of deteriorating buildings and disincentives of continued investment (Megbolugbe et al., 1996).

Grigsby (1963) is also credited with shifting the filtering concept from one centered on neighborhoods viewed simply as a collection of housing to one that considered neighborhoods as a collection of attributes in addition to housing. Coining the term ‘Locational Obsolescence’, a neighborhood is hypothesized to become obsolete when the demand for the attributes of a neighborhood including its location, housing and site characteristics decreases. Based on the notion that cities are comprised of distinct, yet interrelated housing submarkets dynamically shaped by supply and demand, Grigsby and colleagues (1987) formally outlined a theory of neighborhood decline where a filtering process of neighborhood change is linked to both macro and micro forces. Rather than viewing filtering as a process in terms of housing conditions, filtering was described as a change in neighborhood residential composition. As a city’s overall population declines, the demand for housing decreases, reducing house prices, and enabling lower-income residents to purchase homes formerly occupied by higher income residents. Supply of housing is controlled by construction of new residential buildings available to high income residents. Housing, and subsequently, neighborhood deterioration occurs when housing becomes occupied by residents so poor they are unable to cover the costs of operating and maintaining the home, ultimately leading to a state of vacancy followed by permanent abandonment (Megbolugbe et al., 1996).

Closely related to these concepts are ideas laid out by Leven et al. (1976) in their ‘Arbitrage Model’ of neighborhood change which also relied on the notion of housing submarkets, but also specified the role of a neighborhood's changing socioeconomic and racial composition as critical factors in triggering neighborhood change. These changes in racial or income composition effectively alter the housing bundle characteristics of all units in that neighborhood, shifting the demand for that neighborhood, eventually resulting in occupancy and price changes. The authors also note the importance of the anticipation of the future state of neighborhoods by consumers, as households make investment decisions based on the presumption that while many neighborhood characteristics are quite stable over time, others, including income or racial composition may change quickly, and thus impact the future value of their investment. This notion was later echoed by Galster (2001) who states that neighborhood change is ultimately a result of the risky decisions made by the consumers (residents, businesses, local government) of a neighborhood.

In their various models of neighborhood change, Galster (2001), Grisby et al. (1997), and Leven (1976) all base their ideas on the concept of housing submarkets, and all acknowledge the importance of the interconnectedness of these submarkets within the larger urban area, suggesting that a major force in neighborhood's change may be completely exogenous to the neighborhood itself; in this perspective it is a consequence of changes elsewhere within the larger metropolitan context. More recently, the filtering concept has been revisited and modified to suggest that the relationship between housing age and neighborhood decline is non-linear. As older homes are prime for revitalization, middle aged homes are left most susceptible to decline (Brueckner and Rosenthal, 2009; Rosenthal, 2008).

Related to filtering models are neighborhood life-cycle models developed by economists Hoover and Vernon (1959) who proposed that neighborhoods move through a series of five stages including: development, transition, down-grading, thinning out, and renewal. According to Schwirian (1982), several characteristics change as a neighborhood traverses each stage including: the neighborhood's demographic composition in terms of age and race; the land use intensity; the population density; and the quality and condition of housing. It is also important to note that not all neighborhoods will evolve through an entire life cycle in chronological order; some will repeat steps, or remain at one stage.

Within this broad framework of neighborhood filtering and life-cycles, housing decline is not necessarily an unfavorable outcome as some have argued that it provides a mechanism for lower class residents to improve their social mobility and move up in status. Richard Radcliff is attributed with initially attaching a social value to the filtering model, arguing that the construction of new housing, which initiates the filtering process, eventually leads to an overall increase in housing for all residents, resulting in the increase in the wellbeing of all. This argument was largely influential in post WWII housing policies (Leven et al., 1976). It however, has been critiqued for its failure to account for the fact that if housing quality is assumed to decline over time, then the poor may not in fact be better off. It also ignores the neighborhood context that poorer households move into, which may include higher crime rates, worse schools or other public services (Leven et al., 1976).

2.2.3. Residential Choice Models

Another stream of literature dealing with neighborhood change has examined individual behavioral decisions in regards to residential choice. These decisions collectively establish an aggregate-level sorting of neighborhoods by income, education level, or race, for example. Change according to these models occurs when individuals decide to relocate from their existing neighborhood because of changes in their family lifecycle, or because changes to the characteristics of a neighborhood induce a relocation decision. Included under this category are bid rent models where consumers make location decisions in an attempt to maximize their economic utility by considering a tradeoff between the cost of commuting and lot sizes. This tradeoff results in an ordered landscape where the wealthiest households, most able to afford higher commuting costs, live furthest from the city center and consume larger housing lots, while less wealthy households reside in smaller homes close to the urban core (Muth, 1969). It should be noted that urban patterns resulting from this model are identical to those generated by the filtering process.

2.2.4. Subcultural Considerations

The previous three classes of models largely ignore the role of individuals and social interactions in influencing the trajectory of neighborhoods over time. Subculturalists, on the other hand, argue that neighborhoods with similar physical and structural characteristics are not destined to follow a trajectory of decline and possibly renewal. Quite the contrary, community residents play a major role in defending against change or decline. To the subculturalists, social networks, attachment, and identity are the primary determinants of a neighborhood's trajectory over time, and for this reason, two neighborhoods of identical physical characteristics may follow very different paths over time. Urban policies based on these ideas have sought to enhance a neighborhood's sense of place in order to strengthen its collective defense or create a proactive environment against change. Critics of these policies point to their lack of consideration of the larger political economy on influencing neighborhood change as a significant limitation in their ability to stabilize neighborhoods (Temkin and Rohe, 1996).

Citing limitations with any one of these model foundations, a number of researchers have attempted to develop new models which combine ideas or incorporate new twists to existing frameworks. For example, Temkin and Rohe (1996) contend that change is neither the inevitable result of ecological processes, nor solely the outcome of rational economic behaviors, but that a neighborhood's trajectory over time is a result of the physical, social, and locational characteristics of the community. The authors suggest that a strong social network is a necessary, but not sufficient condition for stability.

2.2.5. Revitalization\Gentrification

The human ecological model, the filtering process, and the residential premium placed on larger lots and low housing density over accessible locations all describe a one-way process of urban decline in older neighborhoods towards the center of the city, and a movement of the wealthiest urban residents to the farthest suburban extents. Beginning in the 1960s, a different phenomenon slowly began to emerge in some of the largest cities around the world; inner-city neighborhoods began experiencing a reinvestment in capital by more affluent residents. Thus the urban 'gentry' was slowly returning into previously devalued neighborhoods, and the term gentrification was born. Given that gentrification contradicts the most prominent neighborhood change theories, the subject has received considerable, and often contentious, attention in the literature in its attempts to both develop a theory describing the process of gentrification and to present a narrative of the consequences of this movement.

At its most general, gentrification describes the reinvestment of capital into central urban locations through the rehabilitation and redevelopment of both residential and commercial properties. This structural revitalization coincides with an increase in the socio-economic status of neighborhood residents and results in an economic alteration in the land and housing market. Gentrification therefore involves the social (or cultural), physical, and economic change of a neighborhood (Hamnett, 1991; Smith, 1979). The process is also often associated with the direct or indirect displacement of poor residents from these neighborhoods, although the extent to which this occurs is still very much in debate in the literature (Mckinnish, 2010; Wyly, 2010).

Explanations for how the process of gentrification occurs typically involve two, originally disparate, but more recently combined considerations: production and consumption-based explanations. On the consumption side, population changes in terms of fewer children, delayed marriages, rising divorce rates, and an increase in dual worker families reduced the seemingly insatiable demand for single-family suburban housing witnessed at the end of World War II (Laska et al., 1982; Smith, 1996). These factors helped create a shift in housing demand from suburban to more aesthetically unique buildings, centrally located with respect to downtown employment and other urban amenities. Just as suburbanization in Muth's residential bid rent model resulted from consumer preference for space, gentrification can be explained as a modification to this preference.

Others have argued that focusing solely on consumption, ignores the role of builders, developers, landlords, mortgage lenders, government agencies, and real estate agents, or the producers of the city. Neil Smith (Smith, 1979; Smith, 1996) developed a theory of gentrification which emphasizes profit-seeking behavior as the key to understanding why some neighborhoods are redeveloped while others are not. His Rent Gap theory acknowledges some role for consumer preference, but notes that the production end is ultimately the dominant force driving gentrification. This theory is based on the observation that in the early part of the 1900s and prior, the price of land in most cities followed a linear gradient, highest toward the urban core and monotonically descending toward the periphery. However, as suburbanization of both industries and population increased rapidly, land values in the inner city fell relative to the CBD and suburbs, creating a 'valley' in the land value gradient. The crux of this theory is the relationship between land value and property value; as depreciation of existing housing on land within this valley continues, a point is reached when the capitalized ground rent of the property is less than its potential ground rent in its 'highest and best use', making these properties prime for redevelopment or gentrification. Recent research on gentrification theory has sought to reconcile these consumption and production factors into a comprehensive explanation of the phenomenon.

2.2.6. Neighborhood Social Outcomes\Change

Given that the previous theories were largely concerned with the factors influencing the demographic processes that give rise to a neighborhood's economic or racial composition, a logical next question is how do these population changes translate into social outcomes such as crime, educational, or other social conditions often associated with quality of life indicators (high school dropout rates, teenage birth rates, etc.)? The link between concentrated poverty and the prevalence of social problems is primarily attributed to Wilson (1987) and Massey and Denton (1993) who both articulate, through different demographic processes, that concentrated poverty exacerbates social problems as youths growing up in these neighborhoods are not exposed to role models, are isolated from employment both physically, and via social job networks, and are detached from social norms and behaviors. According to these views, social problems are hypothesized to increase in concentration in the poorest neighborhoods through time. A number of formal theories exist on how social influences stemming from neighborhoods explain the concentration of social problems, and they are briefly reviewed here to help place the role of neighborhood change on quality of life in context.

Generally speaking, a neighborhood effect can be defined as a community influence on individual social or economic outcomes (Dietz, 2002). A fundamental concern in the vast neighborhood effects literature is the distinction between neighborhood effects that offer the potential to cause individual outcomes, and those that are simply a result of the residential sorting processes that occurs as a result of neighborhood changes described in the previous section. Charles Manski (Manski, 1993; Manski, 2000) has classified three different types of neighborhood effects: endogenous, correlated, and exogenous. With endogenous effects, also known as bandwagon or peer effects, the behavior of an individual has a direct influence on the behavior of every other individual in the neighborhood. In this context, neighborhoods have a causal effect on individuals as the behavior of individuals varies with the average behavior of the group (Manski, 1993). As a result of this direct causality between individuals, social multipliers emerge which enables the aggregate change in behavior to be captured as a result in the change in one person's action (Dietz, 2002).

Correlated effects are the result of the residential sorting process; individuals residing in the same neighborhood tend to have similar characteristics or opportunities. Causation in this context could be the result of geographic factors (exclusion from workplace because of distance) or because of a lack of public service, for example (Dietz, 2002). However, observed neighborhood effects could also simply be a result of people with similar unobserved behaviors or characteristics living together establishing aggregate outcomes; the neighborhood does not cause or influence behaviors in any way. Finally, with contextual or exogenous effects, individual actions or behaviors are influenced by the exogenous characteristics of the individual's neighbors such as the socio-economic or racial composition of a neighborhood. For example, the educational achievement of a student may be influenced by the surrounding socio-economic conditions of his neighborhood if high unemployment results in a lack of role models, and causes student underachievement.

Distinguishing between and testing for causal versus non-causal effects is very important from a public policy perspective because if causal neighborhood effects do exist, then policies that attempt to disperse poverty or achieve a more equal distribution of individuals across the urban landscape may serve to reduce the overall negative social outcomes of a city. On the other hand, if concentrated poverty, for example, does not cause any amplified negative outcomes, then the motivations for such policies are limited as social problems will simply be more dispersed, but not lower in number.

There are several non-mutually exclusive sociological and economic theories which attempt to explain the mechanisms through which neighborhood effects may arise and operate. These include contagion and endemic theories which describe the spatial and or temporal spread of social problems, and are based on the notion that if some members of a community or neighborhood exhibit nonnormative social behaviors, other members are more likely to do the same. Formally articulated by Crane (1991), an analogy of social problems is made with the spread of infectious diseases, suggesting that these problems are contagious and spread through peer influences. A central tenet of the epidemic theory, which is a special case of contagion models, is the idea that there may be a critical point for a given population at which time the process will explode, creating an epidemic of social problems. Given this, Crane (1991) notes that the relationship between neighborhood quality and the incidence of social problems should be non-linear; towards the bottom of the distribution of quality, there should be a spike in the rate of increases in social problems as the endemic neighborhoods should have much higher rates of problems than other neighborhoods.

A second theory is based on the idea of collective socialization which suggests that if social groups gain enough power, they are capable of influencing others to conform to their customs, norms, and behavior (Dietz, 2002; Quercia and Galster, 2000). Collective socialization theory allows for both positive and negative influences on social behavior as adults may serve as positive role models and sources of control, while groups exhibiting negative behaviors may have the opposite effect. In either case, the group must be of sufficient critical mass to exert power and influence over individual behaviors (Quercia and Galster, 2000).

Preference models are a third type of explanation, and describe a situation where residents or actors within an environment or neighborhood respond to changes in the aggregate condition of a given attribute of that neighborhood. Most commonly, this type of model is used to explain 'tipping points' in neighborhood racial, income, or other socio-economic composition. As each resident has a particular threshold of tolerance he or she is willing to live with, when the aggregate value of the neighborhood exceeds that critical value, the resident will respond, presumably by relocating to a more preferable neighborhood. This process begins with the resident with the lowest tolerance and iterates through each residential move (Galster et al., 2007).

2.2.7. Spatial Process of Change

Given that neighborhoods are spatially situated units, interconnected within a broader urban and regional context, the role of space – in terms of spatial location within the city and spatial proximity to neighborhoods with better or worse quality of life indicators, is of great interest for understanding the dynamics of change for both theoretical and methodological reasons. A number of different spatial processes exist in the geography literature to explain how the outcome at one location is at least partially affected by events at other locations. These processes include, but are not limited to: spatial diffusion, or the gradual adoption of a new attribute by a fixed population where the probability of adoption is greatest in close proximity to previous adopters; spatial spillovers, which are based on the concept that locations are interconnected so that ideas may freely be exchanged and transferred across invisible borders; and, spatial interaction, the movement of goods, people, or ideas between spatial locations (Paez and Scott, 2004). The outcome of the unfolding of these spatial processes is a geographic ordering of observations so that objects or geographic units with similar attributes are located in close spatial proximity to one another; a phenomenon also referred to as spatial association, autocorrelation, or dependence. In other words, it represents a lack of independence between units that are spatially arranged (Cliff and Ord, 1973). In a neighborhood quality of life context, spatial dependency may arise in a number of ways; neighborhoods close to one another often have similar structural housing characteristics if they were built or developed around the same time period, and will share local amenities. Over time, these structural characteristics will age similarly, and thus, these spatially proximate neighborhoods will have similar values within a metropolitan housing market which, in turn, affects the socio-economic composition of a neighborhood, which may then affect subsequent quality of life indicators of a neighborhood. Similarly, the physical decline of houses or neighborhood features could place a negative externality on adjacent or nearby neighborhoods, so that the demand for one neighborhood depends on the conditions of its neighbors. From a more social perspective, the sociological processes leading to both positive and negative neighborhood effects described in the previous section could also spillover across invisible neighborhood boundaries, creating a spatial spread of social outcomes. Analytically, the boundaries utilized to delimit neighborhoods and aggregate their characteristics may not coincide perfectly with the actual boundaries in which the social, physical, and economic processes are taking place, thus creating a different type of spatial dependency effect.

While spatial dependency and heterogeneity are violations of fundamental statistical analyses and cause inefficiencies, biases, and potentially flawed results when not dealt with, they also offer the possibility to provide additional insights into the process of change. Currently, the role of spatial spillovers or spatial dependence in neighborhood change over time remains an under-studied research area (Ellen and O'Regan, 2010) although is an important consideration from a place-based policy perspective as recognizing potential effects could either help guide the placement of such policies (in the case of positive spillovers), or ignoring them could undermine neighborhood efforts in the case of negative externalities (Thompson, 2008).

2.2.8. Summary of Theoretical Background

A summary of the predominant points of the theoretical neighborhood change literature that are most relevant to this dissertation is provided below.

- In the United States, demographic and economic forces have generally established urban landscapes featuring the poorest and highest concentration of minorities living in small, deteriorating homes toward the urban core, while the wealthiest occupy the newest structures on the outskirts of the city.
- The two major variables contributing to these sorting patterns are distance from the central business district (or employment accessibility) and housing age.
- Neighborhood decline may also be caused by factors completely exogenous to the characteristics of the neighborhood itself; it may be a consequence of being part of a larger, interconnected housing market and submarket.
- Gentrification or inner-city revitalization can be explained as the product of two forces (consumption and production):
    - A shift in <u>consumer preference</u> from large, inaccessible, suburban structures to older, aesthetically unique homes located amidst urban amenities.

    - The devaluation of structures on highly valued land driving producers to make a profit by refurbishing or rehabilitating existing homes.

- Inner-city concentrations of poverty are thought to lead to increases in social problems over time as youths growing up in these neighborhoods are detached from social norms, networks, behaviors, and role models.
- There is a debate in the literature on whether neighborhoods actually cause social outcomes and shape individual behaviors, or if concentrated social problems are simply a reflection of similar people with similar behaviors residing together.
- Social problems may spread across populations, over time.
- Spatial proximity may be important in the neighborhood change process.

2.3. Empirical Studies on Neighborhood Change

The previous section reviewed theoretical foundations for explaining processes or urban neighborhood change. The following section provides an overview of some empirical studies examining neighborhood change according to individual QoL dimensions (economic composition, crime, youth outcomes, and homeownership), and from a multidimensional point of view.

2.3.1. Economic Change

A number of studies have examined change in neighborhood income over time, typically at ten-year intervals, and at the Census tract geography level. Aaronson (2001) described change across all Metropolitan Census tracts within the United States from 1970, 1980, and 1990, and discovered tract median income to be very persistent across time, especially at the higher end. Neighborhood income change was also found to be influenced by spatial spillovers, or the economic conditions of a neighborhood's surrounding area.

In terms of explanatory factors linked to neighborhood income gains or declines, Brueckner (1977) uncovered supporting evidence for filtering theories, showing housing characteristics to be related to neighborhood decline, including lower rates of homeownership and older homes. Similarly, Rosenthal (2008) identified both newly built and very old homes as positively linked to neighborhood income gains. Initial homeownership rates and the presence of college educated individuals were additional significant variables associated with neighborhood economic gains, while a higher concentration of minority residents was associated with losses. Glaeser (2008) further argues that the availability of public transportation plays a role in concentrating lower-income residents within center cities, as the auto-less are necessarily confined to centrally located urban areas where access to public transportation is greatest. Brueckner and Rosenthal (2008) substantiate this notion in an empirical study, concluding that access to public transit reduces neighborhood economic status; however, their measurement of transit access is merely a dummy variable indicating whether more than 10 percent of the census tract population relied on public transit when traveling to work. Such a measure does not capture the *potential* or geographic accessibility available to residents, but simply reflects the need. In other words, there may be higher-income neighborhoods where a large portion of the population is within walking distance to public transit, but residents of these neighborhoods are more likely to own a vehicle and therefore not depend on public transportation as a means of travel. Furthermore, residents that rely upon public transit to travel to work do not necessarily reside in neighborhoods where spatial accessibility to transit is greatest. Therefore, this relationship would benefit from further examination utilizing a measure of spatial accessibility to public transit.

Several studies have focused on change in the most poverty stricken or poorest neighborhoods over time. They have generally uncovered a nationwide increase in poverty concentrations within urban areas between 1980 and 1990 (Kasarda, 1993), and a decline in poverty rates during the 1990s, signifying an improvement in inner-city and downtown neighborhoods nationwide (Ellen and O'Regan, 2008; Jargowsky, 2003; Lee and Leigh, 2007). Spatially, US metropolitan areas have established a general concentration of high poverty neighborhoods in the urban core, while in rapidly growing cities, high poverty neighborhoods have increased in inner-ring suburbs between 1990 and 2000, drawing a link between overall metropolitan economic conditions, and the spatial arrangement of neighborhood poverty concentrations (Cooke and Marchant, 2006; Lee, 2011a).

In predicting the mobility of the highest poverty tracts, both Lee (2011a) and Galster et al. (2003) find a significant, positive relationship with the percentage of renters in a neighborhood and increases in poverty over the course of a decade. This is all the more the case in predominantly white poor neighborhoods as compared to black and Hispanic dominated neighborhoods (Lee, 2011b). Other significant variables related to poverty gains include neighborhood income inequality (Fogarty, 1977) and unemployment levels (Lee, 2011a). Declines in poverty on the other hand, have been shown to be a much more difficult phenomenon to explain, with some evidence pointing towards older, vintage homes (pre-1950s) and higher percentages of owner-occupied housing (Galster et al., 2003). The finding on housing age is consistent with Brueckner and Rosenthal's (2009) updated non-linear filtering model.

Another stream of research has sought to quantify the equality, or inequality, of neighborhood income and explore how disparities evolved over time. This research has provided some evidence that economic inequality increased during the 1990s, but exhibited a slight reversal of that trend during the last decade (Yang and Jargowsky, 2006). This result has varied across metropolitan areas, however, with rapidly suburbanizing or sprawling cities witnessing greater economic disparities between suburban or inner-city neighborhoods as compared to their more compact counterparts (Lee, 2011b; Yang and Jargowsky, 2006). Brueckner and Rosenthal (2009) point to three mechanisms that contribute to the suburban/central city discrepancy in neighborhood economic status: local amenities, public transit access, and the spatial distribution of dwelling ages. Of these, only dwelling age is suggested to have a dynamic component capable of driving changes in the spatial distribution of incomes within a metropolitan area.

2.3.2. Multidimensional Social Change

While neighborhood economic conditions are important predictors or descriptors of a neighborhood's overall quality of life, it is only one aspect of this multidimensional issue. Chow and Coulton (1998) have argued that focusing solely on changes in poverty or economic conditions ignores the greater complexity of social processes in which neighborhoods evolve. Moreover, studies have shown that neighborhoods with high levels of poverty are heterogeneous in nature and so, while some may experience severe social problems, others may not fare as poorly across all dimensions (Longley and Tobón, 2004; Morenoff and Tienda, 1997).

As compared to economic changes which tend to be based on readily available Census data, studying social change across multiple dimensions is often hampered by the availability of longitudinal data. As such, the studies in this vein are limited in number. Chow and Coulton (1998) address the hypothesized increase in social problems in poor, inner-city neighborhoods over time as suggested by Wilson (1987) and Massey and Denton (1993). Utilizing a factor analysis of neighborhoods within the city of Cleveland in 1980 and 1990, the authors reveal an increased interdependence among three categories of neighborhood distress over time and conclude that social conditions did in fact worsen during the decade. No mention is made on the spatial dynamics of change, however. Similarly, in an examination of three dimensions of suburban communities between 1960 and 1970 on Long Island, NY, Collver and Semyonov (1979) found education, occupation, and income to follow different patterns of change across time, warning that a one-dimensional examination of change may overlook this phenomenon.

With a specific focus on the spatial evolution of neighborhood social change in Chicago, Morenoff and Tienda (1997) discovered an increasing spatial concentration of both the wealthiest neighborhoods during the 1980s as well as a spatial spread of ‘ghetto underclass neighborhoods’ during the 1970s, ultimately resulting in an urban landscape of increasing income polarization and inequality. Utilizing a cluster analysis on ten socioeconomic variables to develop a typology of urban neighborhoods in four groups (stable middle class, gentrifying yuppie, transitional working class, and ghetto underclass), the authors identified transitional working class neighborhoods with lower or average socioeconomic characteristics and low levels of education and homeownership to be the most likely to change between 1970 and 1990. These neighborhoods changed by either improving to stable middle class or gentrifying yuppie neighborhoods, or by worsening to become underclass neighborhoods. Neighborhoods that became transitional working class neighborhoods by 1990 were associated with a rapid Hispanic population increase. Underclass and gentrifying/yuppie neighborhoods exhibited the most stability across the study period.

Other empirical work has examined whether or not certain neighborhood QoL indicators exhibit threshold effects, a type of causal relationship where once an indicator reaches a critical value it either causes a dramatic change on itself (endodynamic relationship), or on another indicator (exodynamic relationship). Drawing from contagion and epidemic theories, collective socialization, and preference models, among several others, which all allude to either a critical value or threshold in order for the process of neighborhood social changes to emerge, Quercia and Galster (2000) propose the notion of threshold effects as a working hypothesis after reviewing a number of empirical studies. They find evidence of such threshold effects with regards to both racial and income dynamics of a neighborhood, although the review was unable to detect a single value which represents a 'tipping point'; rather, the cases were unique depending on the neighborhood and metropolitan area context. With regard to socio-economic and housing investment studies, however, more consistent findings were uncovered, leading the authors to conclude that as a neighborhood falls below the median value on a variety of socioeconomic and housing reinvestment indicators, a subsequent increase in a number of problematic behaviors arises, and a decline in favorable behaviors occur. As a neighborhood falls below the lowest tenth percentile of all neighborhoods in terms of disadvantage, an even wider range of problems ensue. Finally, for cases with the top two to three percent poverty and/or non-professional worker rates, the authors conclude that the literature points to a major increase in teen childbearing rate, high school dropout rate, and violent and property crime rate; the definition of a 'major increase' is left ambiguous and in need of further empirical validation.

In a subsequent study, Galster et al. (2000) utilized a spline regression analysis to empirically explore the possibility of both endodynamic and exodynamic threshold effects for conditions in 1980 that may have triggered changes in the following decade. These relationships were tested on four quality of life indicators for all US Census tracts: percentage of female headed families; high school dropout rate; poverty rate; and unemployment. In the endodynamic exercise, the authors examined whether a variable exhibited a threshold-like change on its own value in 1990, and uncovered a clear threshold value only for poverty rate. When poverty rates were as high as 54 percent in 1980 (less than 1% of the sample), a rapid increase in poverty the next time period was recorded. For the exodynamic process, the effect of five variables in triggering a subsequent change in the initial four quality of life variables was tested: percent of people who moved into their home since 1975; percentage of workers not employed in professional/managerial jobs; percentage of occupied units with no car available; vacancy rate; and percentage of renter occupied housing. In this case, the percentage of non-professional/managerial residents exhibited a threshold-like effect on three of the four QoL indicators: female headed families, non-employment, and poverty rate, when its value was in the range of 77 to 83 percent in 1980. Similarly, the concentration of rental housing demonstrated a threshold-like effect on the same three indicators at a rate of approximately 85 percent. The authors note the exploratory nature of the study which was restricted to simple bivariate relationships between two time periods, and specify a need for future work to simultaneously model these relationships in a multivariate setting to better untangle the interrelated complexities of neighborhood change.

Seeking further explorations onto the dynamic processes of neighborhood QoL indicators, Galster et al. (2007) utilized yearly data for several indicators for 3 cities for at least 7 consecutive time periods to determine how neighborhoods respond to exogenous shocks. In other words, do they return to an original stable state, settle in another stable state, or diverge from a stable state? A self-regulating adjustment process promoting stability was found for a number of indicators (rates of tax delinquency, low-weight births, teenage births, and home sales volumes). Violent and property crime rates also exhibited this tendency, but the pace at which neighborhoods reverted back to their initial state was considerably longer, especially in cases of high crime and high poverty rates.

2.3.3. Suburban Neighborhood Change

The spatial and temporal evolution of first-ring suburbs, or those constructed before, during, or immediately after World War II has garnered some attention, as these older suburbs have undergone socio-economic and racial transformations since the 1970s. This more recent work is a continuation of a branch of research that has examined whether and how suburban neighborhoods have changed over time in respect to racial and socio-economic composition. Beginning in the 1960s, the subject of suburban differentiation emerged following two different camps: those that investigated – and found supporting empirical evidence for – the idea of suburban persistence, that even as populations within suburban neighborhoods change, their socio-economic characteristics persist as these neighborhoods consistently attract the same types of people, and those who followed a more ecological view of suburbs, suggesting that suburban neighborhoods do change over time, and the trend followed is one of gradual decline (Vicino, 2008). In the 1990s, several studies began reporting on the changing diversity and decline of suburban neighborhoods (Lucy and Phillips, 2000; Orfield, 1997).

Vicino (2008) analyzed the changing composition of first-tier suburban neighborhoods in Baltimore between 1970 and 2000 (first-tier suburbs were delimited based on distance to CBD and a concentration of housing constructed before 1970). Utilizing a principal components analysis on six categories of data including population characteristics, educational attainment, housing characteristics, and labor market descriptions, the author uncovered shifts in these factors for neighborhoods between the two time frames. Overall, the spatial structure of neighborhood typologies present in 1970 persisted along the class dimension, but changed in terms of racial and age composition. A dramatic decline in overall economic status in these neighborhoods was unveiled, leading to an increase in the overall diversity of neighborhood income levels. Homeownership generally remained high except for in poor and university neighborhoods. Similarly, Lee and Leigh (2007) studied spatial differentiation and inner-ring suburban decline in 4 metropolitan areas between 1970 and 2000. Utilizing a factor analysis on 12 variables representing demographic, socioeconomic, and housing characteristics, the authors compared a factor score representing neighborhood 'distress' between downtown, inner-city, inner-ring, and outer-ring areas for Atlanta, Cleveland, Philadelphia, and Portland, revealing a consistent trend of decline of inner-ring suburbs across all cities, regardless of the city's overall growth trajectory.

Hanlon (2010) provides a summary of recent research that has examined the various aspects of suburban decline. Collectively, the evidence suggests that these older neighborhoods have increased in poverty, declined in income relative to other suburbs, increased in income segregation, experienced a population slowdown and aging existing cohort of residents, and finally, they are undergoing physical deterioration in terms of housing stock, local infrastructure, and obsolete commercial retail strips. Inner-ring suburbs are particularly vulnerable to decline given that they possess neither the accessibility to center city employment and amenities attractive to inner-city revitalization, nor the new, large residences and housing developments growing along the metropolitan fringe (Lee and Leigh, 2005), thus they are caught between two urban spatial dynamics: suburbanization and gentrification. The emergence of other social problems associated with quality of life including crime rates and youth outcomes are often implied to have increased in these same neighborhoods, but there are few, if any, studies which explicitly examine whether or not these problems have too spread to older, suburban neighborhoods.

2.3.4. Crime and Neighborhood Change

Neighborhood crime rates are often thought of as an outcome of the demographic processes that lead to concentrated, inner-city poverty and a subsequent breakdown of social order. Much research on neighborhood crime is based on the notion of social disorganization theory which posits that neighborhoods with high levels of residential instability, economic disadvantage, and physical and social disorder will experience increases in property and violent crime over time (Sampson and Groves, 1989). Ample cross-sectional studies have in fact linked such neighborhood level structural and socioeconomic characteristics with high levels of crime rates (Krivo and Peterson, 1996; Patterson, 1991; Sampson and Groves, 1989).

More recent research has begun to examine the possibility that crime rates may serve as a catalyst for change and ultimately aid in shaping the urban landscape over time. For example, in one of the foremost papers on the subject, Morenoff and Sampson (1997) demonstrated that neighborhood level homicide levels were a significant predictor of population change in the city of Chicago. Furthermore, they provided evidence of an effect of spatial dependence on change over time, showing that rising crime rates in areas surrounding a neighborhood fuels ensuing population losses over the course of the decade. Disparities in the racial response to changes in neighborhood composition have also been shown as violent crime rates generally lead to a decline in white populations, while concentrations of blacks increased within the same neighborhoods (Hipp, 2010; Morenoff and Sampson, 1997; Xie and McDowall, 2010), potentially a result of housing market discrimination or unequal opportunities for residential selection between the two groups.

Recently, Hipp (2010) has conjectured that crime rates elicit a neighborhood's downward trajectory by encouraging an out-mobility of those with the financial resources to relocate and by lowering home values. His study on the reciprocal relationship between crime rates and neighborhood instability concluded that in terms of neighborhood change, crime exerts a stronger impact on a neighborhood's level of disadvantage and residential stability than the reverse, proposing that crime reduces the desirability of a neighborhood and leads to an inflow of lower-income households. This argument finds support in several longitudinal studies that have associated rising violent crime rates with falling home values (Kirk and Laub, 2010; Schwartz et al., 2003; Tita et al., 2006), in some cases dropping below a critical level leading to abandonment and population loss (Cullen and Levitt, 1999). The effect of increasing violent crime rates on housing values has not shown to hold true for property crime rates (Kirk and Laub, 2010). Both property and violent crime rates have been shown to lead to an increase in the number of home sales following higher bouts of crime (Hipp et al., 2009).

Declining crime rates within inner city neighborhoods have also been suggested to spur revitalization or gentrification within a neighborhood, although the empirical evidence on whether or not this occurs is limited (Kirk and Laub, 2010). Schwartz et al. (2003) do find a link between declining crime rates and rising property values in New York City. However, they stress that crime rates alone do not tell the complete story of escalading home values as other factors including changes in school quality and community and public housing investments all aided in increasing neighborhood quality, thereby elevating prices; this work further stressing the importance of a multidimensional study on neighborhood change.

2.3.5. Youth Outcomes

Given the theoretical background of the neighborhood effects literature, which largely seeks to explain youth outcomes, as described in Section 2.2.6, a number of empirical studies have found supporting evidence for a relationship between neighborhood economic conditions – primarily the effects of poverty – and the likelihood of completing high school (Crowder and South, 2003; Harding, 2003), the risk of teenage pregnancy (Harding, 2003), and overall educational achievement (Ainsworth, 2002).

In turn, youth indicators or outcomes such as educational test scores are also hypothesized to shape a neighborhood's income or economic composition as these indicators serve as an assessor of local school quality. School test scores are often readily available online for residents to evaluate in the residential selection process, and thus, the value of the highest performing schools become capitalized in local housing values as the demand for properties assigned to the most desirable schools increases (Bayer et al., 2007; Black, 1999). Thus, as with crime rates, a reciprocal relationship seemingly emerges, youths growing up in the wealthiest neighborhoods are expected to increase in their educational attainment, and refrain from juvenile problems such as dropping out of high school, or unintended pregnancies. As these youth-related indicators improve, the demand for their neighborhoods increase, and the subsequent economic conditions of a neighborhood rises. On the other hand, poor youth indicators may result in a downward spiral, just as crime rates are hypothesized to do.

In addition to enacting economic responses, youth social problems and crime rates are expected to impact one another: educational attainment is commonly associated with crime rates, as education has been argued to be a crime reducing mechanism (Lochner and Moretti, 2004; Machin and Olivier, 2011), while neighborhood violence has been shown to be a significant mechanism affecting adolescent outcomes including high school dropout rates and teenage pregnancy (Harding, 2009).

2.3.6. Homeownership

Homeownership has emerged as a critical factor in neighborhood outcomes – both in the academic literature, as well as in a host of public policy initiatives aimed at reinvigorating struggling urban neighborhoods (Cummings et al., 2002). A high concentration of homeowners in a neighborhood is thought to bring about stability in terms of the length of time residents stay in a home, in maintaining property values and the upkeep of their investments, and in the overall social conditions of the neighborhood (Rohe and Stewart, 1996). A commitment to continued investment in properties by homeowners as compared to renters is thought to lead to increases in housing values, thus elevating the economic status of these neighborhoods, keeping in mind that homeowners in general tend to be wealthier, better educated, and in later stages of their lives (Rohe and Stewart, 1996). A number of studies have also uncovered a direct link between homeownership and several QoL outcomes including a positive relationship with school performance, and a negative relationship with high school graduation rates and teenage pregnancy (Aaronson, 2000; Green and White, 1997; Haurin et al., 2002). Policies aimed at increasing homeownership rates are therefore suggested to produce economic and social benefits to residents.

2.3.7. Summary of Empirical Change Literature

A brief summary of the major relevant points of the empirical change literature is provided below.

- Neighborhood economic inequality is greater in rapidly suburbanizing cities as compared to their more compact counterparts.
- Spatial dependence was found to be a significant explanatory factor of neighborhood economic change and crime rates.

- Middle-aged homes, low homeownership, few college educated individuals, and high public transit access are all associated with neighborhood economic declines.
- Poverty declines are related to older, vintage, pre-1950s housing, and a high percentage of homeowners.
- High poverty neighborhoods are suggested to be heterogeneous in social problems.
- An endodynamic threshold effect was identified for neighborhoods with the highest poverty rates – meaning that a rapid increase in poverty followed ten years later.
- The percentage of non-professional/managerial residents and concentration of rental housing exhibited a threshold-like effect on three QoL indicators in an exploratory study.
- Middle-ring suburban neighborhoods have undergone significant increases in poverty, declines in incomes, experienced physical deterioration and an aging population.
- Crime has been shown to be not just an outcome of neighborhood instability and disadvantage, but also a catalyst for it; increases in neighborhood crime triggers population loss, home sales and declining home values.
- Youth outcomes (education scores juvenile problems such as high school dropouts or teenage pregnancy) are significantly tied to neighborhood-level poverty rates and economic conditions.

- Youth outcomes, in turn, influence a neighborhood's economic growth as neighborhoods assigned to high performing schools witness increased demand and housing values.
- Youth indicators and crime rates have also been shown to influence one another; education has been shown to be a crime reducing mechanism, while youth's growing up exposed to violence do worse in schools.
- Homeownership is linked to neighborhood stability, rising property values, and a direct relationship with youth outcomes.

2.4. Methods For Space-Time and Multidimensional Change

Empirical research on the spatial multidimensional dynamics of neighborhoods has been impeded by two considerable challenges. First, consistently collected datasets of multiple indicators of quality of life at a fine level of geography and time are in short supply. Secondly, there are methodological difficulties associated with analyzing change over time, across space, and across multiple dimensions. This section addresses the literature on that latter point, reviewing some of the methods that have been employed thus far for exploring multidimensional change over time for neighborhood studies, their limitations, and the potential contribution of computational and visualization techniques to overcome these limitations. Methodologies for the statistical analysis of longitudinal datasets from a confirmatory analysis approach are also reviewed briefly.

2.4.1. Multidimensional Change

Given the challenges of examining change across multiple variables, for several time periods, the predominant approach in the literature to these types of analyses is to either create a composite index of variables, or to create typologies of neighborhoods with similar characteristics in order to reduce the number of dimensions. In this regard, principal components analysis (PCA), cluster analysis, and factor analysis, both confirmatory and exploratory, are methods commonly utilized in the literature.

In the PCA approach, typologies are established by reducing a large dataset into several predominant factors, or principal components, and then a clustering technique such as *k*-means is often utilized to group neighborhoods with similar characteristics. In order to visualize change, cluster maps can be compared between time periods to determine the spatial location of neighborhoods that have moved from one class to another (Randall and Morton, 2003; Vicino, 2008). Similarly, factor analysis has been employed to create typologies of neighborhoods based on multiple indicators, and change is determined by examining differences in factor loadings between two time periods (Chow and Coulton, 1998; Randall and Morton, 2003). Pratschke and Haase (2007) extend this factor analysis approach to explore spatial patterns of social disadvantage in Ireland by using factor weighting to compute a standardize score and mapping values for 3 different time periods and visually comparing 3 groups of deprivation: very affluent, about average, and very disadvantaged.

Recently, Kitchen and Williams (2009) proposed a methodology for examining multidimensional social change for neighborhoods where multiple indicators are combined into a single, aggregate score to characterize the socioeconomic status of neighborhoods and neighborhoods are then grouped into ‘high’, ‘medium’, and ‘low’ categories. Contingency tables report on the number of neighborhoods that transition between these groups in 3 different time periods. In the second phase, PCA is used to combine variables and then change in the resulting components is compared across the three time periods. Finally, spatial change is visualized using a series of static maps and symbols for each time period to depict situations of decline, improvement, or stability across time. This methodology is quite limited in its representation of change which is supposed to enable one to identify patterns and trends across time, but only facilitates change as occurring in three states: improvement, decline, or stability, while more details on change between factors must be interpreted from tables of eigenvalues of PCA extracted groups.

All of the studies on multidimensional neighborhood change mentioned thus far are limited in their ability to explore and depict spatial patterns and trends of change over time by their use of static map comparisons which restrict the number of time frames that can be represented and analyzed, provide minimal amount of information related to the changing variables, and rely on human observation to visually detect change (Andrienko et al., 2010b; Skupin and Hagelman, 2005). In addition, the clustering and group techniques utilized provide no mechanism for determining the magnitude of change, or learning about how much change occurs within the clusters themselves. Finally, PCA and factor analysis are constrained in their ability to only consider linear trends or relationships between variables while several QoL indicators have shown to exhibit non-linear trends across time (Galster et al., 2000).

Increasingly, the combination of computational and visualization approaches have been proposed as an effective method to explore large, multidimensional spatial and temporal datasets (Andrienko et al., 2010a; Andrienko et al., 2010b; Guo et al., 2006; Yan and Thill, 2009). Computational methods such as data mining make fewer assumptions regarding data structures and relationships as compared to traditional statistics, while visualization techniques exploit the ability of human vision and intelligence in recognizing patterns, relationships, trends, and anomalies (Yan and Thill, 2009). As an intermediary between purely computational or visual analytical methods, the Self-Organizing Map (SOM) offers advantages of both. It is neural network-based computation method for reducing the dimensionality of large datasets and revealing embedded structures and it generates an inherently visual output for exploring results (Andrienko et al., 2010a; Guo et al., 2005).

Recently, in the context of the analysis of intra-urban neighborhoods, SOM has been used to examine spatial positions of neighborhoods with similar demographic attributes (Spielman and Thill, 2008), to define or examine changes within housing submarkets (Kauko, 2004; Kauko, 2009a; Kauko, 2009b) or of indicators related to neighborhood deprivation (Pisati et al., 2010). In order to analyze multi-temporal, multi-dimensional, spatial data, Skupin and Hagelman (2005) propose a methodology based on the self-organizing map to visualize attribute change of Census tracts by creating trajectories across the SOM attribute space, thus eliminating the need for multiple maps depicting the state of the attributes at each period of time.

The SOM trajectory approach builds upon the more traditional methods of creating multidimensional typologies of neighborhoods, but it enables individual neighborhood trajectories of change to be visualized and explored in relation to these clusters. Because clustering through SOM is controlled by the size of the output space, observations do not necessarily need to be grouped into discrete clusters, as is the case with *k*-means, but can be arranged on the output space according to their similarity across multiple dimensions. This enables research questions to go beyond how many neighborhoods have transitioned from one group to another, but can also explore through which paths neighborhoods follow in attribute space. Further, the visual approach provides a way of identifying neighborhood trajectories that have clearly differed from other neighborhoods with similar characteristics, or outlier trajectories.

While offering a number of advantages over traditional statistical analyses, geocomputational or data mining approaches, such as SOM do suffer from some limitations and criticisms. One major objection leveled at computational methods is that they are a-theoretical, letting the data drive results, rather than testing a stated theory as is the case in statistical analyses. The methods are therefore best suited towards an exploratory data analysis setting where the purpose is to generate, rather than test hypotheses through a process of detecting and describing patterns, trends, and relationships in data.

2.4.2. Modeling Longitudinal Trends

In order to understand or identify factors associated with changes in a neighborhood over a certain time period, a number of longitudinal or panel statistical techniques are available. These include, but are not limited to, multi-level or hierarchical models (Raudenbush and Bryk, 2002), latent growth models (Duncan and Duncan, 2004), group-based finite mixture models (Nagin, 2005), as well as cross-lagged autoregressive models (Finkel, 1995), and fixed and random effects panel models (Arellano and Honoré, 2001). Collectively, these models seek to explain or describe the trajectories followed by individuals (or neighborhoods in this case) over time, the differences between individual trajectories, and enable the identification of explanatory variables to describe why neighborhoods exhibit varying patterns of change. The primary advantage of longitudinal or panel modeling approaches over cross-sectional analytical designs is that they enable a closer approximation of causal processes due to the inherent time ordering of observations. Cross-sectional analyses contain no direct measurement of change in variables over time, or the influence of one variable on the change in a second variable, rather, this relationship must be inferred from a relationship between two variables at a single point in time (Finkel, 2008). Of course all statistical models are accompanied by numerous assumptions that often make truly causal inferences unrealistic.

One category of longitudinal statistical models focus on modeling temporal trajectories followed by observations over time, enabling the estimation of underlying trends utilizing information from full temporal sequences. Examples include multi-level or hierarchical longitudinal data models and latent growth curve models based on a structural equation modeling (SEM) framework. While both sets of models differ slightly in their underlying assumptions and capabilities, they are nearly equivalent in their foundations, and have been shown to produce identical results in most cases (Singer and Willett, 2003). These models provide group-level statistics regarding the average growth rate of the population being modeled, the mean intercept, as well as the individual variation of cases away from this mean. The methods enable hypotheses regarding individual trajectories to be taken by incorporating both time-varying and time-invariant covariates as predictors or explanatory factors of both the slope and intercept variability around the average trend. Individual variability is captured through random effects, allowing each observation to vary according to a normal distribution, while the average slope and intercept are modeled with fixed effects. This multi-level framework can be mapped exactly onto a structural equation modeling setting (Singer and Willett, 2003).

The SEM framework is advantageous in that it enables the simultaneous modeling of change for multiple variables or dimensions. This modeling strategy has recently been employed to help disentangle the relationship between housing turnover/residential instability and crime (Boggess and Hipp, 2010) by simultaneously modeling the two trends.

Both multi-level and SEM growth methods assume that the parameters of the growth curve being estimated are continuously distributed throughout the population according to a multivariate normal distribution. As an alternative, Finite Mixture Models or group-based trajectory approaches use multinomial modeling to distinguish homogenous or distinct clusters of trajectories over time, each of which can have different functional forms (Nagin, 2005). This method rests on the assumption that there are unobserved subgroups or subpopulations within a dataset, each having its own parameter values.

The research questions to be answered help dictate the choice of modeling framework. While the group-based trajectories approaches are useful in depicting ‘clusters’ of neighborhoods that have followed similar trajectories across time, standard growth curve models are better suited towards identifying predictors that help shape the trajectories followed by individual neighborhoods across time (Nagin, 2005). Following some methodological debate and controversy in the literature regarding the Group-Based method’s ability to ‘test’ for the presence of distinct groups within a population, the technique is probably best suited for exploratory analyses of longitudinal trends. One specific limitation of the method is that its semi-parametric nature requires the number of clusters of distinct groups to be determined first, and the procedure will always create or 'find' the specified number of groups within the dataset, even if these are not necessarily statistically distinct groups, as was shown in simulation experiments by Skardhamar (2010). Guidelines do exist to help minimize the arbitrary selection of groups by choosing a model with the fewest number of groups that results in the lowest BIC, for example. A second limitation of the technique is that it assumes that all observations within each group follow the exact trend, without any variability – in contrast to the ML and SEM latent trajectory approaches which model both the mean trajectory and the individual variability around the mean, and enable predictors to explain this individual variability.

Trajectory or growth modeling approaches all operate under the assumption that change is systematically related to time, and that change follows an underlying trajectory of some form. The methods are most appropriate when the objective is to understand the shape of the developmental trajectory over time of a particular response variable. As an alternative, other linear panel analyses can be used to examine change between two or more time points when the research objective is to identify indirect or direct relationships between explanatory variables and the outcome of interest. The simplest example of such a model is a so-called change score model where the dependent variable for an observation represents the difference between its value at time 2 and its value at time 1. This model serves to determine whether change over time is related to a set of fixed characteristics of an individual (or neighborhood) and can be estimated via an ordinary least squares estimator (Finkel, 1995). In order to examine the relationship between two (or more) variables over time, cross-lagged models (also referred to as simplex, autoregressive, conditional, or transition models) provide a framework that enables the testing of reciprocal relationships. Capitalizing upon the temporal ordering of panel data, one can determine if a first dependent variable, *x*, at time point 1 has an effect on a second variable, *y*, at a second time point, and if the value of *y* at time point 1 influences the change in variable *x* at time point 2 (Finkel, 1995).

Other panel analysis methods developed in the econometrics tradition strive to correct for problems of unobserved variables in the causal system, also referred to as unobserved heterogeneity. This problem refers to the fact that when predicting the value of *y* at time t by a variable *x* at time t-1, the change in *y* may be caused by some unmeasured variable, or may be due to some unobservable characteristic of *y*. In either case, the omission of this factor will bias results and potentially lead to a spurious association between *x* and *y* (Finkel, 2008). Econometric models then attempt to correct for this bias by 'removing' or purging the equation of any unobserved or omitted influences, often by pooling all waves of data together and estimating either fixed or random effects. Although there are a number of variations of these models, fixed effects models generally enable intercepts to vary across observations or groups and allow the model error term to be correlated with independent variables; they also prohibit the inclusion of time invariant regressors. Random effects models incorporate a random error term that is uncorrelated with the model error term. Both fixed and random effects models assume that the coefficients of the same covariate remain equal across all waves of data.

CHAPTER 3: RESEARCH QUESTIONS

The previous section provided an overview of the multidisciplinary fields of research contributing to our current understanding on the way in which neighborhoods change over time, and their subsequent consequences on the multifaceted concept of 'quality of life'. One of the major contributions of this research is to link together these fields to help disentangle some of the causes and consequences of change within a dynamic, multidimensional setting. This dissertation will utilize three distinct analytical methodologies that all seek to garner a greater understanding of how neighborhoods change in terms of their QoL, the role of space or geographic location in the process of change, and the impact of differing metropolitan-level economic conditions on neighborhood change.

3.1. Spatial-Temporal evolution of neighborhood quality of life

This first research objective examines the general change patterns and evolution of a combined neighborhood quality of life index over a 10-year time span. It explores the process of change under the context of a rapidly growing and suburbanizing metropolitan area during a decade of that featured two contrasting macro-level economic conditions: the prosperous, 'housing boom' years of 2000-2007, and the economic downturn of 2008-2010. The research reviewed in the previous section suggested that urban neighborhood economic disparities increased in suburbanizing sunbelt cities such as Atlanta during the 1990-2000 decade. How did the more multidimensional measure of QoL evolve across a similarly growing southern city in the following decade? The literature further produced evidence that metropolitan-level economic conditions translated into declining inner-city neighborhood conditions. Utilizing a longitudinal design, this first section also aims at exploring whether or not the *process* of neighborhood change shifted with the change in economic climate. Finally, the literature pointed towards the need for a better understanding of the role of spatial spillovers on change over time (Ellen and O'Regan, 2010). The modeling framework employed in this first analysis explicitly tackles this question.

Specifically, the following research questions will be addressed:

- Has the distribution of QoL values across neighborhoods exhibited signs of a convergence or divergence over time?
- How has the spatial distribution of neighborhood QoL evolved over time?
- Has the probability of a neighborhood moving upward or downward remained consistent throughout the decade?
- Is a neighborhood’s QoL mobility dependent on its past conditions?
- Is a neighborhood’s probability of transitioning dependent upon its immediate local vicinity or is its mobility independent of geographic location?
- How well can we forecast a neighborhood’s QoL status based on spatial-temporal patterns?
- Are there identifiable characteristics of neighborhoods that did not perform as well as their anticipated space-time pattern predicted or of those that performed better?

3.2. Trajectories of multidimensional neighborhood change

Following the aggregate, pattern-based analysis of the previous section, this next research objective seeks to identify individual, disaggregate trajectories of change across the multidimensional attribute space. The literature reviewed in the previous section on multidimensional neighborhood change over time was constrained by both methodological and data limitations to the study of two or three decennial time stamps, leaving much on the intra-decennial dynamics of change unknown.

The purpose of this section is to address some of the limitations of previous work by employing a combined computational and visualization technique based on the Self-Organizing Map to explore the dynamics of neighborhoods across an array of quality of life indicators. This analysis aims at providing insights into the paths (in attribute space) through which neighborhoods change, and contrasts these trajectories for neighborhoods with differing characteristics. The visualization method also enables outlier trajectories to easily be identified, and further examined. Finally, these trajectories are linked with the spatial location of neighborhoods to identify which neighborhoods have become more similar in their QoL characteristics over time.

The specific research questions addressed in this section are:

- What QoL attributes exhibit similar cross-sectional distributions?
- What is the typical QoL profile of neighborhoods that experienced the most change or stability?
- How did neighborhoods that began the decade with a given QoL profile change ten years later?
- Where are neighborhoods with similar QoL profiles located geographically?

- Did geographically adjacent neighborhoods undergo similar transformations in terms of QoL?
- Are there apparent outlier trajectories?

3.3. Explaining QoL indicator trends over time

The previous two sets of research questions largely rely on exploratory analyses. Conversely, this final portion of the study seeks to identify explanatory factors through a confirmatory statistical approach. The objective of this third section is to attempt to disentangle some of the causes and consequences of neighborhood quality of life change through a longitudinal research design. Because the dimensions that comprise neighborhood QoL can be considered both causes and consequences of change, the research questions here explore which QoL dimensions are most responsible for triggering change, and which are a result of changes, thus capturing the reciprocity between dimensions. For example, does the economic condition of a neighborhood determine subsequent changes to the social, crime, and physical dimensions, or do social changes within a neighborhood lead to greater economic changes? Furthermore, variables drawn from the literature review on neighborhood change will also be tested for shaping neighborhood QoL including housing age composition, employment and transit accessibility, and the racial\ethnic composition.

Specifically, the research questions to be addressed:

- What are the temporal relationships between 4 QoL dimensions? Is there evidence that the dimensions exert reciprocal relationships on one another?
- How do independent variables such as house age, distance from CBD, racial\ethnic composition influence change across these dimensions?

- What is the role of spatial dependence in shaping change across these dimensions?
- How do the dynamic processes change at different temporal lags, and throughout the decade?

CHAPTER 4: RESEARCH DESIGN

4.1. Data and Study Area

Charlotte is the largest city in the state of North Carolina and one that has experienced rapid population growth and urban expansion in recent years. According to US Census estimates, between 2000 and 2010, the city grew from 540,828 to 731,424 residents, a 35 percent increase, while its county, Mecklenburg, experienced a 32 percent change in population. This population growth spurt has been accompanied by a rapidly suburbanizing landscape, combined with center city construction in the form of high end apartment buildings and condominiums giving rise to the downtown skyline. Figure 1, below illustrates the extent and spatial distribution of residential housing construction within Mecklenburg County during the 2000-2010 decade. The study area for this research, the city boundary, and its 'local sphere of influence' defined as areas of the county that are anticipated to be incorporated or annexed by the city are also illustrated to place the growth in context of the greater region. Notably, the city has also witnessed a sharp increase in its Hispanic population since the 1990s, primarily residing in older, suburban neighborhoods where the availability of rental housing is prevalent (Smith and Furuseth, 2004).

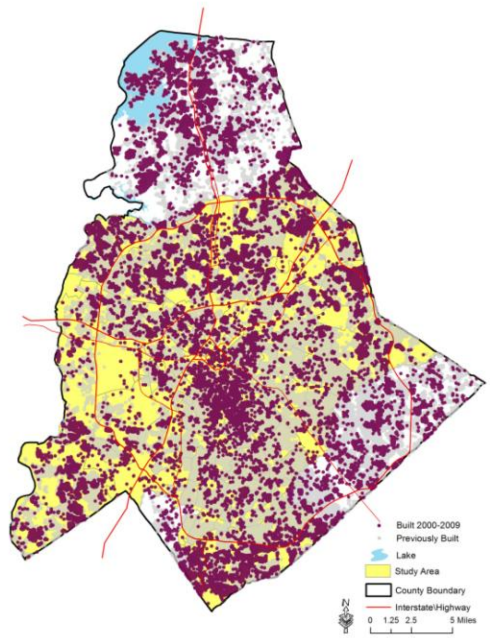

Figure 1. Mecklenburg County Residential Housing Growth, 2000-2009

Economically, this population growth has been supported by the second largest banking concentration in the country, home to Bank of America's headquarters and until very recently, Wachovia, now Wells Fargo's eastern headquarters, along with a host of supporting financial services. Downtown gentrification and revitalization has been aided by these corporations in hopes of attracting skilled workers to the city (Smith and Graves, 2005).

The primary source of data for this research comes from the Charlotte Neighborhood Quality of Life Study, which was first developed in 1997 for 73 inner-city neighborhoods, but expanded to encompass 173 neighborhood statistical areas (NSA), units of analysis similar to US Census block groups, but customized for the Charlotte region based on community feedback to more closely represent perceived neighborhood boundaries, covering the entire city limits and its sphere of influence in 2000. The index is created with a set of variables representing the social, economic, physical, and criminal aspects of each NSA and is repeated on a two year basis. The selection of variables to include was initially made through a collaborative effort with city and county representatives and over time, variables were added to the index while others were removed, but for the purpose of this study, only the common variables available for 2000-2010 are incorporated. Table 1 below provides a description of the variables used to create the QOL index as well as the source of data.

Table 1. Variables used to compute QoL Index

	Impact on QoL	Description	Source
Social Dimension			
% Age 64+	Negative	Percentage of Population age 65 years and older	Claritas
Kindergarten Score	Positive	Average math and verbal score for each kindergarten student at the end of each year	Charlotte-Mecklenburg School System
Dropout Rate	Negative	Percent of high school students who dropped out of the school system	Charlotte-Mecklenburg School System
% Passing Competency Exam	Positive	Percent of students passing 9th grade competency exams	Charlotte-Mecklenburg School System
% Births to Adolescents	Negative	Percent of children born to women 18 years and younger	Mecklenburg County Health Department
Youth Opportunity Index	Positive	Measure of potential opportunities for youths to be involved in.	Charlotte Area YMCAs Charlotte-Mecklenburg Library system, Parks and Recreation department, School System
Physical Dimension			
Appearance Index	Negative	Index of code violations	Neighborhood Development

Table 1 Continued

Home Ownership	Positive	Percent of owner-occupied residential units	Mecklenburg County Property Records and Land Management
Infrastructure Improvement Costs	Negative	Estimated public construction costs for sidewalk, curb, minor drainage	Charlotte Engineering and Building Maintenance
% Access to public transportation	Positive	Percent of housing units within ¼ mi. of bus stop, ½ mi. light rail station.	Charlotte Area Transportation System
% Access to basic retail	Positive	Percent of housing units within ¼ mi. of grocery store or pharmacy	Mecklenburg County Property Records and Land Management, Bell South Yellow Pages, Charlotte
Economic Dimension			
% Change in Income	Positive	Percent change in median household income	Claritas, Census
% Food Stamps	Negative	Percent of population receiving food stamps	Mecklenburg County Department of Social Service Office of Planning and Evaluation
Crime Dimension			
Violent Crime Rate	Negative	Location Quotient of homicides, rapes, robberies, aggravated assaults for each NSA	Charlotte-Mecklenburg Police Department
Juvenile Arrest Rate	Negative	Location Quotient of arrests of individuals under the age of 16 for each NSA	Charlotte-Mecklenburg Police Department
Property Crime Rate	Negative	Location quotient of burglaries, larcenies, vehicle thefts, arsons, vandalism	Charlotte-Mecklenburg Police Department
Crime Hot Spots	Negative	Proportion of NSA that has a durable concentration of violent crime	Charlotte-Mecklenburg Police Department

4.2. Research Objective 1 Methodology

The first research objective utilizes a combined QoL Index to explore its evolution across space and time, and to understand the process of change through an examination of neighborhood transitions. The overall index is computed as follows: for each variable in each year, a z-score is computed; then the values associated with each of the four dimensions (social, physical, economic, and crime) are summed (or subtracted if the variable has a negative impact on QoL), and the summed component values are standardized. Finally, a weighted sum is computed to create the overall QoL index where the social, physical, and crime dimensions receive a weight of 0.3 and the economic dimension is weighted at 0.1. The difference in weighting scores is reflective of the fact that the economic dimension has only two variables, so giving that dimension equal weighting in the overall Index as dimensions with 4 and 6 variables would give the two comprising variables, change in income and food stamps, a stronger influence than the other individual variables[1]. Finally, the overall index is once again standardized to create each year's score. The standardization procedures effectively make all neighborhood scores relative to other neighborhoods in the same time period. The benefit of this method in examining transitions is that is enables the probability of improving or declining relative to other neighborhoods to be isolated from larger, uncontrollable effects. For example, education competency scores fluctuate yearly depending on the test, so a neighborhood may appear to improve drastically, whereas in reality all students

[1] To examine the influence of this weighting scheme on the overall results of the study, the analysis was also performed utilizing a variable where each component was weighted equally (0.25). The conclusions reached from both analyses were identical, and estimated transition matrices were qualitatively the same. Similarly, the analysis was also run utilizing each of the 4 dimensions separately resulting in qualitatively equivalent results.

across the city may have performed better on that particular test. Similarly, changes in annual city budgets stipulate the amount of money to be spent on infrastructure or policing. The standardization procedure also controls for an overall improvement trend experienced by all neighborhoods in Charlotte over the decade as the city has grown economically. Moreover, from a consumer perspective, evaluating relative neighborhood change in deciding to invest in a neighborhood is argued to be more relevant than absolute change; Galster (2001) notes that market prices are often based on comparisons of competing neighborhoods, and so if the absolute value of a neighborhood's income, crime, or school quality, for example, does not rise at least as quickly as other neighborhoods within a metropolitan area, the absolute change will not factor in the consumer perception of the neighborhood's quality. Standardization therefore controls these effects and allows this study to focus on relative transitions over time; additionally, the method is consistent with the economic convergence literature employing Markov chain analyses which use relative per capita income to control for inflation, business cycles, and global shocks (Bickenbach and Bode, 2003). One drawback to the approach is that it eliminates the possibility of making statements regarding a neighborhood's absolute improvement or decline.

4.2.1. Markov Process

In order to assess the improvement or decline of neighborhoods over time, Markov chains provide a simple, stochastic framework for describing the biennial transitions over the course of the decade. Theoretically, a first order Markov chain states that the probability of a random variable, X, being in state (or class) j at time t depends only on the state i of X, at time $t-1$, and not on states at previous time periods. The probability of transitioning from states *i* to *j*, represented in a Markov transition matrix (***M***) is simply the relative frequency of transitions between states over the entire time period, each transition probability m_{ij} is estimated by a maximum likelihood estimator (Eq. 1) (Bosker, 2009).

$$\widehat{m}_{ij} = \frac{\sum_{t=1}^{T-1} n_{it,jt+1}}{\sum_{t=1}^{T-1} n_{it}} \quad (1)$$

Where $n_{ij,jt+1}$ is the number of neighborhoods moving from class *i* in year *t* to class *j* in *t* +1 and n_{it} is the total number of neighborhoods in class *i* over the entire time period (*t*). ***M*** is the (k,k) matrix representing the probability of transitioning between states:

$$\boldsymbol{M} = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1k} \\ P_{21} & P_{22} & \dots & P_{2k} \\ \dots & & \dots & \dots \\ P_{k1} & P_{k2} & \dots & P_{k3} \end{bmatrix}$$

States, or classes, in this case are established by pooling the six time periods together and calculating quintiles to serve as cutoff values, thus creating classes with similar numbers of observations within each group (Bickenbach and Bode, 2003; Bosker and Krugell, 2008; Le Gallo, 2004). There exists some debate in the literature on the formation of classes as changes to class breaks can lead to alternate results (Magrini, 1999), a situation that is especially problematic when using matrices to estimate ergodic distributions, which is not the objective of this study. The discretization procedure suggested by Magrini (1999) is to more closely approximate class breaks that follow continuous kernel density plots, however, as pointed out by Bosker (2009) and Le Gallo and Chasco (2008), the classes representing the tails of the distribution contain few observations making transition probabilities unreliable. Given that this study has only 6 time periods and 173 observations to work with, having adequate observations per class is the first priority.

Five classes are therefore established: 1) values in the 0-20th percentile, 2) 20-40th percentile, 3) 40-60th percentile, 4) 60-80th percentile, and 5) > 80th percentile. Classes 1 and 2 contain values below the mean of the entire decade, while classes 4 and 5 are greater than the mean.

4.2.2. Time Independence

Given that a first order Markov transition probability depends on values from the previous time period, but is independent of its state in time periods prior to that, it is necessary to test temporal independence to determine whether or not this is a reasonable assumption in the case of neighborhood QOL dynamics. Furthermore, such a test helps shed light on the time lag of transitions. In the first order case, the assumption is that a neighborhood's state or class in time *t* + 1 (2 years) depends on its class two years prior (in time *t*), but not on its class 4 years ago (*t*-2). A second order process would depend on both time *t*- 1 and *t*- 2, and higher orders would continue to depend on longer time periods. Following (Bickenbach and Bode, 2003; Le Gallo and Chasco, 2008; Tan and Yilmaz, 2002), orders are tested in sequence, beginning with order 0 which assumes that the temporal process is completely independent of the past. In this test, the null hypothesis is that the Markov chain is of order 0, and the alternative is of an order greater than 1 $(H_0: \forall_i: p_{ij} = p_j(i = 1, \ldots K), H_a: \exists i: p_{ij} \neq p_j)$. If the hypothesis cannot be rejected, the process is taken to be of order 0, otherwise, higher orders are tested. H_0 is computed as $\hat{p}_j = n_j | n$, where $n_j = \sum_t n_j\,(t)$ and the alternative is calculated according to Eq (1). A likelihood ratio test statistic following a chi-square distribution is used to compare transition matrices:

$$LR^{(O(0))} = 2 \sum_{i=1}^{K} \sum_{j \epsilon A_i} n_{ij}(t) \ln \frac{\hat{p}_{ij}}{\hat{p}_i} \sim asy\, \chi^2[(K-1)^2] \quad (2)$$

Where $\hat{p} > 0 \forall j (j = 1, \dots K)$ $A_i = \{j\colon \hat{p}_{ij} > 0\}$ is the set of nonzero transition probabilities for H_a.

To test for higher orders, beginning with the second, the transition matrix is decomposed to include the state of the neighborhood at time *t*-2 as an additional condition. For example, all neighborhoods in class 1 at *t*-2 are assigned to a first sub-matrix (*k*=1), and transition probabilities from class *i* to *j* between time *t*-1 and *t* are estimated ($\hat{p}_{kij}$); this is continued for all sub-matrices (*k=1…K*). The null hypothesis, order 1, is tested against the alternative, order 2: $H_0\colon \forall k : p_{kij} = p_{ij} (k = 1, \dots, K), H_a : \exists k : p_{kij} \neq p_{ij}$. The likelihood ratio test statistic is as follows:

$$LR^{(O(1))} = 2 \sum_{k=1}^{K} \sum_{i=1}^{K} \sum_{j \epsilon C_{hi}} n_{kij} \ln\left(\frac{\hat{p}_{kij}}{\hat{p}_{ij}}\right) \sim asy\ \chi^2 [\textstyle\sum_{i=1}^{K} (c_i - 1)(d_i - 1)] \quad (3)$$

Where $C_i = \{j : \hat{p}_{ij} > 0\}, \mathrm{c}_i = \#C_{i,} C_{ki} = \{j : \hat{p}_{kij}\}$ and $d_i = D_i = \#\{k : n_{ki} > 0\}$. The degrees of freedom are therefore computed by summing the number of cells in first row (*i*) of the first order transition matrix (from Eq. 1), subtracting 1, and multiplying by the number of *k* matrices which contain a non-zero value in the corresponding row, minus 1.

4.2.3. Time Homogeneity

In addition to time independence, Markov processes are assumed to be time homogenous, meaning the transition probabilities between classes are similar throughout the entire time frame. To test the assumption, the data are divided into two *m* time subsets: 2000-2006 and 2006-2010. It is desirable to select subdivisions so that they are approximately the same length of time (Bickenbach and Bode, 2003). The likelihood ratio test statistic is calculated to determine if the two matrices are statistically different from one another and from the overall matrix:

$$LR^{(M)} = 2\ \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j\in A_{i|j}} n_{ij|m}\ln\frac{\hat{p}_{ij|m}}{\hat{p}_{ij}} \sim asy\ \chi^2\left(\sum_{i=1}^{N}(a_i-1)(b_i-1)\right) \quad (4)$$

where $A_{i|m} = \{j\colon \hat{p}_{ij}>0\}$ are the non-zero transition estimates in row i, for the mth sub period and $A_i = \{j\colon \hat{p}_{ij}>0\}$ are the same estimates for the entire time period, estimated by Eq(1). To further examine the process of change before and after the economic downturn, the last time frame can be segmented between 2006-2008 and 2008-2010. While the number of observations within this case may be too small to make statistical inferences, a comparison of the transition matrices can provide a descriptive insight into whether or not the process differed.

4.2.4. Spatial Markov Matrices

The purpose of the spatial Markov analysis is to decompose the transition matrices presented above and make transitions conditional upon the class of a neighborhood's spatial lag, or the average value of its neighbors (Odland, 1979; Rey, 2001). When the conditional spatial matrices are compared to the non-spatial matrix, the effect of spatial dependence on transition over time can be examined. This test is identical to the time independence test where probabilities were made conditional on their past states, but here they are conditional on the average value of the neighbors. In addition to the average, other neighborhood specifications can also be tested such as the median, mode, and upper and lower quintiles to examine the robustness of the spatial spillover effects.

To calculate the spatial Markov matrices, the entire sample is divided into *S* subsamples, so that all observations for neighborhoods whose neighbors fall in the lowest QoL class are allocated to the first subsample (s=1), and so on. In order to test the hypothesis that the initial transition probabilities are independent of space, and do not depend on the values of surrounding neighborhoods, or the spatial lag, the transition probabilities under $H_0\colon \forall s : p_{ij|s} = p_{ij} (s = 1, \ldots, S)$, are compared to those under $H_a : \exists s : p_{ij|s} \neq p_{ij}$, using the LR test statistic similar to (4) (Bickenbach and Bode, 2003). The Markov analyses and corresponding tests are all computed using customized scripts written in the Python programming language.

4.3. Research Objective 2 Methodology

For the second research objective, the input variables are not combined into a single indicator. Rather, for each NSA, all variables are entered into the SOM procedure, described in the following section, for each of the 6 time periods. One modification is made to the variables in Table 1 for the SOM analysis, percent change in median household income is replaced with median household income, as change in each of the variables is explicitly explored through the analysis procedure.

4.3.1. Self-Organizing Map

A self-organizing map is an artificial neural network (ANN) developed by Kohonen (1990) that projects multidimensional input data onto a lower dimension output space (normally 2 dimensions) in such a way that similar observations across the multiple attributes are located in proximity to one another on the output space; thus, the SOM performs both clustering (quantization) and dimensionality reduction (projection). Like all neural networks, a SOM consists of a set of input and output nodes, also referred to as neurons. Each neuron, *k*, is represented by a weight, or an *n*-dimensional vector such that $m_k = [m_{k1} \ldots m_{kn}]$ where *n* is the dimension of the input space. The set of weight vectors is referred to as a codebook and neural network training or learning is largely concerned with determining the weights associated with each neuron. As an unsupervised neural network method, the input nodes are not associated with a given set of outcomes or classes (as is the case in supervised learning); rather, the output nodes compete for input vectors according to a similarity function and the weights of the winning nodes are adjusted accordingly (Skupin and Agarwal, 2008).

Output nodes have a definite topological position (an x, y coordinate) and shape, which determines the connectivity between a given node and adjacent nodes. The most common topology type is hexagonal, which forms a connectivity of six neighborhoods per neuron (a square topology would connect with 4 neurons). The size of the output grid is determined a priori, with a small number of output nodes forcing the SOM to behave solely as a clustering technique, and a very large number of nodes (exceeding the number of input observations), enabling the emergence of structures. Kohonen (1990) recommends an asymmetrical shape be used, rather than a symmetrical one to avoid edge effects. His recommendation is that the short size length should be at least ½ as long as the longer side. For the purpose of this research, an intermediate number of nodes is selected, smaller than the number of input nodes to allow clustering where observations are very similar, but with enough output space to visualize longitudinal change. The final map size of 20x8 neurons is determined by a procedure built into the SOM toolbox in Matlab which seeks to establish an output space that minimizes the chance of creating a SOM with too many empty cells, thereby increasing the computational efficiency of the training algorithm.

The first step in the training process is to assign initial weight values to each neuron, a procedure referred to as initialization. There are two commonly used strategies for this step: a random initiation, where the weight vectors are assigned a random value, and linear initialization, where weight vectors are designated according to a linear estimate derived from the two principal components of the input dataset. This latter method is computationally more efficient and therefore recommended (Skupin and Agarwal, 2008; Vesanto et al., 1999).

Training the SOM is an iterative process, at each step, a random input vector, *x*, is selected and presented to the output neuron grid, where the nodes 'compete' for *x* based on the similarity of the input's vector of attributes, and each neuron's weight value. Similarity is computed as a Euclidean distance between *x* and all of the codebook vectors; it is therefore imperative that all of the input attribute values be normalized onto the same measurement scale before entering into the SOM procedure. The neuron with the weight vector closest to *x* is denoted the Best-Matching Unit (BMU). This winning output node's codebook values are then updated, and neighboring nodes are moved towards the input vector *x* according to the following update rule:

$$m_k(t+1) = m_k(t) + \propto(t) h_{ck}(t)[x - m_k(t)], \qquad (5)$$

where t represents the time step, h_{ck} is a neighborhood kernel centered on the winning node, m_k, and $\propto(t)$ is the learning rate at time t. Once the BMU is determined, the radius of the neighborhood around that BMU is calculated and the weight of any node that falls within that radius is updated to become more similar to the input vector; the closer the node is to the BMU, the greater its weight is impacted. Different functions can be used to represent the neighborhood area, the most common being a Gaussian function. The learning rate can take also on a number of forms including a linear function, a function inversely proportional to time, or according to a power series. Both the neighborhood radius and learning rate are set to higher values initially, for example, the size of the

Gaussian kernel may begin at a size covering nearly the entire map, but gradually decreases as the number of training iterations increases to fine tune the output SOM map (Skupin and Agarwal, 2008; Vesanto et al., 2000).

The previous paragraph described the traditional sequential training algorithm of the SOM, however, one variation of that algorithm which achieves significantly improved calculation time with equally good, if not better results (Vesanto et al., 1999) is the batch training algorithm. Also iterative, in the batch algorithm, the entire dataset is presented to the output space prior to any adjustments being made, whereas the sequential algorithm processed each vector individually. Weight vectors are then calculated as:

$$m_i(t+1) = \frac{\sum_{j=1}^{n} h_{ic}(t) x_j}{\sum_{j=1}^{n} h_{ic}(t)}, \qquad (6)$$

where c = the index of the BMU of data sample x_j. The new weight vector is a weighted average of the data samples, where the weight of each data sample is the neighborhood function value $h_{ic}(t)$ at its BMU c.

Once the SOM is trained, and each neighborhood, at each time period has been assigned to a node, the location of these nodes can be used to create change trajectories of each neighborhood on the output space. This procedure, along with the format of the input data, is illustrated in Figure 2. In the figure, the location of a neighborhood on the hexagonal output space is identified for six time periods. A line connects the centroids of the hexagons, creating a directed line where the nodes for each time period serve as the vertices of the line.

Sample Input Data

NSA-ID	Year	Age64	Kinder	Label
1	2000	-0.32	-0.34	NSA1Yr1
1	2002	0.60	0.29	NSA1Yr2
1	2004	0.53	1.67	NSA1Yr3
1	2006	0.78	0.00	NSA1Yr4
1	2010	0.89	0.02	NSA1Yr6
2	2000	-0.78	0.22	NSA2Yr1
2	2002	0.48	0.29	NSA2Yr2
...	...	...	...	...
173	2010	1.84	0.83	NSA173Yr6

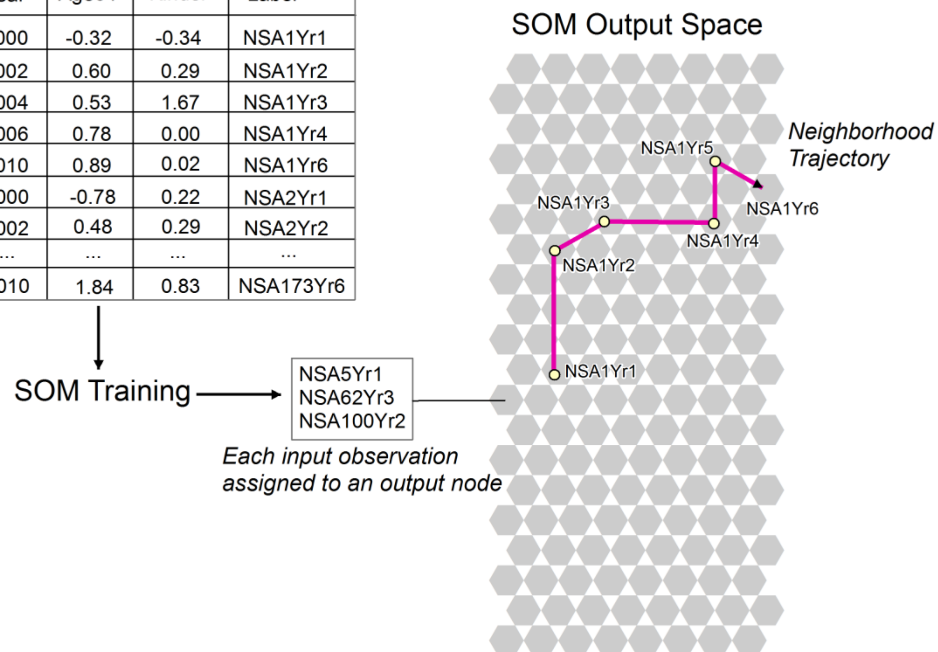

Figure 2. Creation of neighborhood trajectory on SOM output space.

Displaying the trajectories of all neighborhoods simultaneously on the output spaces creates an un-interpretable situation. Therefore, to make sense of the results and to address the specific research questions, a clustering procedure is used on the neuron weights to establish homogenous regions of nodes. Trajectories corresponding to very similar neighborhoods can then be displayed at once to make comparisons across groups. Figure 3 illustrates these steps; the first image shows the 20x8 hexagonal output space, the second shows all neighborhood trajectories displayed at once, and finally the third highlights two clusters on the output space, and 1 set of trajectories. The clustering phase is performed in two steps, first a Ward's hierarchical clustering will be used on the codebook values to determine an appropriate number of clusters, followed by a *k*-means approach to delimit the extent of the clusters.

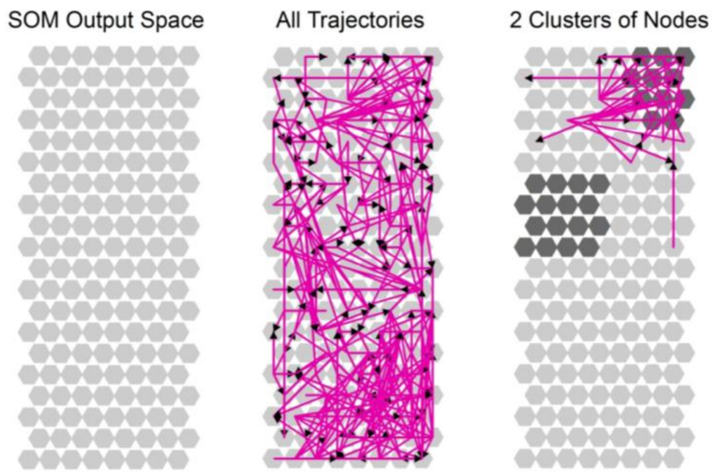

Figure 3. Example of SOM Trajectory Methodology

SOM Toolbox for Matlab, a free extension program (Vesanto et al., 1999) is used for the SOM training portion of the study, and subsequently, output nodes, codebooks, and labels are then all imported to ArcGIS for visualization. The batch training algorithm is utilized with a Gaussian neighborhood function. The Matlab procedure trains the map in two phases where the initial learning rate begins at 0.5 in the first phase and 0.05 in the second phase, while the neighborhood radius starts from max(mapsize)/4 initially and reduces to ¼ of that in the first phase (unless the value is reduced below 1), and in the second phase, the raidus begins where it stopped in the first phase and diminishes to 1. In order to create change trajectories, a Python script is written that creates directed lines for each neighborhood observation where its location at each of the 6 time periods on the output space serves as the vertices of its trajectory. Finally, trajectories, output nodes, and the geographic map of Charlotte are all linked within ArcGIS via relational joins.

4.4. Research Objective 3 Methodology

The third research objective utilizes a confirmatory statistical approach to model the temporal relationships between 4 QoL dimensions: youth social indicators, economic, crime, and homeownership[2]. For this analysis, a cross-lagged panel model is selected as it enables the testing of the hypothesized reciprocal relationships between QoL dimensions. The models are estimated within a structural equation model framwork, which enable the simultaneous estimation a system of equations. While other longitudinal modeling approaches such as multilevel models or latent trajectory approaches possess some appealing attributes, they have a number of limitations which render them unsuitable for this analysis. Perhaps foremost is the assumption that the dimensions being modeled follow a consistent trend or trajectory across time (linear, quadratic, or any other function). This is a problematic assumption for two reasons: first, there is no theoretical reason to suggest that neighborhood QoL or any of its comprising dimensions follow such a persistent trend across time, and second, data used in the analysis are removed of any trends during the normalization process. A second major limitation to those approaches is the number of observations (n=173) available in the dataset: in order to simultaneously model the changes across multiple dimensions for an entire longitudinal series, a much larger number of observations would be needed. The number of parameters to be estimated will quickly exceed the number of observations. Given these realities, the cross-lagged model will be used to examine change between two time points (again, larger number of panels is infeasible given the data constraints).

The cross-lagged model features a temporal autoregressive parameter of the dependent variables so that prior values of Y have a direct influence on Y at a given point

[2] The explanation and justification behind the selection of these dimensions is in Section 5.3.1

of time. There are a number of theoretical reasons why the four dependent variables (crime concentrations, youth social indicators, economic conditions, and homeownership levels) are assumed to exhibit such a so called 'state dependence' in the neighborhood change processes; in fact it would be unreasonable to expect that the values of these variables would be created anew at each time interval. The inclusion of this autoregressive parameter offers insight onto the stability of the change process, and also provides some protection against unobserved heterogeneity bias (Finkel, 2008).

The model specification for two temporal variables with a set of time independent predictors can be represented by the following equations (more than two time periods can be generalized from this example):

$$Y_{1(t+1)} = \beta_1 Y_{1t} + \beta_2 Y_{2t} + \Gamma_1 \mathrm{X_t} + \zeta_1 \tag{7}$$

$$Y_{2(t+1)} = \beta_3 Y_{2t} + \beta_4 Y_{1t} + \Gamma_2 \mathrm{X_t} + \zeta_2 \tag{8}$$

Where in eq. (7), the outcome of $Y_{1(t+1)}$ is the value of variable 1 in an NSA at the next time point, Y_{1t} is variable 1 in NSA at the current time point, which has a β_1 effect on variable 1, in the next time period (autoregressive parameter), Y_{2t} is variable 2 for a neighborhood that has a β_2 effect on variable 1, $\mathrm{X_t}$ is a matrix of other neighborhood characteristics measured at the beginning of the decade, and Γ_1 is a vector of parameters showing the effects of these characteristics on variable 1, and ζ_1 is a disturbance term. In equation 8, all terms are the same, and $Y_{2(t+1)}$ represents the value of the second variable in the second time period. In the equations, the values of β show the relationship between the temporally measured variables. The model assumes a time-lag in the causal system and so none of the endogenous (dependent) variables are assumed to cause the others instantaneously, rendering the model recursive, and easily identifiable.

Furthermore, the disturbances between the endogenous (dependent) variables (ζ_1 and ζ_2 in eq. 9 and 10) are allowed to covary in case a common correlation among error terms exits. Such error correlation may be due to an omitted variable that simultaneously causes several of the outcome variables. Allowing for disturbance correlation among the system of equations produces a model similar to a set of seemingly unrelated regression equations (Bollen and Davis, 2009; Drukker, 2011). Failing to account for this potential error covariance will lead to biased estimates in the equations, and is one of the motivations for modeling the equations simultaneously (Felmlee and Hargens, 1988). The model operates under the assumption of multivariate normality of all variables; it is furthermore assumed that the disturbances are uncorrelated with any of the independent variables, and that the variables contain no measurement error.

The model can also be extended to incorporate spatial lag effects, or the influence of surrounding neighborhoods on the outcome. For example, Hipp (2010) illustrates the inclusion of a spatially lagged outcome variable, or spatial autoregressive parameter, as well as a spatially lagged cross-lagged measure. In this regard, equations 9 and 10 would be expanded so that the value of $Y_{1(t+1)}$ is also a function of its value in surrounding neighborhoods, and the value of Y_2 in surrounding neighborhoods in the current time point. This is expressed as follows:

$$Y_{1(t+1)} = \rho_1 WY_1 + \rho_2 WY_2 + \beta_1 Y_{1t} + \beta_2 Y_{2t} + \Gamma_1 \mathrm{X_t} + \zeta_1 \quad (9)$$

$$Y_{2(t+1)} = \rho_3 WY_1 + \rho_4 WY_2 + \beta_3 Y_{2t} + \beta_4 Y_{1t} + \Gamma_2 \mathrm{X_t} + \zeta_2 \quad (10)$$

where all terms are defined as before, W is the spatial weight matrix, WY_1 is the spatially lagged outcome variable that has ρ effect on the outcome (spatial autoregressive parameter), WY_2 is the spatially lagged cross-lagged measure that has ρ_2 effect on the outcome. The inclusion of these parameters controls for spatial effects where the conditions of surrounding areas are presumed to have a causal influence on a neighborhood's condition. The omission of spatial lag effects when present is equivalent to omitted variable bias.

All models are estimated using a Maximum-Likelihood (ML) procedure in the software LISREL 8 (Jorenskog and Sorbom, 1994). Within an SEM framework, the ML procedure effectively finds the estimates of the unknown parameters, which, taken together, minimize the difference between the implied and actual variance-covariance matrices (Finkel, 2008). Model fit of the system of equations is evaluated on how well the hypothesized model is consistent with the data. A number of model fit parameters are used to gauge this consistency.

One key unresolved issue in the neighborhood change literature is the length of time it takes for neighborhood changes to become realized (Hipp, 2010). In other words, what is the appropriate time lag in which to expect to observe the hypothesized temporal relationships? Ten year time lags are commonly used in empirical change studies – the justification for this is generally data-driven: Census surveys are released at decennial intervals. However, this length of time may be too long to capture some shorter term changes, especially in a rapidly transforming urban area such as Charlotte. Furthermore, the temporal lags for recording changes may not be equivalent across all dimensions – for example, modifications to a neighborhood's homeownership or income levels may be slower than changes to its crime rate. One of the contributions of this analysis is to examine changes across four different time lags during the previous decade, specifically: 2000-2002; 2000-2004; 2000-2008, and 2000-2010. In addition to providing some insight as to the pace of changes, this temporal analysis also highlights the dynamics of QoL change at various time intervals during Charlotte's decade of both suburban and downtown growth.

CHAPTER 5: RESULTS

5.1. Research Objective 1

5.1.1. Distribution of QoL

The distribution of the combined QoL index for neighborhoods over the six time periods is first explored both spatially and non-spatially. Kernel density plots provide a non-parametric look at the numerical distribution of values in each time period; the six plots are shown in Figure 4 and can be interpreted as continuous histograms. Overlaid on one another, the plots reveal a general improvement of low QoL values over time and a shrinking disparity between low and high-valued neighborhoods from 2000-2010. This increase in inequality is evidenced by the difference in peaked values between 2000 and 2010. The plot for 2000 has a lower peak and is skewed towards the higher QoL values; in addition, a small plateau is shown for the curve around -2, indicating a larger number of neighborhoods with negative values. In contrast, the peak for 2010 is closer to the mean, creating a narrower curve, indicating that fewer observations have values above and below the mean. A small crest is also shown to the right of 0 for 2010, again indicating a general improvement trend over the 10 years. Collectively, these kernel estimations provide some evidence that neighborhoods within the city of Charlotte and its immediate surrounding area have exhibited a convergence of QoL values over the course of the decade, in spite of the recent hardship created by the great recession.

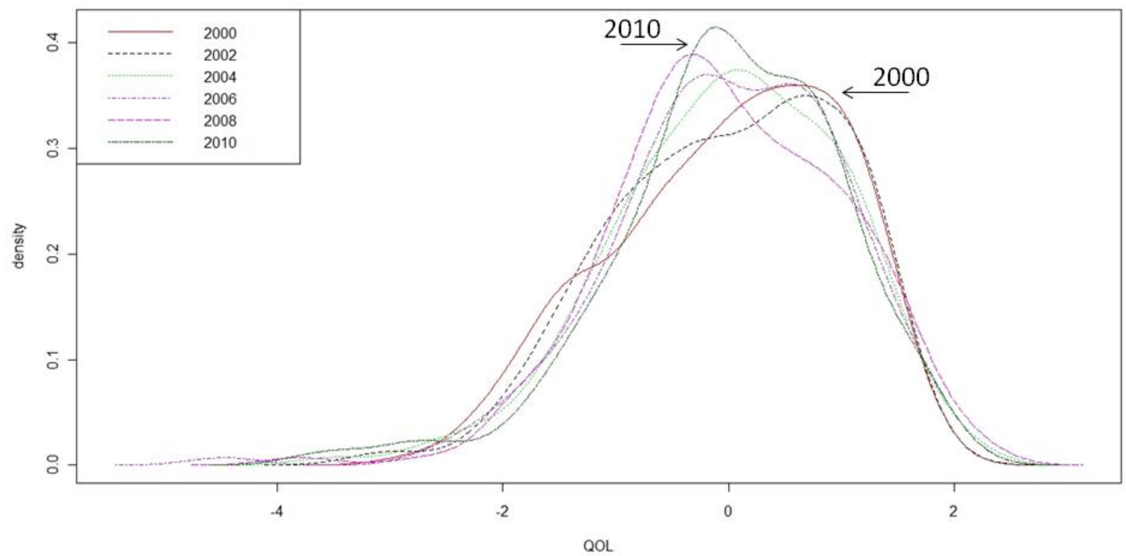

Figure 4. Kernel density plots of QoL values, 2000-2010

The spatial distribution of the overall quality of life index over the 10 year time span is mapped in Figure 5. Data are classified according to quintile breaks for the pooled data set, consistent with the Markov methodology described in the previous chapter. The maps clearly illustrate several distinct patterns including a concentration of high QoL neighborhoods in the southeastern corridor of the city and a group of low values forming the first ring around the center city. As time progresses, higher value neighborhoods form a concentration in the northern neighborhoods surrounding the university area and research park (the northern-most non residential neighborhood), while the middle ring of neighborhoods around the city (excluding the southeastern wedge) experiences a consistent decline in values.

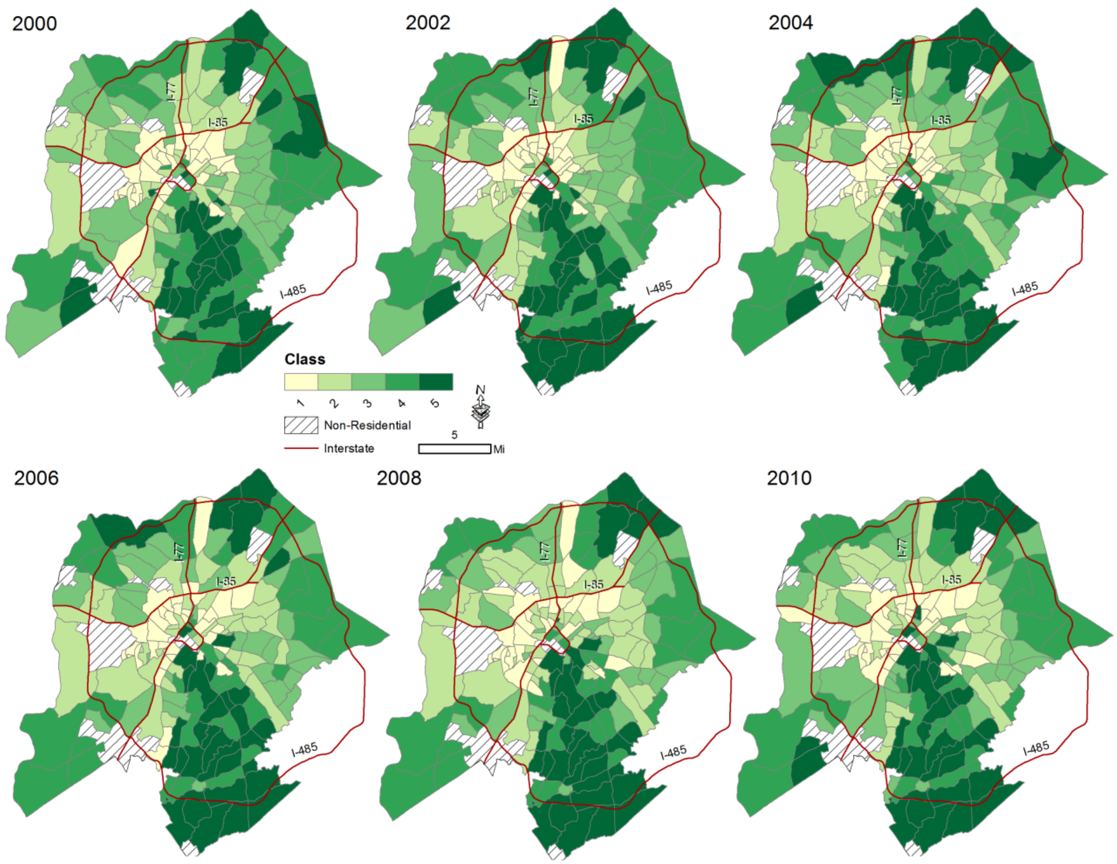

Figure 5. Spatial distribution of QoL index, 2000-2010. Data classified into quintiles

Spatial clusters can statistically be identified by mapping local Moran's *I* values, or Local Indicators of Spatial Autocorrelation (LISA) (Anselin, 1995). The LISA statistic is an exploratory spatial data analysis technique whose objective is to identify local hot spots or local clusters of similar values. This identification is achieved when, for a particular neighborhood, or set of contiguous neighborhoods, the LISA statistic is significant; the test can be used to evaluate the null hypothesis that the variable of interest, QoL, exhibits no spatial association (Anselin, 1995).

Fundamental to this statistic is the definition of a neighborhood's immediate vicinity, or its spatial weight matrix, **W**, given that the statistic for variable of a given observation (neighborhood) is a function of the values of observations in **W**. Common **W** specifications include matrices based on boundary contiguity of polygons, distance-based measures where a neighborhood's immediate vicinity is based upon all neighborhoods within a specified distance, or nearest-neighbor specifications where the *n* closest neighbors are included in the matrix and *n* can take on any given value. For the case of Charlotte neighborhoods, a number of different spatial weight matrices are initially examined including contiguity, distance-based, and nearest neighbor specifications. Ultimately a hybrid definition of the spatial weight matrix is adopted so that the six nearest neighbors within a five mile cutoff limit form the vicinity. This rationale is based on a consideration of the study area, chiefly the unequal area of the neighborhoods within the city limits; those towards the city center are very small, while those on the outer-edge are considerably larger. This is an issue when considering contiguity matrices; in the city center two neighborhoods may be very close to each other in distance and therefore presumably exhibit spatial dependency, but they may not share a common boundary. A nearest neighbor approach would resolve that issue in the city center, but along the boundary, the six nearest neighbors, for example, may be very far in physical distance. Furthermore, neighborhoods along the boundary of the city are subject to an 'edge effect', meaning their adjacent neighborhoods not included in the study area are not counted in the weight matrix specification. Thus, a compromise matrix is decided upon. This matrix will be used throughout the dissertation when examining spatial proximity effects.

The local Moran's I value is computed as follows:

$$I_i = \left(\frac{z_i}{s^2}\right) * \sum_j w_{ij}\, z_j \tag{11}$$

where for a given neighborhood, i, z_i is the difference between its attribute value and the average for the entire city; w_{ij} is a weight value assigned to each neighbor in **W** – each neighbor receives an equal weight based on the total number of neighbors assigned to i; z_j is the deviation of each neighbor from the city average, and s^2 is the variance. A large positive value of I indicates that the neighborhood is surrounded by other neighbors with similar values, either high or low, and a negative value implies that the neighborhood is surrounded by dissimilar neighbors. Resulting values are then tested for significance to determine if the similarity between a neighborhood and its surrounding area could have occurred by chance.

Because the resulting I values are not indicative of whether the values that are clustered are high or low values, it is necessary to simultaneously evaluate the results, the significance level, and the original attribute values to make this determination. To synthesize this information, the maps in Figure 6 show neighborhoods with significant I values ($p < 0.05$) and a corresponding categorization: High-High; High-Low; Low-Low; and Low-High. This assignment is determined by comparing the initial QoL attribute value for a neighborhood with its local mean; if a neighborhood's I value is significant and negative (indicating dissimilarity), and its value is greater than the local mean, it is classified as High-Low. Conversely, if its value is below the local mean, then it is classified as Low-High. If a neighborhood's I value is positive and significant, it then receives a High-High assignment if its value is greater than the local mean, and Low-Low if it falls below the local mean.

According to the figure, high (above-average) QOL values are generally concentrated in the southeastern wedge, and low QoL values are clustered to the west of the city center. Over time, the low cluster shifts westward and by 2006, only one neighborhood east of Interstate 85 (at the 85/I-77 intersection) is part of a significant 'Low-Low' QoL cluster. A second is added in 2008 and 2010. Changes to the high cluster of QOL can be seen along the I-485 beltway in South Charlotte which begins with a small cluster of neighborhoods to the east and expands westward to cover all of the outermost neighborhoods. These LISA results provide evidence of significant spatial dependence patterns at each cross section in time which begs the question whether the process of change is spatially independent. The spatial Markov approach provides a space-time modeling framework to test this query.

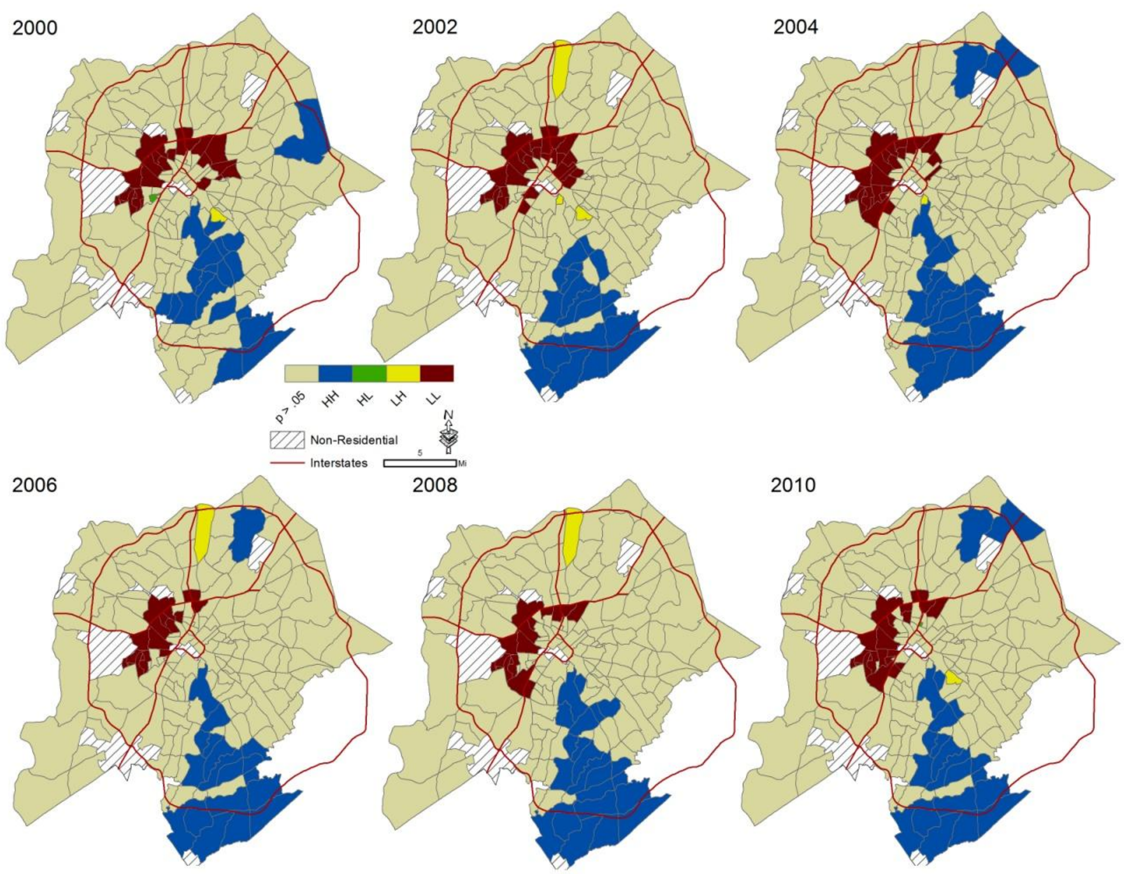

Figure 6. LISA clusters, 2000-2010

5.1.2. A-spatial Markov Chain

Estimates of the first order transition probabilities, estimated with Eq.(1) are shown in Table 2. Standard errors[3] are presented in parenthesis below probability values; these aid in gauging the reliability of estimates as some transitions are based on few observations. The resulting matrix indicates a high degree of stability for neighborhood QoL classes, with the highest probabilities appearing along the diagonals. Of the five classes, class 1 and class 5 have the greatest chance of remaining the same. This is intuitive given that these neighborhoods can only change in one direction while the others have the possibility of moving both up and down. Class 5 neighborhoods are the most stable of all groups. Neighborhoods in the second class are the least likely to remain the same out of all 5 classes, and are slightly more likely to decline than to improve (0.24 vs. 0.22); these neighborhoods are in a transitional stage between the bottom group and higher QoL conditions. Neighborhoods in class 3 which have an equal number of classes to either decline or improve into are similarly more likely to decline than improve (0.25 vs 0.17).

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[3] Standard Errors are calculated by $\sqrt{\frac{\hat{m}_{ij}\ (1-\hat{m}_{ij})}{N_i}}$, $N_i\ =\ \sum_{t=1}^{T-1} n_{it}$

Table 2. Non-Spatial Transition Matrix

t\t+1	Class 1	Class 2	Class 3	Class 4	Class 5
Class 1	0.75 (0.04)	0.22 (0.07)	0.03 (0.08)	0.01 (0.10)	0
Class 2	0.24 (0.07)	0.54 (0.05)	0.17 (0.07)	0.05 (0.08)	0.01 (0.10)
Class 3	0.03 (0.07)	0.22 (0.07)	0.57 (0.05)	0.16 (0.07)	0.01 (0.07)
Class 4	0.01 (0.10)	0.02 (0.07)	0.19 (0.07)	0.59 (0.05)	0.20 (0.07)
Class 5	0	0.01 (0.10)	0.02 (0.07)	0.17 (0.07)	0.80 (0.03)

5.1.3. Time Independence

The first test of temporal dependence is of a zero order process, meaning that the future state of a neighborhood is completely independent of its past; violating this assumption would make a Markov analysis an inappropriate analytical framework for examining the change process. According to the likelihood ratio test in Equation 2, where the resulting transition probabilities in Table 2 are compared with a complete independence scenario (the QoL distribution at time *t*), the neighborhood QoL change process strongly depends on its conditions at time *t*-1 (*LR*=8011; prob<0.001; *df*=16).

The second test investigates whether or not the process of change is dependent upon its conditions 4 years prior in explaining its biennial transition probability. As stated previously, a first order process for this analysis assumes that a neighborhood's condition has only a 2 year temporal dependency. Here, a second order process, which equates to a conditional probability where the probability of transitioning from class *i* to class *j* in time *t*-1 to *t* is conditioned upon its class in time *t*-2, is compared with the results in Table 2. The resulting *LR* value (eq.3) is 167, and with 66 degrees of freedom, the null hypothesis of a first order process is rejected, meaning some time lag greater than 2 years persists in neighborhood transitions. Data limitations restrict the testing of higher orders as the continued decomposing of matrices is required, leading to few observations for each transition, and consequently, unreliable estimates.

The results of this test, however, can provide important insights on the process of change, particularly when investigating the largest contributors to the high *LR* value. Table 3 below shows the result of the test for a second order Markov process. The first column indicates the class at time *t*-2, while probabilities in each of the 5 sub-matrices are estimates of the transition between classes *i* and *j* in time *t* to *t*+1, given the state in time *t*-2. The matrices reveal that the largest contributor to the *LR* statistic, and therefore, the major contributor to temporal dependence is in the case where a neighborhood was in class 1 in time *t*-2, improved to class 2 in the next time period, and then reverted back to class 1 in the following period, indicating that its last position in time *t*+1 is dependent upon its state in class *t*-2. Similarly, the probability of falling back to class 2, after improving from 2 to 3 also has a large *LR* value. These results are indicative that improvements made by the lowest QoL neighborhoods in the short term are not very sustainable over the long term; there is a strong probability that many will relapse to their prior conditions.

Aside from these reversion examples, temporal dependence greater than one time period is also exhibited in the propensity to remain in the highest two classes; the probability of transitioning from class 4 to class 4 and from class 5 to class 5 are both heightened when those neighborhoods were in either class 4 or 5 in time *t*-2, showing the durability or stability of these highest QoL neighborhoods. Finally, the probability of rising from class 4 to 5 increases when a neighborhood was previously in class 5. Just as in the case of the lowest QoL neighborhoods, declines to the best off neighborhoods may be temporary, as they are likely to revert back to their highest standing.

Table 3. Test of First Order Markov Process

t-2	**t-1**	**1**	**2**	**3**	**4**	**5**	**Contribution to LR**				
1	1	0.76	0.21	0.03	0	0	2.05	-0.98	1.15	0.00	0.00
1	2	0.62	0.26	0.12	0	0	19.93	-6.58	-1.39	0.00	0.00
1	3	0	0.50	0.25	0.23	0	0.00	1.64	-0.82	0.45	0.00
1	4	0	0	1	0	0	0.00	0.00	1.66	0.00	0.00
1	5	0	0	0	0	0	0.00	0.00	0.00	0.00	0.00
2	1	0.66	0.28	0.03	0.03	0	-2.17	1.93	0.00	1.10	0.00
2	2	0.15	0.62	0.20	0.03	0	-5.17	6.08	2.28	0.00	0.00
2	3	0.09	0.50	0.32	0.09	0	2.20	9.03	-4.04	-1.15	0.00
2	4	0	0.29	0.57	0.14	0	0.00	5.35	4.39	-1.44	0.00
2	5	0	0	0	0	0	0.00	0.00	0.00	0.00	0.00
3	1	0.60	0.40	0	0	0	-0.63	0.00	0.00	0.00	0.00
3	2	0.06	0.82	0.03	0.06	0.03	-2.77	11.28	-1.73	0.00	0.00
3	3	0.00	0.22	0.63	0.13	0.03	0.00	0.00	5.00	-2.08	2.20
3	4	0.04	0.04	0.22	0.65	0.04	1.39	0.69	0.73	1.45	-1.61
3	5	0	0	0	1	0	0.00	0.00	3.54	3.54	0.00
4	1	1	0	0	0	0	0.30	0.00	0.00	0.00	0.00
4	2	0	0	0.33	0.67	0	0.00	0.00	0.66	5.19	0.00
4	3	0.04	0.15	0.63	0.19	0	0.00	-1.53	1.70	0.86	0.00
4	4	0	0	0.19	0.70	0.11	0.00	0.00	0.00	10.09	-5.38
4	5	0	0	0.07	0.33	0.60	0.00	0.00	2.51	6.63	-5.18
5	1	0	0	0	0	0	0.00	0.00	0.00	0.00	0.00
5	2	0	0	1	0	0	0.00	0.00	1.77	0.00	0.00
5	3	0.25	0	0.25	0.50	0	0.00	0.00	-0.82	2.28	0.00
5	4	0	0	0.08	0.36	0.55	0.00	0.00	-1.73	-4.45	14.41
5	5	0	0	0	0.10	0.90	0.00	0.00	0.00	-5.84	11.19

5.1.4. Time Homogeneity

Tests of time homogeneity examine the assumption that the process of change has been consistent throughout the decade; in other words, if the transition probabilities of any subset of the decade are examined, they should be equivalent to one another, and to the overall transition matrix produced in Table 2. Guidelines on evaluating this Markov property suggest that the entire time period be subdivided in a manner that results in the largest number of observations in each subsample as to produce the most statistically robust results. In this case, the sample would be divided into two groups: 2000-2006 and 2006-2010, and the transition probabilities of each subset are compared to the Table 1 utilizing the likelihood ratio test in Equation 4. According to this temporal split, the process is deemed homogenous across time following the likelihood ratio test with *LR* values of 12.71 for the first subset, 3.60 for the second, and 18 degrees of freedom; the null hypothesis of time homogeneity is not rejected (p>0.59).

While less statistically powerful, a more meaning temporal subdivision would investigate the process of change leading up to the height of economic and real estate growth in the city (2000-2006), the height of growth (2006-2008), and following the economic recession[4] (2008-2010). The resulting sub-matrices for these three time periods (Table 4) provide a descriptive analysis on neighborhood change dynamics amidst changes to the larger urban economy. The most apparent distinction among the results is the probability of remaining in the lowest class. Between 2000 and 2006, the probability of remaining in class 1 was 79 percent, leaving only a 21 percent chance of improvement, however, during the pinnacle of the economic and real estate boom, that probability dropped to 53 percent, heightening the chance of improvement to 48 percent. Following the economic recession, this transition probability reverted back to 83 percent, demonstrating that the economic prosperity experienced during the 2006-2008 time period had a positive effect on the upward mobility of the lowest QoL neighborhoods, but

[4] Technically, the economic downturn began in 2008, however, the data corresponding to the downturn is captured in the 2010 QoL dataset.

the recession essentially reduced it to levels more consistent with the beginning of the decade. To further break down these findings, from 2006 to 2008, 15 neighborhoods in the lowest QoL class transitioned upward to class 2. Of those 15 in 2010, one continued on an upward trajectory into class 3, 4 remained in class 2, and ten of them reverted back down to class 1. Thus, these results are entirely consistent with the previous test of temporal independence which illustrated a strong reversion tendency of improvements made to the lowest QoL neighborhoods; however, this analysis establishes that these declines were very prevalent in the time period following the economic downturn. Figure 6 shows a map of the spatial distribution of the 15 neighborhoods that improved from 2006-2008 and their subsequent status in 2010; they are generally concentrated close to the city center of Charlotte.

These findings are important for understanding the influence of the large macro-economic conditions of the urban environment on local neighborhood development initiatives. One of the initial major motivations of the QoL study in Charlotte was to identify low performing neighborhoods to receive targeted initiatives. As a result many of the neighborhoods falling within the class 1 designation have received sustained funding throughout the decade, yet the results of this analysis demonstrate that their mobility is largely linked to the greater economic conditions of the city; local initiatives and policies are unable to overcome the hardships imposed by the great recession.

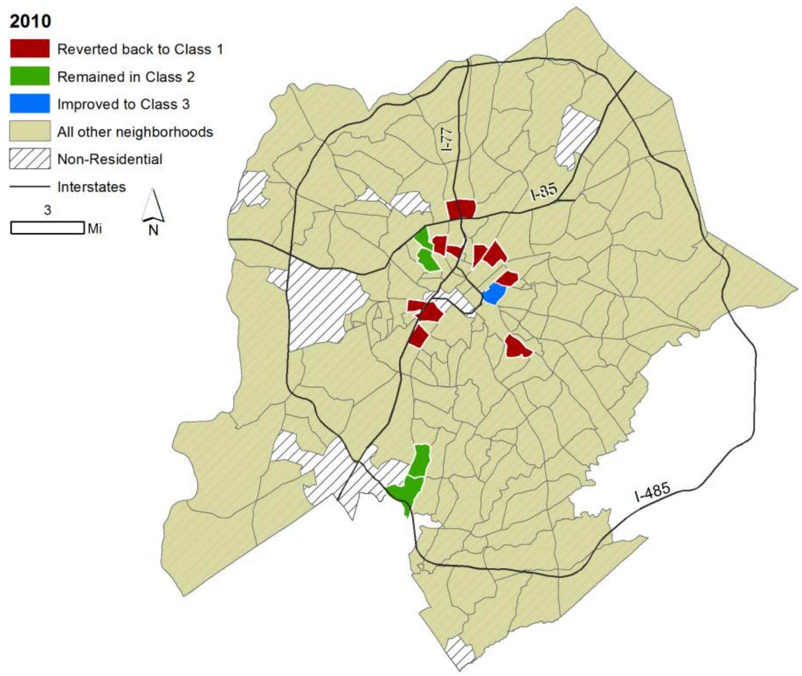

Figure 7. Status of neighborhoods in 2010 that improved from Class 1 to 2 between 2006 and 2008.

Because the QoL scores are relative to all other neighborhoods in the city, essentially representing the rank order of neighborhoods, if neighborhoods in class 1 exhibited a strong upward mobility from 2006-2008, then neighborhoods in other classes should have experienced a decline in relative status in that same time period. In this case, average neighborhoods, those in class 3, were more likely to decline (37 percent) during that time frame as compared to 2000-2006 (24 percent), and 2008-2010 (19 percent). Finally, throughout the decade the stability of the highest QoL neighborhoods increased, revealing no negative impact from the economic recession on the mobility of the best off neighborhoods. The propensity to remain in the highest class reached 89 percent in the final time period. This evidence implies that improvements made to the lowest QoL neighborhoods in the more prosperous and growing years of 2006-2008 were the most impacted by the economic recession of 2008-2010, returning those worst-off neighborhoods back to the pre-prosperous conditions.

Table 4. Test of Time Homogeneity

t\t+1	**1**	**2**	**3**	**4**	**5**
2000-2006					
1	0.79	0.18	0.03	0	0
2	0.22	0.57	0.17	0.04	0
3	0.04	0.20	0.58	0.16	0.02
4	0	0.02	0.17	0.59	0.23
5	0	0.01	0.03	0.21	0.75
2006-2008					
1	0.53	0.42	0.03	0.03	0
2	0.25	0.50	0.17	0.08	0
3	0.03	0.34	0.47	0.16	0
4	0.03	0.03	0.24	0.56	0.15
5	0	0	0.03	0.11	0.86
2008-2010					
1	0.83	0.13	0	0	0
2	0.27	0.51	0.18	0.02	0.02
3	0.03	0.16	0.65	0.16	0
4	0	0.03	0.19	0.63	0.16
5	0	0	0	0.11	0.89

5.1.5. Spatial Dependence

Next, the influence of the surrounding vicinity, or spatial spillovers, on a neighborhood's QoL mobility over time is investigated. Similar to the test of temporal independence, the test of spatial independence utilizes a conditional probability approach to compare the likelihood of transitioning between classes, given the average value of the surrounding neighborhood falls in class *i*. When the conditional spatial matrices are compared to the non-spatial matrix (Table 1), the effect of spatial dependence on transition over time can be examined. Table 5 below presents the five conditional matrices where the first column represents the class that the average value of a neighborhood's neighbors[5] falls within. Standard errors are again presented in parenthesis below the probability estimates.

Results indicate that spatial dependence, in the form of the mean value of surrounding neighborhoods, does have an impact on transitions over time. The likelihood ratio test rejects the null hypothesis of spatial independence (*LR* = 111, p<0.003, 72 DF). In the first sub-matrix of Table 5, where the average value of neighbors falls in the lowest class, the probability of remaining in the lowest class is 0.80 compared to 0.74 for the non-spatial estimate. More pronounced on having neighbors in the lowest class are the effects on the probability of declining from class 2, which increases to 37 percent (a 13 point increase), and the chance of declining from class 3 to either class 2 or 1 which more than doubles from 0.25 to 0.61 percent.

In the second sub-matrix, the proximity effects to neighborhoods in class 2, the most mobile class are less prominent than those of the lowest class. This contrasts with the downward pull of both classes 2 and 3 neighborhoods shown in the previous sub-matrix; these effects are nearly eliminated when a neighborhood is surrounded by neighborhoods falling in a slightly higher QOL class. In the third matrix, the effect of neighbors in the average class, 3, shows both positive and negative impacts of spatial dependence on transitions. For example, the probability of a neighborhood remaining in class 1 when its neighbors are in class 3 drops to 0.56 (compared to 0.80 when its neighbors were equally bad, or 0.74 without considering space), and consequently its chance of improving increases to 0.44, exemplifying the positive effects of better neighbors on transitions over time. On the other hand, the probability of a neighborhood

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[5] The Neighborhood or, weight matrix specification, is defined as the 6 nearest neighbors falling within a 5 mile radius.

declining from Class 4 when its neighbors are in class 3 rises to 0.36, compared to 0.22 for the non-spatial estimate, pointing to the negative effect on better neighborhoods. Finally, these patterns continue in the cases of the highest sub-matrices. Having neighbors whose average QoL value falls in either Class 4 or 5 increases the upward mobility of lower-classed neighborhoods. The general spatial patterns can easily be depicted when examining the probabilities of remaining in either class 1 or 5 in each of the submatrices, which consistently improve as the average value of the surrounding area increases.

Table 5. Spatial Markov Matrices (Average value of neighbors)

Lag Class	**t\t+1 (*i*|*j*)**	**1**	**2**	**3**	**4**	**5**
1	1	0.80 (0.05)	0.19 (0.09)	0.01 (0.10)	0	0
1	2	0.37 (0.12)	0.51 (0.11)	0.12 (0.15)	0	0
1	3	0.22 (0.21)	0.39 (0.18)	0.33 (0.19)	0	0.06 (0.24)
1	4	0	0	1 (0.00)	0	0
1	5	0	0	1 (0.00)	0	0
2	1	0.73 (0.07)	0.24 (0.12)	0.04 (0.14)	0	0
2	2	0.21 (0.11)	0.55 (0.08)	0.21 (0.11)	0	0
2	3	0.02 (0.14)	0.20 (0.13)	0.68 (0.08)	0.08 (0.14)	0.02 (0.14)
2	4	0	0.05 (0.22)	0.20 (0.20)	0.45 (0.17)	0.30 (0.19)
2	5	0	0.08 (0.27)	0.08 (0.27)	0.25 (0.25)	0.58 (0.19)
3	1	0.56 (0.22)	0.22 (0.29)	0.11 (0.31)	0.11 (0.31)	0
3	2	0.15 (0.13)	0.54 (0.09)	0.20 (0.12)	0.11 (0.13)	0
3	3	0.01 (0.10)	0.21 (0.10)	0.55 (0.07)	0.23 (0.10)	0
3	4	0.02 (0.14)	0.05 (0.13)	0.29 (0.11)	0.55 (0.09)	0.09 (0.13)
3	5	0	0	0.04 (0.20)	0.20 (0.18)	0.76 (0.10)
4	1	0.33 (0.27)	0.56 (0.22)	0.11 (0.31)	0	0
4	2	0.36 (0.26)	0.55 (0.20)	0	0.09 (0.29)	0
4	3	0	0.25 (0.22)	0.63 (0.15)	0.13 (0.24)	0
4	4	0	0	0.14 (0.10)	0.64 (0.07)	0.22 (0.10)
4	5	0	0	0	0.22 (0.11)	0.78 (0.06)

Table 5 Continued

5	1	1.0 (0.00)	0	0	0	0
5	2	0	1 (0.00)	0	0	0
5	3	0	0	0.57 (0.25)	0.43 (0.29)	0
5	4	0	0	0.04 (0.20)	0.65 (0.12)	0.30 (0.17)
5	5	0	0	0.02 (0.14)	0.09 (0.13)	0.89 (0.04)

To further explore these dependency effects, alternate specifications of the spatial lag beyond the mean are tested including the median, mode, and upper and lower quartiles of neighboring values. The median of the neighbors produces nearly indistinguishable results with the mean, while the mode, which assigns the most common class of neighbors as the spatial lag generates very similar results to both the median and mode. Most differences occur in the case of very few transitions which are statistically unreliable. The full matrices produced from the mode can be found in the Appendix.

Utilizing the upper or lower quartile of a neighborhood's surrounding region as the spatial lag value results in similar, but slightly amplified spatial effects, particularly at the extremes of these values. For example, if the upper quartile of a neighborhood's surrounding area only falls in the lowest class, the probability of remaining in the lowest class is at its highest value, 84 percent (Table 6). In other words, neighborhoods situated in areas of concentrated disadvantage were very unlikely to exhibit any upward mobility during the 2000-2010 decade. Likewise, neighborhoods in class 2 or 3 that were situated in such concentrated disadvantage were likely to decline, although the number these transitions that took place were very few.

A stronger negative influence on declining for class 3 neighborhoods when the upper quartile of their neighbors only reaches class 2, in this case, the chance of declining to either class 1 or 2 is 38 percent, compared to 22 percent when the mean of the neighbors fell in class 2.

Table 6. Spatial Markov Matrices - Upper Quartile of Neighborhoods

Class	**t\t+1 (*i**j*)**	**1**	**2**	**3**	**4**	**5**
1	1	0.84 (0.06)	0.16 (0.13)	0	0	0
1	2	0.40 (0.35)	0.40 (0.35)	0.20 (0.40)	0	0
1	3	0.67 (0.33)	0.33 (0.47)	0	0	0
1	4	0	0	0	0	0
1	5	0	0	0	0	0
2	1	0.75 (0.06)	0.23 (0.11)	0.02 (0.14)	0	0
2	2	0.36 (0.15)	0.52 (0.15)	0.11 (0.16)	0	0
2	3	0.13 (0.24)	0.25 (0.22)	0.56 (0.17)	0	0.06 (0.24)
2	4	0	0	1 (0.00)	0	0
2	5	0	0	0.25 (0.43)	0.25 (0.43)	0.50 (0.35)

On the opposite end of the spectrum, when the lower quartile of neighbors reaches the top two classes, some similar amplified effects are exhibited. For example, when the lower quartile of a neighboring region is in the highest class, the probability of improving from class 4 to 5 is heightened as compared to the results using the mean (0.30 vs. 0.22) (Table 7). These results point to the fact that spatial dependence influences are non-linear, amplified at the extremes, and are therefore analogous to the tipping point literature reviewed. Once a neighborhood is geographically located amidst the highest concentrations of disadvantage, it is very unlikely to improve, while neighborhoods located in proximity of concentrated advantage are very likely to improve or remain in the highest class. Overall, the various, alternative geographic neighborhood definitions have demonstrated a consistency in their results, showing that in general, a neighborhood's surrounding area influences its chances of both upward and downward mobility.

Table 7. Spatial Markov Matrices - Lower Quartile of Neighborhoods

Class	**t\t+1 (*i**j*)**	**1**	**2**	**3**	**4**	**5**
4	1	0.50 (0.35)	0.50 (0.35)	0	0	0
4	2	0.33 (0.33)	0.50 (0.29)	0	0.17 (0.38)	0
4	3	0	0.22 (0.29)	0.44 (0.25)	0.33 (0.27)	0
4	4	0	0	0.07 (0.15)	0.56 (0.10)	0.38 (0.12)
4	5	0	0	0	0.17 (0.10)	0.83 (0.05)
5	1	0	0	0	0	0
5	2	0	0	0	0	0
5	3	0	0	0.50 (0.50)	0.50 (0.50)	0
5	4	0	0	0	0.78 (0.16)	0.22 (0.29)
5	5	0	0	0.04 (0.20)	0.12 (0.19)	0.84 (0.08)

5.1.6. Prediction & Errors

If past trends of neighborhood QoL are indicative of the future (as the time homogeneity test suggests is a reasonable assumption), then the space-time transition probabilities estimated in the previous sections can be used as a means for forecasting future neighborhood conditions. Two predictive frameworks are therefore developed to explore the reliability of these pattern-based estimates in anticipating the future conditions of neighborhoods. The first approach evaluates a neighborhood's current class, its neighbor's class, and then assigns its future state according to the highest probability obtained from the conditional spatial matrices. For the second method, a Monte Carlo simulation is developed based on the transition matrices to account for uncertainty inherent in the highest probability estimates. Both techniques are evaluated by comparing the observed QoL classes with predicted values.

For the highest probability method, spatial Markov matrices are estimated based on the 2000-2008 data, and the class of each neighborhood in 2010 is forecast and compared with its actual 2010 class. This method yields a 66 percent prediction accuracy rate. In the simulation approach, 100 Monte Carlo simulations are run and of all of the runs, the maximum number of neighborhoods predicted correctly is 58 percent. When all runs are averaged together, the accuracy is raised to 60 percent correct. Therefore, while conservative in its estimates – meaning uncertainty is not accounted for - the highest probability approach proves more accurate in its forecasting ability. As a policy or planning tool, extrapolating past trends to describe the near future can be expected to provide correct predictions more than half of the time. Perhaps more meaningful, however, is to understand which neighborhoods deviated from their expected space-time patterns.

Figure 8 shows the spatial distribution of neighborhoods in 2010 that were over or underestimated estimated by a class (or two) as well as those predicted correctly. Several of the over-predicted neighborhoods are those previously discussed and mapped in Figure 7 that improved between 2006 and 2008 and then declined in 2010. A second group of neighborhoods that underperformed according to the space-time estimates are in the eastern, inner-ring of the city. This area was highlighted in Figure 5 as a transitional section of the city, exhibiting a noticeable amount of change during the decade. Neighborhoods that fell in a higher than predicted class (meaning they were under-predicted) form an apparent spatial cluster around and just south of the University research park.

In order to gain a better sense of the characteristics of neighborhoods assigned to three prediction groups – over-predicted, correctly predicted, and under-predicted – Figure 9 displays box plots of four variables drawn from the neighborhood change literature. The first variable represents the percentage of housing within a neighborhood constructed between 1951 and 1969; housing built during this time frame is typical of the older, post-war, suburban neighborhoods cited in the literature as undergoing a nation-wide decline. According to the figure, on average, neighborhoods that had worse QoL conditions in 2010 than their space-time patterns predicted, have a higher concentration of these post-war homes than either the correctly predicted or under-predicted groups.

The second variable depicts housing constructed during the 2000-2010 decade; new housing is pivotal to urban economic theories of neighborhood dynamics. As Quercia and Galster (2000) note, in order for an aggregate characteristic, such as QoL, of a neighborhood to change, at least one of the following population changes must occur: shifts in the number or composition of in-movers, out-movers, and/or the behavior of residents who remain. According to filtering theories developed in the 1960s, the movement of people within a metropolitan area is controlled by the local housing market supply and demand; therefore, new housing construction encourages in-movers to a neighborhood, thus altering its socio-economic or demographic composition, and may also influence the out-migration of residents from other neighborhoods interconnected to the greater urban housing market. Accordingly, neighborhoods that performed better than anticipated, on average, had the highest concentration of new housing construction of the three groups, while the over-predicted group had the lowest concentration of new housing. With little or no investment on the part of developers, the over-predicted group reveals signs of economic stagnation, or, according to William Grigsby (1963), locational obsolescence.

The literature review frequently cited homeownership levels as a predictor of neighborhood change given that homeowners tend to stay in their homes for a longer duration than renters, and hence bring about stability to a neighborhood. The third box plot in Figure 9 lends some support to this notion as both of the incorrectly predicted groups have, on average, a higher percentage of renters as compared to the correctly predicted group. The stability associated with a high percentage of homeowners may lead to a greater predictability. Finally, the racial contrast of these three prediction groups is illustrated in the fourth box plot, clearly showing that on average, the neighborhoods that fared worse than predicted in 2010 have a larger concentration of minorities as compared to neighborhoods that did better than predicted or were predicted correctly. These statistics are intended to be exploratory in nature; the final section of this dissertation employs a confirmatory approach to test the drivers of change.

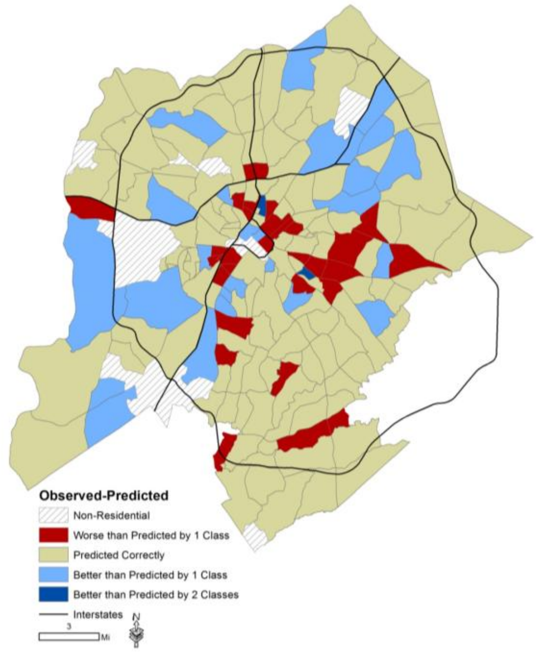

Figure 8. Distribution of 2010 prediction errors.

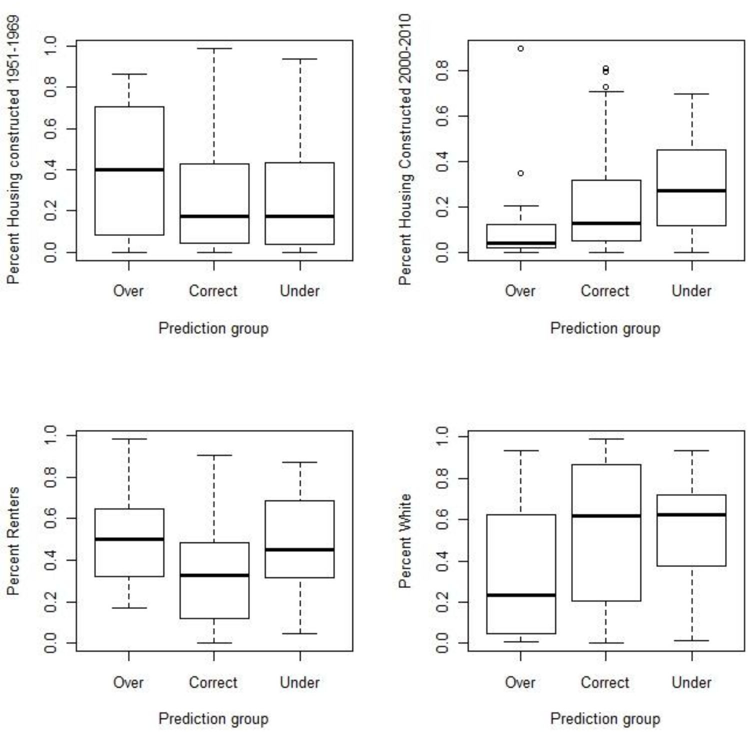

Figure 9. Box plots of housing constructed 1951-1969; housing constructed 2000-2010; percent renters; and percent white for 3 prediction groups.

5.1.7. Summary of Results

A summary of the major findings of the analysis conducted in relation to the first objective is provided below.

- Kernel density distribution plots of the QoL index over time provide evidence of a convergence of values and decreasing disparity.
- The lowest QoL neighborhoods are generally concentrated to the west of the city center near the urban core, while clusters of high QoL neighborhoods are found in the south eastern wedge of the city.
- Neighborhoods belonging to the upper-most (class 5) and lowest (class 1) quintiles are most stable through time; class 2 neighborhoods are transitional.
- Upward transitions from the lowest two classes are not very sustainable over the long term; they are susceptible to reversions back down.
- Class 5 neighborhoods are more resilient – declines down to class 4 are likely to be temporary.
- The propensity to improve from the lowest QoL class was elevated during the 2006-2008 time period when the probability of remaining in the lowest class dropped to 53 percent (compared to 79 percent in 2000-2006 and 83 percent in 2008-2010).
- Between 2006 and 2008, 15 neighborhoods moved from class 1 to 2. Of those 15 10 reverted back down to class 1 in 2010. These neighborhoods were generally located toward the urban core.
- The probability of a neighborhood improving or declining is not independent of its immediate vicinity; neighborhoods surrounded by equally bad or worse areas

are more likely to decline, while those surrounded by better neighborhoods have a greater chance of improving.

- The spatial effects are amplified when looking at the extremities of the upper and lower quintiles of other neighborhoods in the local vicinity – neighborhoods situated in concentrated disadvantage are very unlikely to improve over time.
- Neighborhoods that did worse in 2010 than their space-time patterns predicted, on average, had a larger concentration of housing constructed between 1951-1969, a lower concentration of housing built between 2000 and 2010, had a higher percentage of renters and a higher concentration of minorities than neighborhoods that were predicted correctly or did better than anticipated.

5.2. Research Objective 2 – Trajectories of Multidimensional Change

This second research objective disassembles the aggregate QoL index utilized in the Markov analysis, and examines individual trajectories of change across the multidimensional attribute space, utilizing a self-organizing map approach.

5.2.1. Cross-Sectional View

One primary output of the SOM procedure are so-called component planes, which are visual depictions of the relative contribution of each QoL attribute to the overall sorting of neighborhoods in the final layout of the SOM output space. These planes reveal non-linear and partial correlations between variables, and thus provide an interesting cross-sectional view on the 17 input variables. Figure 10 depicts the resulting component planes for this analysis, and shows a distinct ordering of observations across the SOM output space. For example, the first four components in Figure 10: income, homeownership, kindergarten and competency exam scores, all exhibit a similar pattern of high values towards the top of the planes (depicted in red), descending towards low values (blue) at the bottom portion of the output space. Conversely, attributes commonly associated with lower QoL have a largely opposite pattern of low levels of food stamps, appearance violations, high school dropout rates, teen births, and crime rates at the top of the space, and increasing in value towards the bottom.

Partial correlations can also be identified from the plots, including a high concentration of youth social problems (HsDo, TeenBirths) and physical deterioration indicators (Appear, Infrastr) in the lower right corner, while high crime concentrations mainly appear on the opposite, lower left hand corner. The plots also indicate that while neighborhoods located along the top of the output space generally fair well across all QoL dimensions (with the exception of accessibility to transit and retail), those towards the bottom, representing the lowest income neighborhoods, are less homogenous in terms of their social, physical, and crime QoL characteristics.

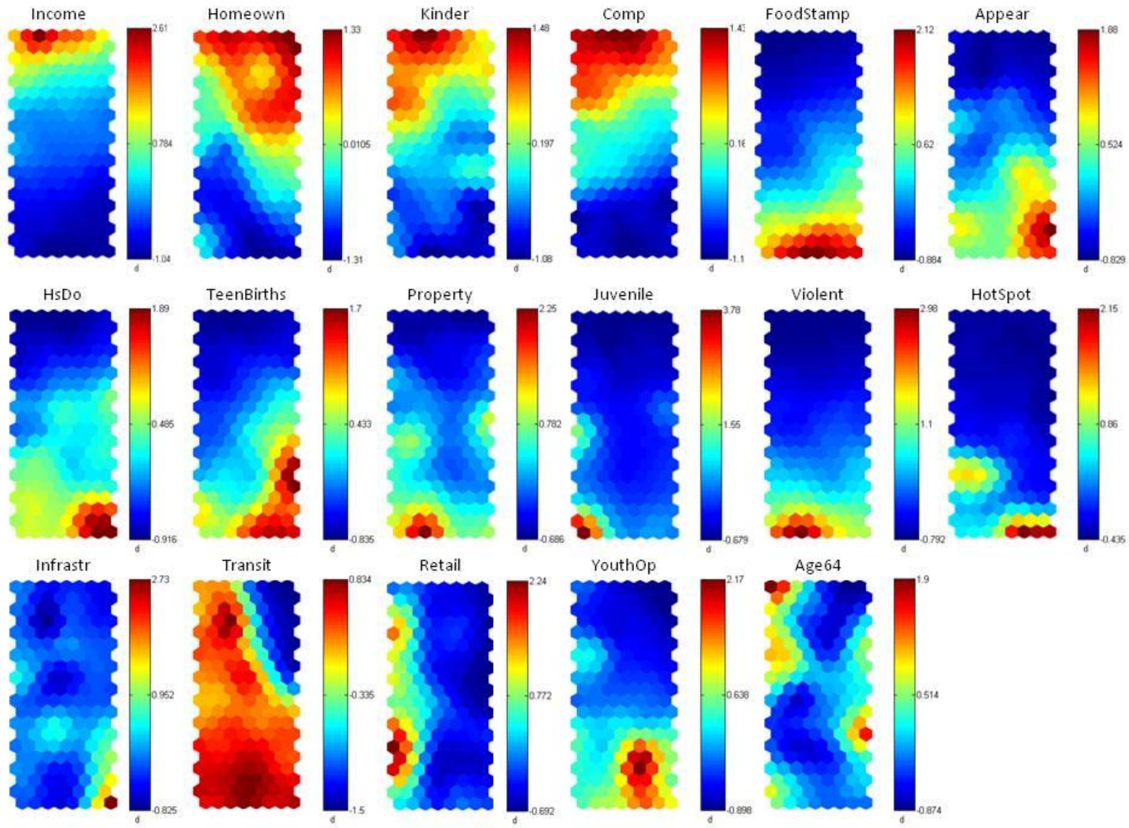

Figure 10. Component Planes

Next, the SOM output space is delimited into homogenous clusters to facilitate the analysis of longitudinal changes across the output space. The purpose of this step is the aid in the interpretation of results; observations within each cluster remain ordered on the output space and distinctions can be made between neighborhood trajectories within a group. Furthermore, each neighborhood's trajectory belonging to a cluster will be displayed – in other words, change is not generalized into a single case representing the entire cluster. For these reasons, the number of clusters is determined by examining a dendrogram produced by a hierarchical Ward's clustering procedure, a 6-cluster solution offers sufficient discriminating power while satisfying the interpretability requirement[6]. In order to assign nodes to the clusters, a *k*-means analysis is run (where *k*=6), and the resulting output space partition is shown in Figure 11. The contiguity of the nodes within each cluster is a result of the ordering of the SOM; like observations are arranged near one another on the output space. Characteristics of the clusters are obtained by examining the component planes, and are briefly summarized below.

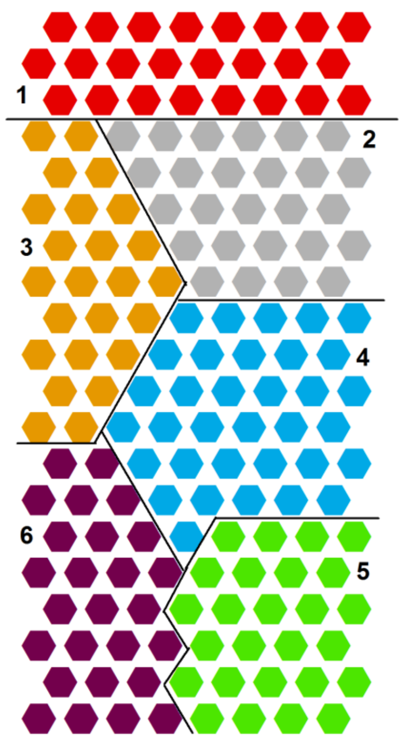

Figure 11. *K*-means clustered output space (*k*=6)

(1) Cluster 1: Characterized by the highest QoL indicators: high income, homeownership, education scores, low food stamp dependency, crime rates, high school dropout, and teen birth rates.

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[6] A 3-cluster solution offered the greatest discriminating power with the fewest number of clusters according to the Calinski-Harabasz pseudo F-statistic, but it masked many of the patterns revealed with a 6-cluster result.

(2) Cluster 2: Middle-Class suburban characteristics: Median incomes, high homeownership rates, median education scores, low crime, low social problems, few appearance violations, and low accessibility.

(3) Cluster 3: Median incomes and median homeownership rates. Slightly higher education scores than cluster 2 (especially for nodes at the top of the cluster; towards the bottom, the education scores become similar to cluster 4) demographically older, with greater access to transit and retail.

(4) Cluster 4: Lower income and education, median homeownership, appearance violations, and high school dropout rates, above average teen birth rates. Low juvenile and violent crime rates, but median property crime. Older population, high transit access, but low retail access.

(5) Cluster 5: Highest concentration of high school dropout rate & teen births, as well as physical deterioration. Median property and violent crime rates, low juvenile crime, but high crime 'hot spots'. Low income, homeownership, high food stamp dependency.

(6) Cluster 6: Highest concentration of violent, juvenile, and property crime rates, median teen births & high school dropout. Low income, homeownership, high food stamp dependency.

The homogeneity of the clusters themselves can be assessed by calculating the average distance between the neurons within each group; in the SOM algorithm, similar neurons on moved closer to one another, and so a smaller average distance is indicative of a greater degree of similarity. Results show that cluster 2 contains the most homogenous group of neighborhoods, followed by cluster 4 (average distances of 0.66 and 0.69, respectively). The least homogenous groups are the two lowest-income groups;

cluster 5 has an average distance of 1.070, and cluster 6 an average distance of 1.088. This latter finding further affirms the heterogeneity of low income neighborhoods in terms of their overall quality of life characteristics.

5.2.2. Trajectories of Change

To analyze the trajectories of neighborhoods across attribute and geographic spaces, the paths of neighborhoods that began the decade belonging to a cluster are displayed on the SOM output space, and their corresponding spatial locations are mapped. Figure 12 illustrates this for the first cluster. Spatially, neighborhoods that began the decade in this group are largely concentrated in the southern 'wedge' of the city, expanding from close to the city center outward to the city's southern edge. During the decade, the majority of these neighborhoods remained within the same group, with the exception of five neighborhoods whose trajectories indicate a downward trend towards characteristics of the more moderate income second group, and one which moved into the third cluster, marginally declining in the concentration of homeowners; these declines are all slight, as evidenced by their ending position in nodes in the first three rows below their starting position.

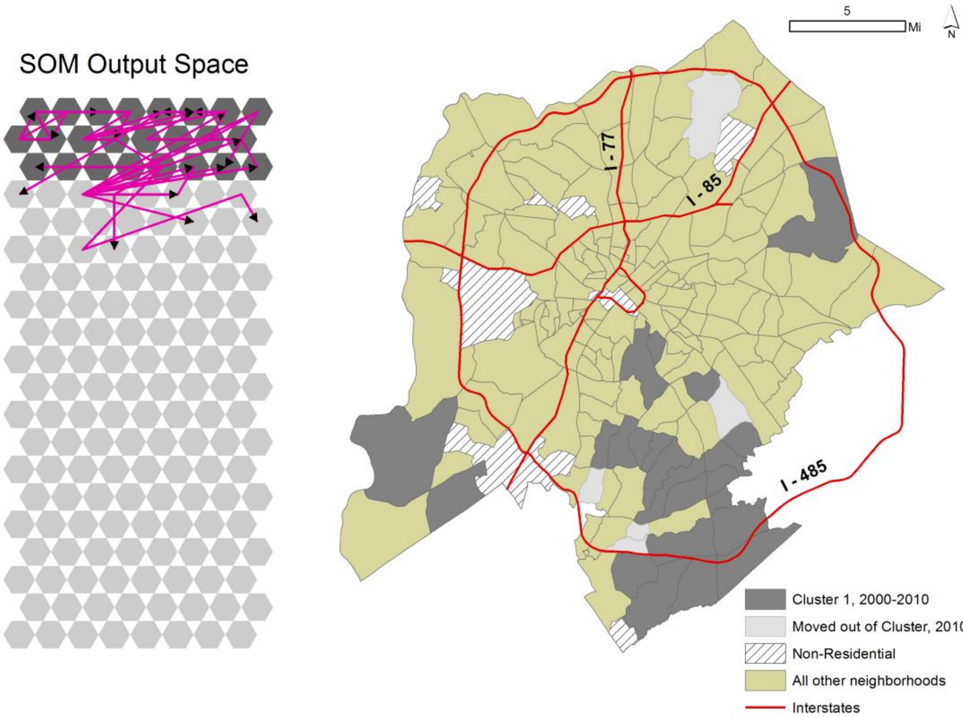

Figure 12. Cluster 1, 2000

In Figure 13, the trajectories of neighborhoods that concluded the decade in cluster one are displayed, illustrating that neighborhoods that transitioned into this highest QoL group came from nearby in attribute space, and have an apparent spatial pattern: they are adjacent to existing neighborhoods in the southern wedge, and along the outermost periphery of the city. Overall, neighborhoods in this group have a large degree of decennial stability.

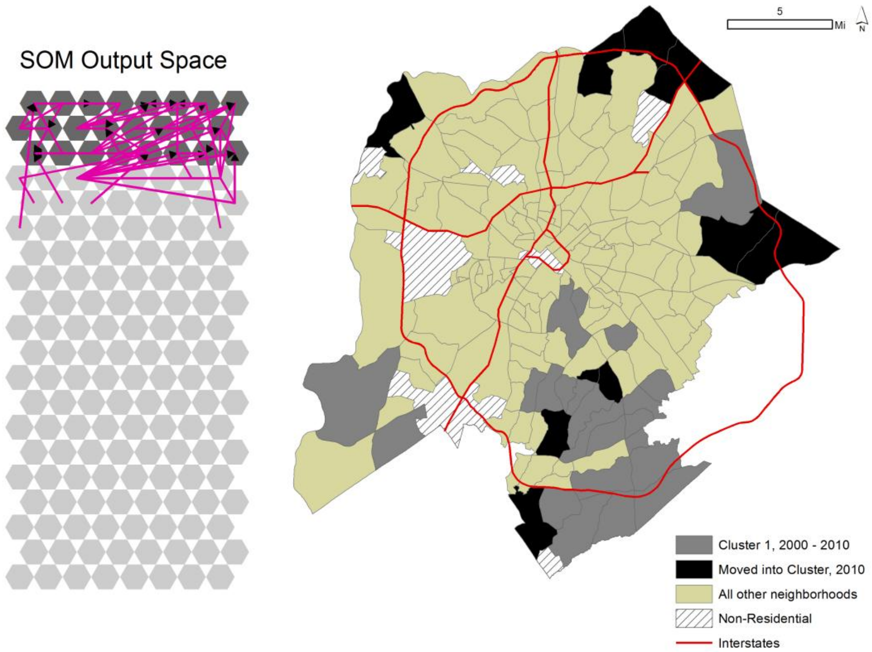

Figure 13. Cluster 1, 2010

For the second cluster (Figs. 14 and 15), the spatial location of neighborhoods corresponding to the output nodes reveals a very suburban pattern along the outermost periphery of the city, confirming the middle class suburban attribute descriptions. The trajectories of neighborhoods that began the decade in this group and left it subsequently follow two distinct paths: one of improvement, joining the first cluster, and one of decline, clearly depicted by the downward facing arrows. While neighborhoods that declined began the decade in the same group as those that improved, their starting positions within the cluster were toward the bottom. Neighborhoods that transitioned into this group were few; the declines from the first group and one neighborhood with a spatial location far from the others, towards the city center (Plaza Midwood). Its trajectory is also distinct, moving from a starting position in cluster 3, but increasing in homeownership, while otherwise maintaining its moderate education scores, and general low social problems.

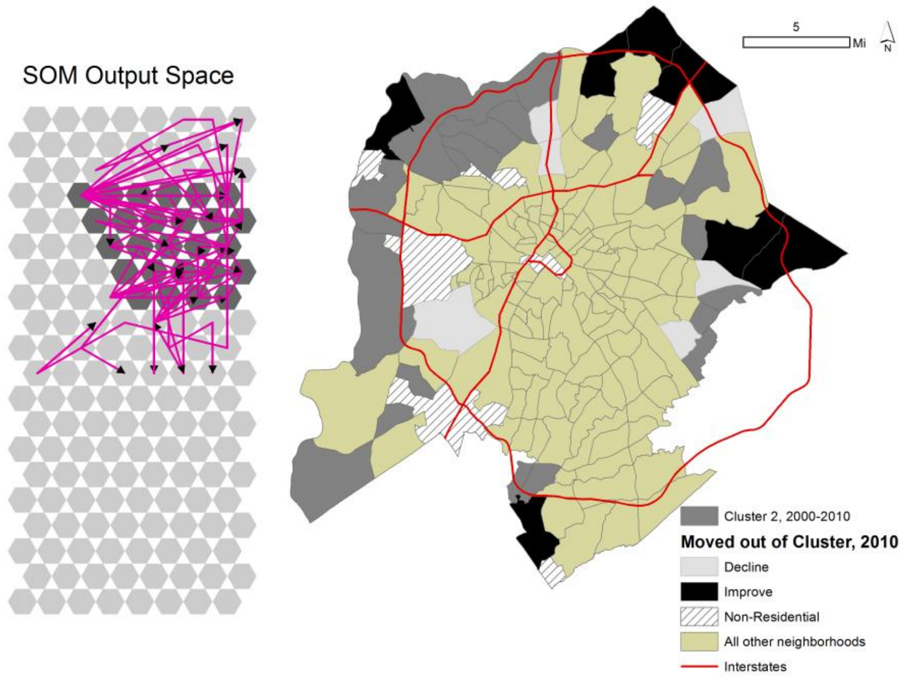

Figure 14. Cluster 2, 2000

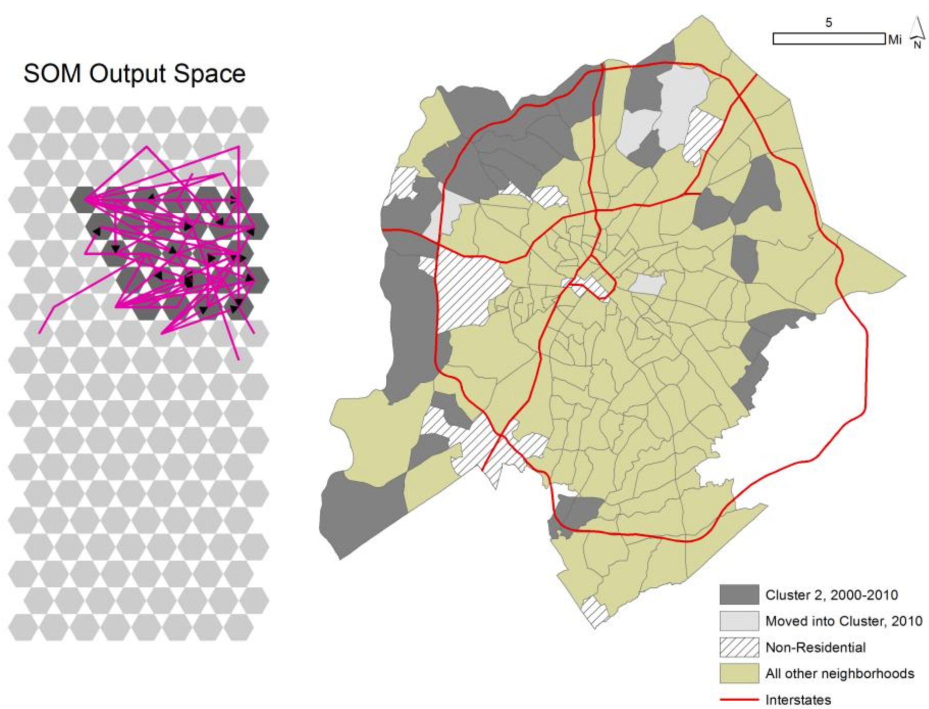

Figure 15. Cluster 2, 2010

Neighborhoods in cluster 3, characterized by lower levels of homeownership and greater accessibility to transit and retail as compared to the second group, have a spatial location within the city beltway, with a larger presence in the southern 'wedge' (Fig. 16). A close inspection of the component planes for nodes within the cluster reveals that neighborhoods towards the top of the group have higher education than those towards the bottom (the horizontal line in Figure 11 separating the 2nd and 3rd cluster serves as this cutoff). This is an important distinction when examining the neighborhoods that left the group by 2010; those that declined all began with lower education scores, and all increased in the number of youth social problems, whereas those that improved began the decade towards the top of the group. The trajectories of neighborhoods that ended the decade in the 3rd cluster (Fig. 17) come from much further distances across the output space as compared to the previous two examples, suggesting that many of the neighborhoods with these characteristics in 2010 are very much in transition (primarily on an improvement trajectory). Given that the right side of the output space contains similar social and crime values, but is distinguished by higher homeownership rates, the resulting trajectories suggest that improvements to these social and crime dimensions preclude increases in homeownership. In addition, a higher concentration of renters may also facilitate larger QoL changes as populations are presumably more fluid.

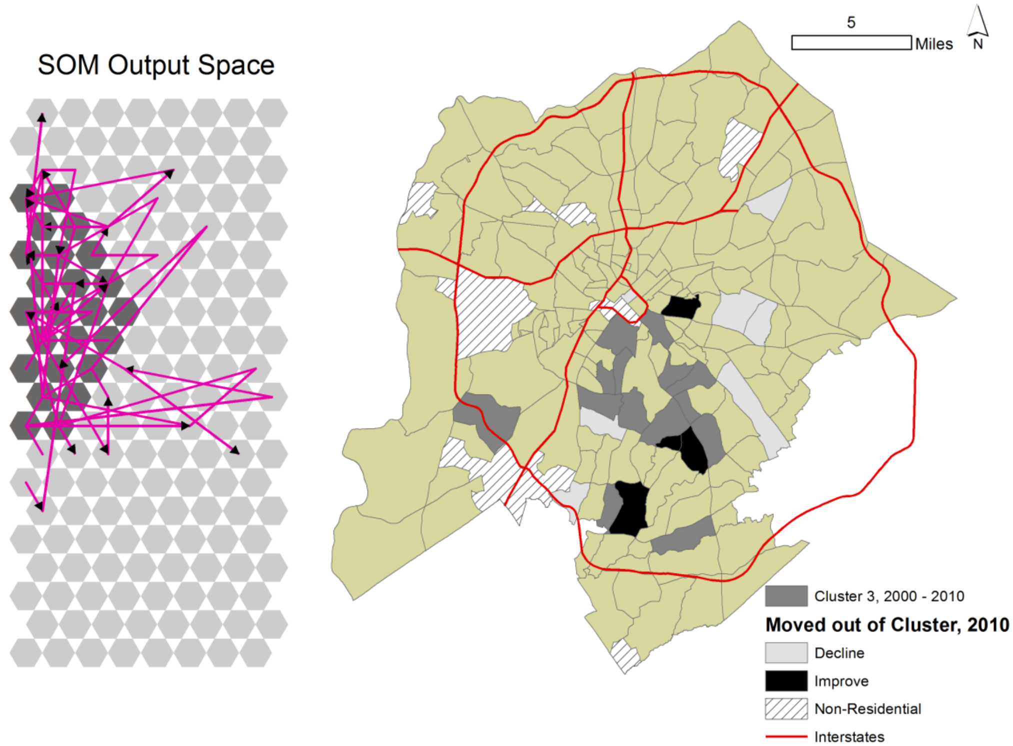

Figure 16. Cluster 3, 2000

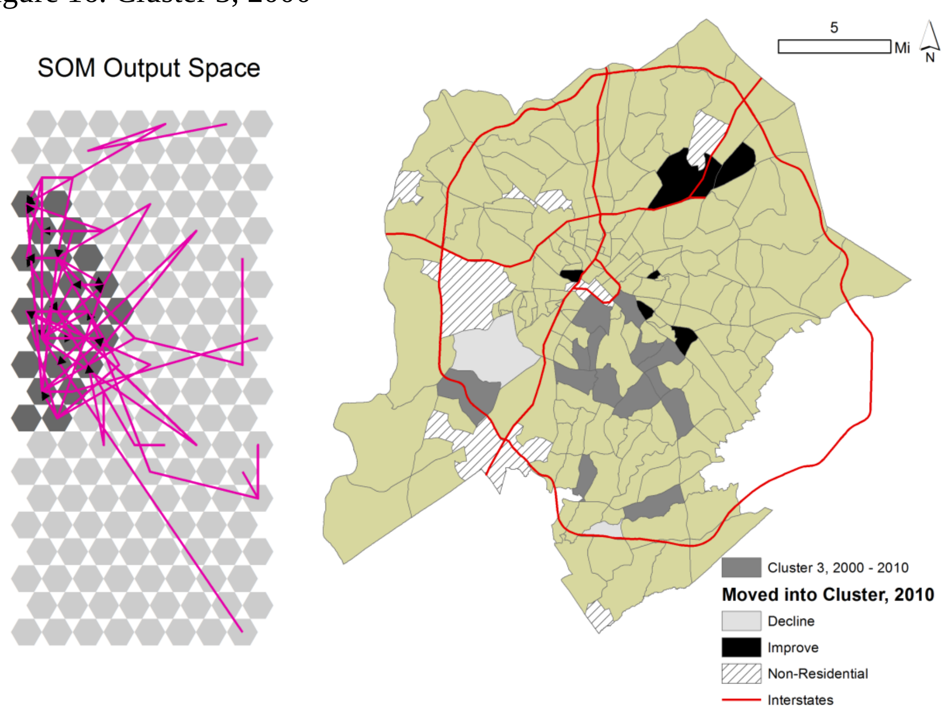

Figure 17. Cluster 3, 2010

The fourth group of neighborhoods has similar, median-levels of homeownership as compared to the previous cluster, but has lower income levels and a higher concentration of social problems. Spatially, these neighborhoods are situated in the middle-ring suburbs around the city, and their trajectories reveal a large amount of variability, showing some movement towards a higher concentration of renters with arrows pointing toward nodes on the left hand side, and a large amount of yearly fluctuation in QoL conditions (Fig. 18). Neighborhoods that moved into this group were largely in decline, with the exception of two located south of the city center, which follow a trajectory of improvement, transitioning to the lowest nodes in the group (Fig. 19).

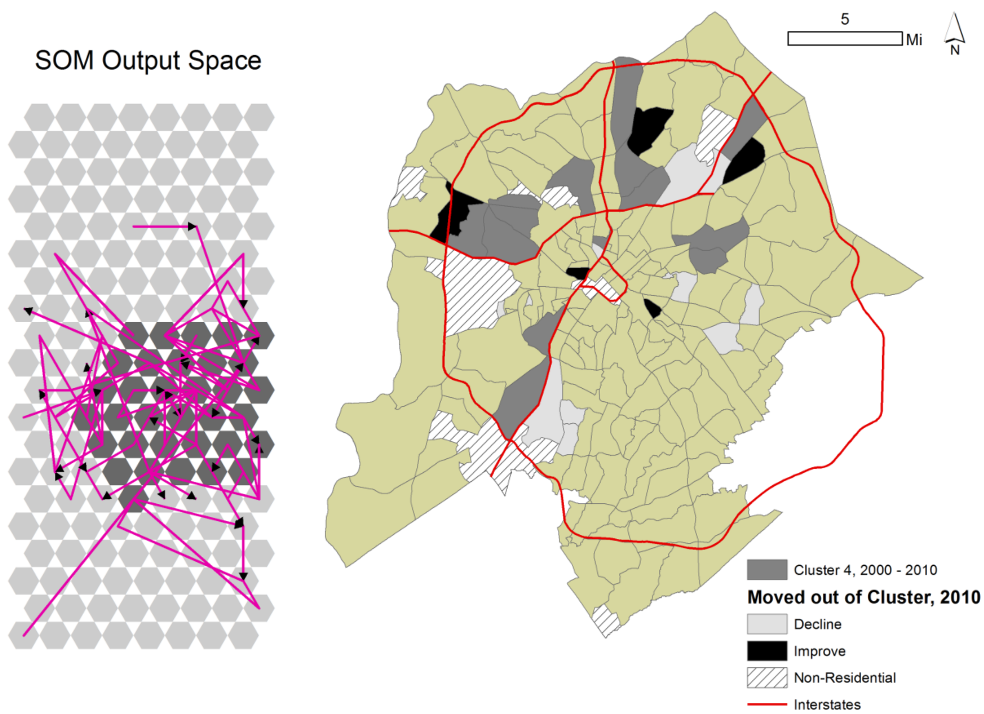

Figure 18. Cluster 4, 2000

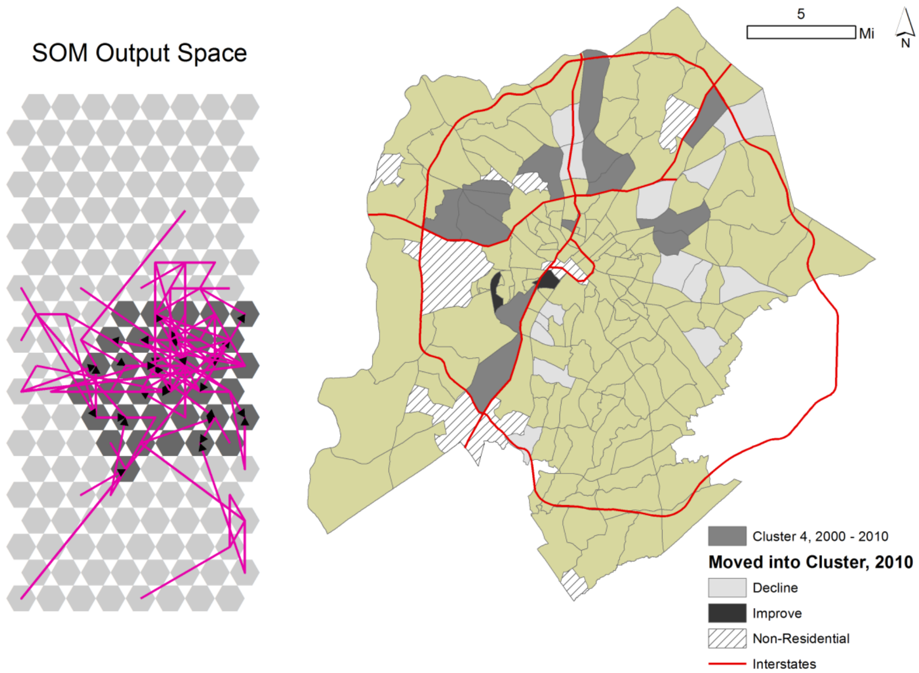

Figure 19. Cluster 4, 2010

Finally, in the lowest two overall QoL groups, those with a greater number of youth-related social problems, cluster 5, and those with the highest crime rates, cluster 6, a swap in social problems is illustrated, suggesting that there may be a temporal, reciprocal relationship between these two sets of social problems. Neighborhoods that began the decade in group 5 and transitioned outward generally moved to the high crime group (Fig. 20), with the exception of two; the first is a small neighborhood north of the city, whose trajectory follows a path more akin to group 3, a neighborhood colloquially referred to as 'NoDa' or North of Davidson street in Charlotte that is well known for its revitalization and gentrification during the decade, and a second neighborhood already highlighted in the previous group, moving to a bottom node in cluster 4. On the other hand, nearly all of the neighborhoods that increased in youth-related social problems began the decade with high crime concentrations. This is apparent in both the plots of neighborhoods that transitioned into group 5 (Fig. 21), as well as in Figure 22, showing the trajectories of neighborhoods that began in group 6. All neighborhoods that exited group 6 moved to group 5; none followed paths of revitalization. Geographically, all but one of the neighborhoods that transitioned into cluster 6 were adjacent to a neighborhood already in the group, or one that also transitioned in, possibly indicating a spatial spillover of high crime (Fig. 23). Neighborhoods in cluster 5 have a much more apparent spatial concentration than the high crime neighborhoods and have a greater presence closer to the urban core. The high crime neighborhoods, especially by 2010, are much more dispersed in older suburban neighborhoods, expanding eastward whereas cluster 5 neighborhoods are largely confined to neighborhoods just north and west of the city center.

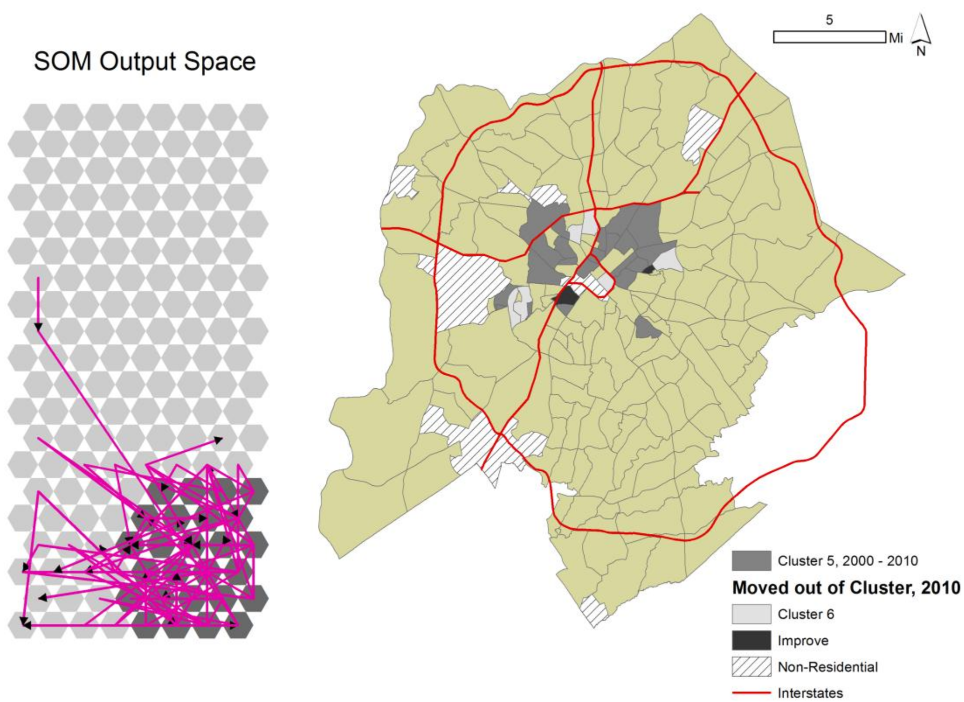

Figure 20. Cluster 5, 2000

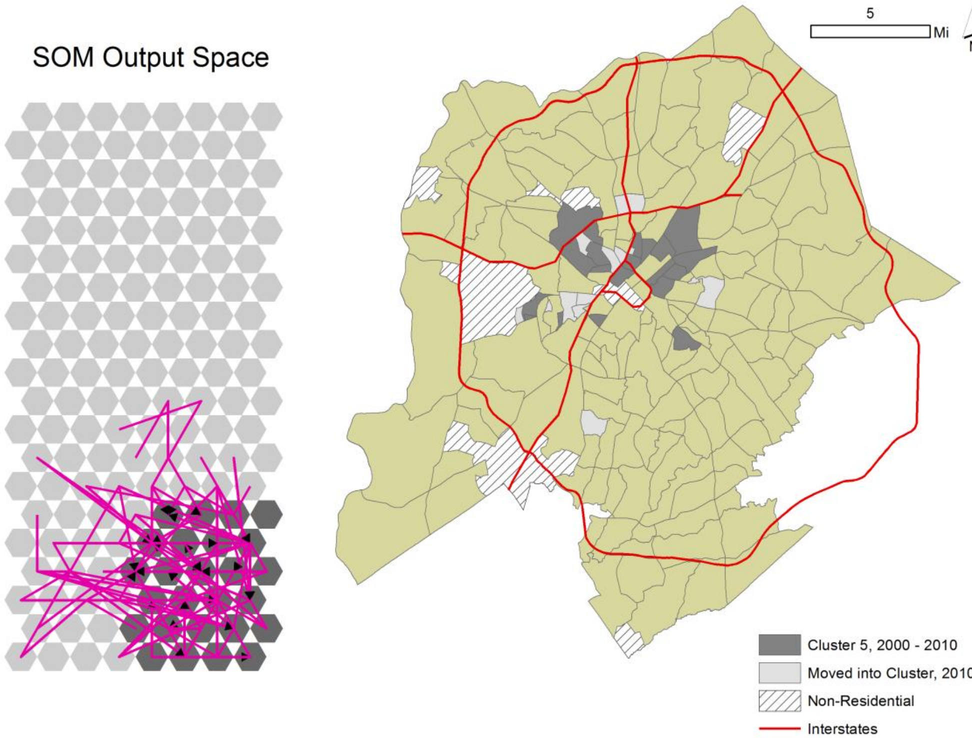

Figure 21. Cluster 5, 2010

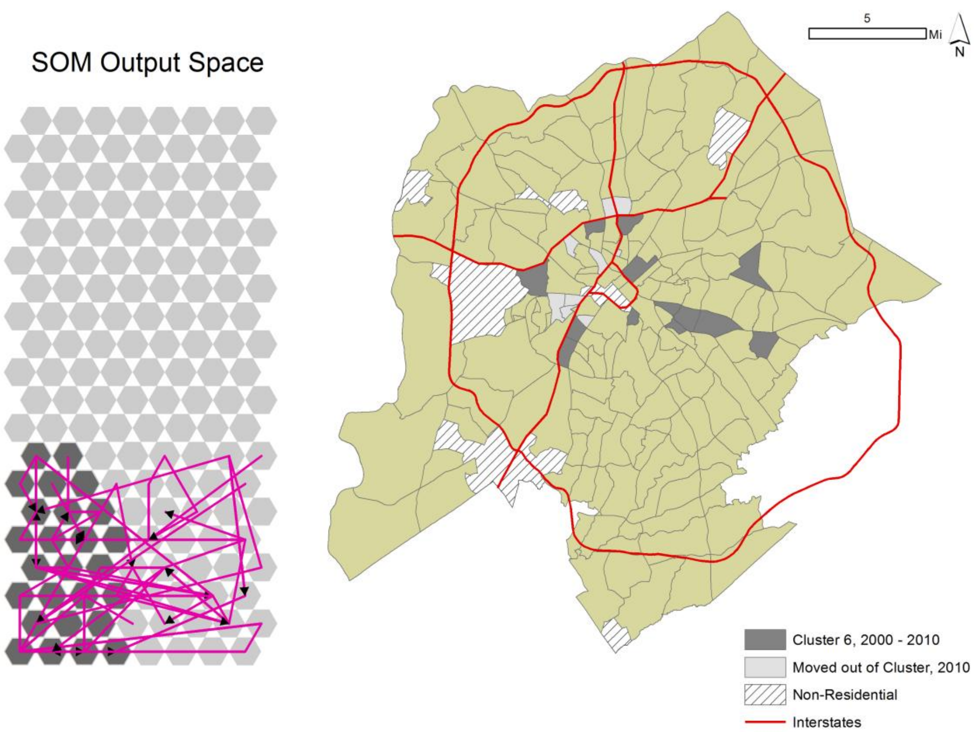

Figure 22. Cluster 6, 2000

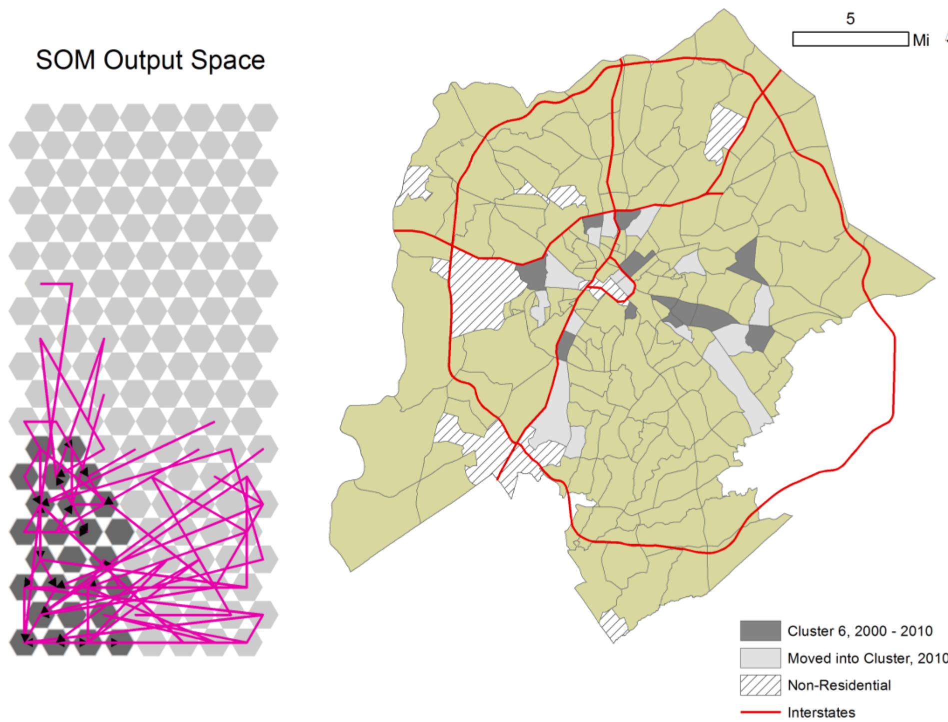

Figure 23. Cluster 6, 2010

The results of this SOM analysis provide some consistency with traditional theories of neighborhood change reviewed in Chapter 2; neighborhoods that enhanced their quality of life had a large spatial presence on the outermost ring of the city, while older, suburban neighborhoods located within the city beltway exhibited signs of decline as recent demographic research has suggested. Evidence of increasing social problems in high poverty neighborhoods as suggested by Wilson (1987) and Massey and Denton (1993) is mixed; when solely examining changes in attributes, there appears to be a reciprocal exchange of problems – neighborhoods that left the high crime group all face deeper youth-related problems, and the majority of neighborhoods that began with youth-related problems and moved to a different group, faced greater crime concentrations. When examining the geographic distribution of these changes, the neighborhoods that increased in crime were more dispersed, away from the urban core. In other words, there is evidence that neighborhoods with low incomes and high food stamp dependency experience an increase in social problems over time. However, the location of these neighborhoods is not necessarily confined to inner-city clusters; there may be a geographic evolution to these problems as well. Given, these exploratory findings, the final research objective will test the observed relationships in conjunction with a number of hypotheses regarding neighborhood change as gleaned from the literature review in a confirmatory, statistical setting.

5.2.3. Summary of SOM Results

Main findings of the SOM analysis are briefly summarized below.

- Low-income neighborhoods are the most heterogeneous in terms of quality of life characteristics.
- Median-income, suburban neighborhoods located on the outer edge of the city limit are the most homogenous.
- Looking at the prevalence of social problems, low-income neighborhoods present two discriminating trends, those with the highest crime rates and those with a concentration of juvenile problems.
- High QoL neighborhoods are the most stable over time.
- Neighborhoods characterized by lower levels of homeownership, median transit and retail accessibility, and a spatial location within the city beltway exhibited the sharpest change trajectories.
- Neighborhoods located in the middle of the city are largely in decline.

- A swap in social problems is observed over time between highest crime rates and youth-related social problems.
- Neighborhoods with the highest concentrations of crime are much more dispersed toward the middle-ring of the city while youth-related problems are concentrated around the urban core.

5.3. Research Objective 3 – Explaining Change

5.3.1. Dependent (Dynamic) Variables

Four dependent variables modified from the initial four QoL dimensions are used in this analysis: economic, youth social, crime, and homeownership. The economic dimension is measured similarly to the Markov analysis: median household income (as opposed to change in median household income – change will be incorporated into the model itself), and the percentage of the population dependent upon food stamps. Once again, the variable is standardized and computed biennially according to its mean and standard deviation, and summed.

The second dimension, youth social, is a subset of the initial social dimension as defined in the QoL study, omitting the variables representing the percentage of population over 64 and the measure of the number of youth opportunities available in a neighborhood. This decision is based in part on the results of the SOM analysis; the prevalence of juvenile problems (teenage births and high school dropout) demonstrated a distinctive potential reciprocal relationship with crime rates, and clearly followed a similar distribution according to the component planes (Figure 9). Education indicators (kindergarten and competency exam scores) are hypothesized to measure the same youth construct, while the age64 and over variable visibly follows a different distribution on the component planes, and youth opportunities are not measures of juvenile success or problems, per se. In addition, the literature points to youth indicators as potential causes and consequences of neighborhood change: education scores have been shown to drive location decisions, while the neighborhood effects literature has suggested that youth outcomes are largely shaped by the immediate social surroundings through peer influences and the development of social norms. Furthermore, education has been suggested to be a crime reducing mechanism while the exposure to violence is expected to lead to increases in youth problems. Therefore, in order to test these hypotheses, a youth indicator variable is constructed. In order to ensure that all four indicators are in fact explaining the same youth-related construct, a confirmatory factor analysis is applied resulting in factor loadings greater than 0.70 for each indicator, justifying their formation of a youth social problem variable (Teenage Birth, 0.75; Competency Exam, -0.92; High School Dropout, 0.72; Kindergarten, -0.74). The four variables are combined in the same manner as the economic dimension.

The crime dimension is also derived from the original compilation of four variables; in this case, the location quotients of property and violent crime are extracted, omitting juvenile crime and crime hotspots. The rationale behind excluding juvenile crime stems initially from an investigation of the spatial distribution of this variable which follows a very different pattern as compared to violent and property crime. The highest concentration of juvenile crime largely occurs in neighborhoods containing high schools, forming outlier concentrations even in very affluent locations of the city; the neighborhood containing Myers Park High School, for example, appeared as a location with a large juvenile crime concentration. Secondly, a confirmatory factor analysis corroborates the contrast between this variable and violent and property crime with a factor loading of only 0.48 onto the crime dimension (property crime loaded at 0.84 and violent crime at 0.96). Although the crime hot spot variable has a high factor loading (0.77), it is a heavily skewed variable, dominated by zeros; eliminating it enables the crime variable dimension to be consistently measured by the location quotients of property and violent crime.

Finally, the fourth dimension to be modeled dynamically is homeownership, a variable extracted from the physical dimension of the initial QoL study. This singular variable is placed in its own category because of its hypothesized importance in the neighborhood change process. The literature frequently cites homeownership as a significant explanatory variable of change; it has been thought to contribute to social outcomes including crime rates and youth indicators and it is a goal of several public policy initiatives aimed at stabilizing or revitalizing neighborhoods. Lastly, the analyses conduced earlier in this dissertation demonstrated that neighborhoods with lower levels of homeownership were largely in transition and neighborhoods with a higher percentage of renters were less predictable over time. Therefore, the role of homeownership in the change process and the explanatory factors of changing homeownership rates will be more formally tested in a confirmatory setting[7].

5.3.2. Independent (Time Invariant Variables)

In addition to the four dynamic, dependent variables, a number of time-lagged

[7] A variable comprising neighborhood physical decline was also investigated; however, the way in which the potential indicators were measured over time was inconsistent. Models tested with this dimension had very poor fit and the variable proved to neither explain, nor be explained by any of the other variables in the model, so it was ultimately removed.

predictor variables are included to account for factors associated with traditional theories of neighborhood change.

Housing Age

Urban economic explanations of neighborhood change are largely centered on two main factors: distance from the central business district – in accordance with the bid rent model, and housing age and subsequent deterioration as postulated by filtering theories of decline. Both of these concepts are incorporated into the modeling framework. For housing age, four variables are constructed from the Mecklenburg County Property Record Database as follows: 1) the percentage of housing units constructed before 1950; 2) in 1951-1969; 3) in 1970-1999; 4) in 2000-2010. The cutoff values for these housing classes are influenced by the literature; housing constructed between 1950 and 1969 is representative of inner ring suburbs, those built during a period of rapid suburbanization fueled by a host of government policies, and were the first neighborhoods constructed with the automobile as the dominant mode of transport (Lee and Leigh, 2005). This latter point helps differentiate these inner-ring suburbs from so-called street car suburbs developed earlier in the century, which tend to have more distinctive architecture, tree-lined streets, walkable commercial areas, and greater transit access (Lee and Leigh, 2005). Maps of the spatial distribution of these variables (Figure 24) reveal that four variables capture the spatial structure of the city, as the first two maps depict housing concentrations in the inner-most and middle ring suburbs, while the final two maps complete the outermost suburban neighborhoods. Notably, in the final map, the highest concentration of residential housing within the city center is constructed, illustrating the dual changes undergone in the city during the 2000-2010 decade:

suburban housing construction combined with city center high-rise, and higher-end apartment or condominium development. In order to remain consistent with the remainder of the variables which are all temporally lagged, only the first three time periods are used, representing housing constructed up until 2000. Including lagged-only variables helps ensure that the causal relationships are not contemporaneous and the model is recursive.

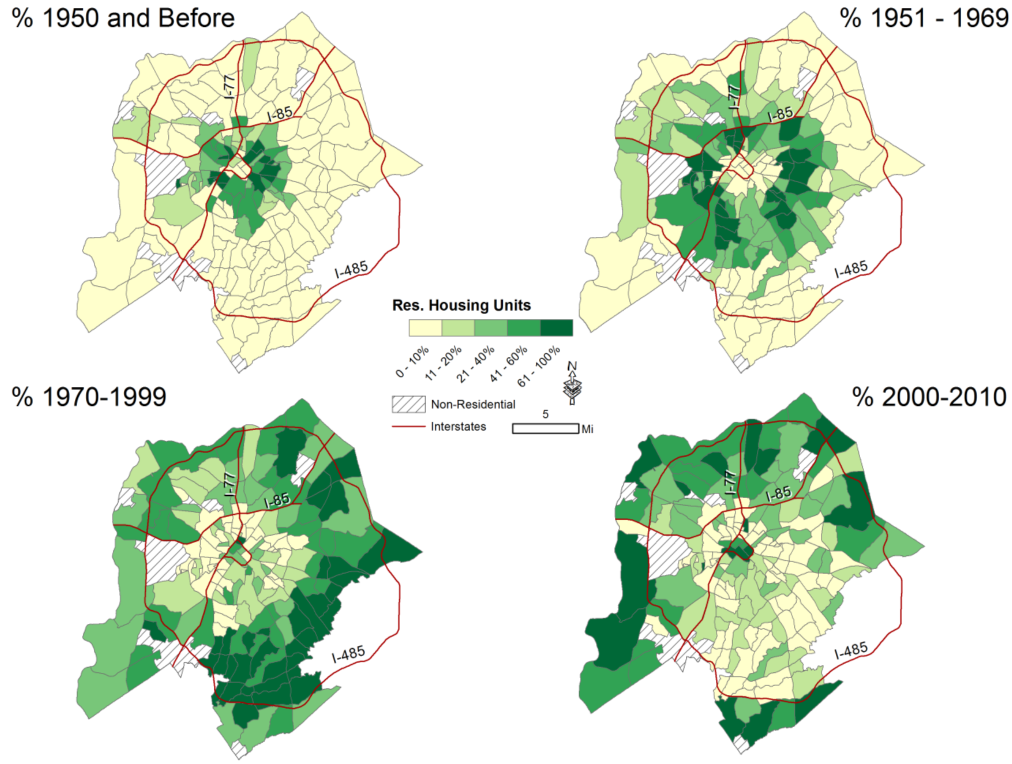

Figure 24. Spatial distribution of residential housing age variables

Employment Accessibility

To measure employment accessibility, this study takes an alternative approach from most empirical studies which often utilize distance to the central business district as a proxy, assuming a monocentric urban form. In this case, an attempt is made to capture employment opportunities or subcenters throughout the urban area to more accurately portray the reality of Charlotte. Therefore, employment accessibility is defined as the number of employees in a given neighborhood plus its surrounding neighborhoods divided by the total area of that region. The same neighborhood adjacency definition used throughout this dissertation is used to define the surrounding neighborhoods (6 nearest neighbors within 5 miles). The US Census publishes the employment data as part of its Economic Census, but the data are only available at the zip code level. Counts are therefore disaggregated to the NSAs by proportional areal interpolation. This GIS-based procedure assigns a proportion of the zip-code employment count to each NSA based on the area of the NSA that falls within each zip-code. It assumes that employment counts are evenly distributed throughout the zip-code area; therefore, if an NSA occupies half of the zip area, it is assigned half of the employment count. The resulting spatial distribution of the employment density variable is shown in Figure 25, below. Clearly, the highest concentration of employment remains around the urban core, as would be expected, but rather than declining at a constant, linear rate, other employment locations including south Charlotte, the airport and the University area have a better representation in this specification.

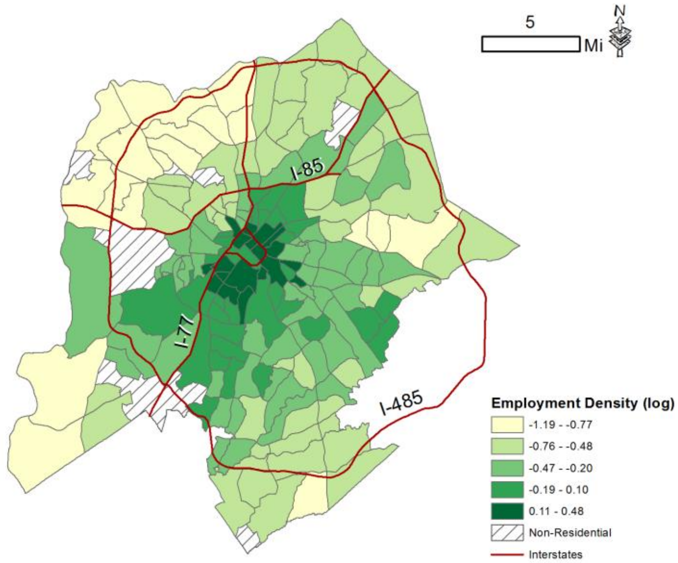

Figure 25. Employment Density in Charlotte, 2000

Racial Composition & Other Variables

Neighborhood racial and ethnic composition in 2000 is obtained from the 2000 Census at the block level and aggregated up to the NSAs (percent black, white, Hispanic). The city of Charlotte is highly segregated according to race, and therefore it is impossible to use both the percentage of blacks and percentage of whites in the same model (they are almost perfectly negative correlated). Therefore, only the concentration of minorities is used in the analysis. The spatial distribution of these two variables (Percent Hispanic, Percent black) is shown in Figure 26. Finally, transit and retail access in 2000 are extracted from the physical dimension of the QoL study and used as explanatory factors in the model; these variables are defined according to Table 1, but because only the 2000 data are utilized, for transit access, walking distance to light rail is not incorporated as it was not constructed until later in the decade.

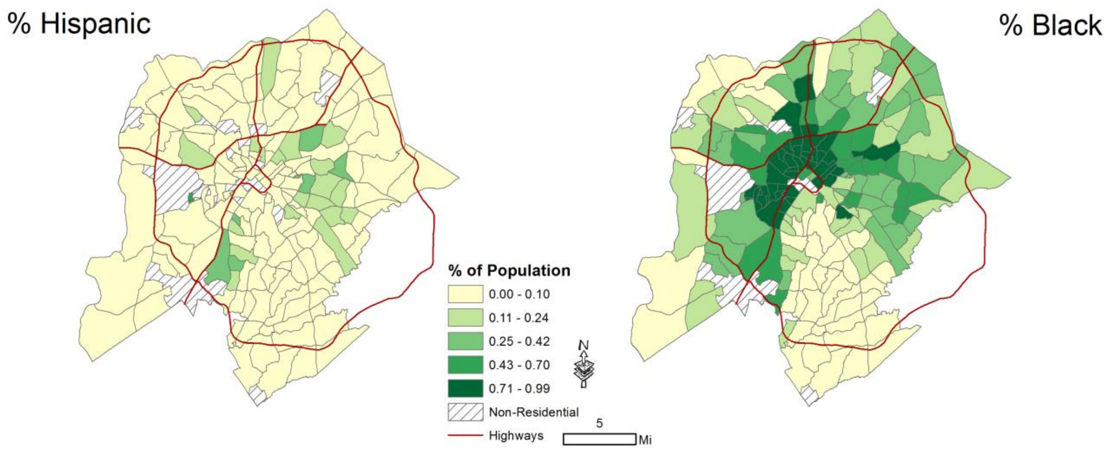

Figure 26. Percent of 2000 Population a) Hispanic b) Black

5.3.3. Model Results

Four separate models are estimated (2000-2002; 2004; 2008; 2010) to examine the temporal dimension of change. In order to ensure that more parameters than observations (n=173) are not estimated, some very insignificant variables are excluded from the final models each year. Second, because of significant correlation between the race variables and a number of the QoL outcomes, only the percent Hispanic variable is included in the final versions of the models to avoid problems with multicollinarity. Finally, distribution plots of a number of variables reveal the need for several data transformations to obtain normal distributions – these include the log of crime and employment density, square root of percent Hispanic, each of the housing age variables, and retail accessibility. Table 8 presents descriptive statistics of each of the dependent variables in the models.

Table 8. Descriptive statistics of dependent variables[8]

	Econ02	Econ04	Econ08	Econ10	Crime02	Crime04	Crime08	Crime10
Min.	-6.17	-6.35	-6.36	-5.52	-0.71	-0.89	-0.68	-0.80
Max.	4.77	6.47	5.98	6.03	1.21	1.12	1.12	1.33
Mean	0.00	0.00	0.00	0.00	0.21	0.23	0.26	0.27
S.D.	1.82	1.82	1.81	1.81	0.42	0.40	0.41	0.42
	Soc02	Soc04	Soc08	Soc10	Own02	Own04	Own08	Own10
Min.	-3.93	-3.27	-3.16	-2.90	0.00	0.00	0.00	0.00
Max.	2.08	1.99	2.00	2.19	0.95	0.95	0.94	0.93
Mean	0.00	0.00	0.00	0.00	0.54	0.54	0.53	0.52
S.D.	1.00	1.00	1.00	1.00	0.24	0.23	0.23	0.22

The first set of equations represents the shortest time lag at two years, and the start of the decade in Charlotte. In Table 9, below, the columns represent the four dependent variables, while the rows are the corresponding independent variables. *R*-squared values for each equation are all very high, due in most part to the dominant temporal autoregressive parameters. In each of the four models, the autoregressive parameter is very significant, meaning that neighborhoods with high crime, youth social indicators, economic conditions, and homeownership levels in 2000 all had high values in 2002. This is most pronounced for homeownership rates, which appear to be very durable at a two-year time lag. Aside from the stability of each of the dependent variables, there is a significant reciprocal relationship between the economic and youth social dimensions as high economic conditions lead to increases in youth social indicators, while youth social indicators lead to increases in neighborhood economic conditions. This is a relationship that was hypothesized given the strong role that school

[8] Dependent variables are abbreviated as follows: economic dimension = econ; crime dimension = crime; youth indicators = soc; homeownership = own. The year follows the abbreviation.

quality plays in the residential selection process; those with the means to do so concentrate in neighborhoods with high perceived youth indicators.

These youth indicators also have a significant, negative impact on crime rates two years later, although the reciprocal relationship is not significant (crime rates do not significantly lead to declines in youth social indicators after two years). From 2000 to 2002, the oldest housing in Charlotte, located closest to the urban core is associated with declines in a neighborhood's economic standing and increases in crime rates, while older, first ring suburban neighborhoods are similarly associated with rising crime as well as declines in youth social indicators. As hypothesized, lower levels of homeownership are associated with increases in crime two years later, however, the reverse relationship is not statistically significant. Two of the spatial lag variables are significant: surrounding areas of high youth social values lead to an increase in a neighborhood's youth social conditions after two years, and homeownership exhibits signs of significant spatial spillover over time. Finally, a significant error covariance between the economic and crime dimensions exists, which may suggest that a common factor associated with rising crime rates and declining economic status (the covariance is negative) is not captured in the model.

Overall, the fit of the system of equations is good; the chi-square value is low (29.19) and insignificant (p=0.15), meaning that the null hypothesis that data fits the model cannot be rejected. The 90 percent confidence interval for the root mean square error of approximation (RMSEA) is (0.00; 0.082), the comparative fit index (CFI) is 1.00 and goodness of fit index (GFI) 0.98. General guidelines suggest that a RMSEA value below 0.6, and a CFI above 0.95 are indicative of a very good fit (Hu and Bentler, 1999). Collectively, these fit indices are indicative that the model is consistent with the data.

Table 9. Estimated Equations for 2000-2002

(independent\dependent)	Soc 2002	Crime 2002	Econ 2002	Own 2002
Crime 2000	-0.04 (-0.82)	**0.62**** **(10.25)**	0.00 (-0.08)	-0.05 (-1.10)
Social 2000	**0.29**** **(7.36)**	**-0.18**** **(-3.32)**	**0.10**** **(3.34)**	-0.02 (-0.46)
Economic 2000	**0.51**** **(10.89)**	0.06 (0.84)	**0.81**** **(25.56)**	-0.03 (-0.68)
%Hispanic	-0.04 (-1.83)	0.05 (1.58)	-0.01 (-0.34)	-0.04 (-1.70)
%House <1950	0.01 (0.15)	**0.14**** **(2.94)**	**-0.07**** **(-2.31)**	0.01 (0.27)
%House 1951-1969	**-0.08**** **(-2.97)**	**0.08**** **(2.06)**	-0.04 (-1.43)	-0.01 (-0.44)
%House 1970-1999	0.01 (0.35)	0.01 (0.20)	-0.05 (-1.45)	-0.02 (-0.41)
Homeownership 2000	0.00 (0.12)	**-0.10**** **(-2.10)**	0.00 (0.03)	**0.95**** **(28.41)**
Transit Access	--	--	-0.03 (-1.03)	0.04 (0.99)
Retail Access	--	-0.02 (-0.40)	0.02 (0.86)	-0.01 (-0.35)
Employment Density	--	--	0.00 (-0.10)	-0.02 (-0.81)
LagCrime00		0.03 (0.52)		
LagSocial00	**0.13**** **(3.21)**			
LagEcon00			0.04 (1.30)	
LagOwn00				**0.08 **** **(2.02)**
R-Squared	0.94	0.88	0.96	0.94
Error Covariance	ECON02 and CRIME02 (-0.02, t=-4.09**)			
Model Fit Indices				
Chi-Square	29.19; 23 df; *p*=0.15			
RMSEA (90% C.I.)	(0.00; 0.083)			
CFI\GFI	1.00\0.98			

** significant at *p<0.05*; Standardized coefficients shown in table, with *t*-values in parentheses.

At a four-year temporal interval (Table 10), a larger number of significant relationships are revealed as compared to the two-year lag. According to these results, high 2000 crime rates in a neighborhood led to a decline in its relative economic status and a drop in its homeownership rate four years later. This result is in accordance with recent studies that have suggested that crime is a significant catalyst for change, not simply an outcome of it. Lower-levels of homeownership in 2000 continued to influence increases in crime, leading to the emergence of a reciprocal relationship between homeownership and crime rates. In this case, lower homeownership rates have a stronger influence on crime rates than the reverse. Neighborhoods with a higher concentration of Hispanics in 2000 also witnessed a decline in their youth-related indicators and in homeownership rates after four years. None of the housing age variables are significant at this time lag, nor are the accessibility indicators. Two spatial lag variables are significant, one of which is a cross-lagged variable: neighborhoods with high surrounding economic conditions in 2000 experienced an increase in youth social indicators four years later. This finding could give support to notions that concentrations of wealth or income creates social capital, positively impacting young people, or, conversely, that concentrations of lower incomes or economic conditions negatively influences these values. Secondly, the spatial lag variable for crime is significant at a four year temporal lag. Model fit indices for this four year time lag offer a slight improvement over the 2002 model and all point to an excellent fit between the model and the data (Chi-square 17.85, *p*>0.27).

Table 10. Estimated Equations for 2000-2004

(independent\dependent)	Soc 2004	Crime 2004	Econ 2004	Own 2004
Crime 2000	-0.05 (-0.54)	**0.52**** **(7.15)**	**-0.12**** **(-2.13)**	**-0.09**** **(-2.16)**
Social 2000	**0.43**** **(5.45)**	**-0.20**** **(-3.07)**	**0.21**** **(4.16)**	-0.07 (-1.45)
Economic 2000	**0.21**** **(2.21)**	0.03 (0.42)	**0.70**** **(11.30)**	0.03 (0.70)
%Hispanic	**-0.10**** **(-2.37)**	0.03 (0.42)	0.02 (0.56)	**-0.08**** **(-3.69)**
%House <1950	0.04 (0.54)	-0.03 (-0.26)	0.01 (0.34)	0.00 (-0.11)
%House 1951-1969	-0.06 (-1.09)	0.01 (0.25)	-0.04 (-1.60)	-0.04 (-1.48)
%House 1970-1999	-0.13 (-1.66)	-0.01 (-0.13)	-0.06 (-1.25)	-0.02 (-0.57)
Homeownership 2000	0.03 (0.53)	**-0.13**** **(-2.71)**	-0.01 (-0.25)	**0.90**** **(31.08)**
Transit Access	--	0.00 (0.78)	-0.04 (-0.97)	--
Retail Access	--	0.04 (0.92)	-0.03 (-1.04)	--
Employment Density	--	0.04 (0.91)	0.04 (0.82)	--
LagCrime00		**0.15**** **(2.27)**		
LagSocial00				
LagEcon00	**0.30** **(3.62)**		--	
LagOwn00				--
R-Squared	0.73	0.82	0.89	0.94
Error Covariance	Econ04 and Crime04 (-0.04, t=-3.96**); Econ04 and Soc04 (0.04, t=3.32**)			
Model Fit Indices				
Chi-Square RMSEA (90% C.I.) CFI\GFI	17.85; 15 df; *p*=0.27 (0.00; 0.086) 1.00\0.99			

Models estimated for the final two temporal lags: 2008 and 2010 produce very similar results to one another, with a few minor distinctions. In general, the most discernable difference between these last two models (Tables 11 and 12) and the prior two sets of models, is the significant negative effect of older homes on the 4 QoL outcome variables. Neighborhoods with a large percentage of housing constructed between 1951 and 1969, primarily shaping the middle ring suburbs around the city (Fig. 23), experienced an increase in crime, a decline in economic conditions, and a decline in homeownership over the course of the decade, while the second oldest suburban group, housing constructed between 1970 and 1999, witnessed significant economic declines during that same time period; results that all cohere to filtering notion's of urban decline. To further illustrate these spatial changes, the maps in Figure 27[9] illustrate the change between 2000 and 2010 for the economic and crime dimensions. A marked improvement in the economic conditions of neighborhoods in the center city vicinity is apparent in the first map of the figure, as are economic gains in several outer-most neighborhoods. Inner-ring suburban neighborhoods are portrayed by clear declines in relative economic status. Improvements in violent and property crime concentrations are similarly revealed in neighborhoods around the urban core, while increases in crime concentrations are located in northwestern neighborhoods and around the eastern ring.

[9] Note that the color scheme is in accordance with the concept of quality of life; economic declines contribute negatively to QoL and are hence depicted in red, while crime declines are positive changes, and shown in blue.

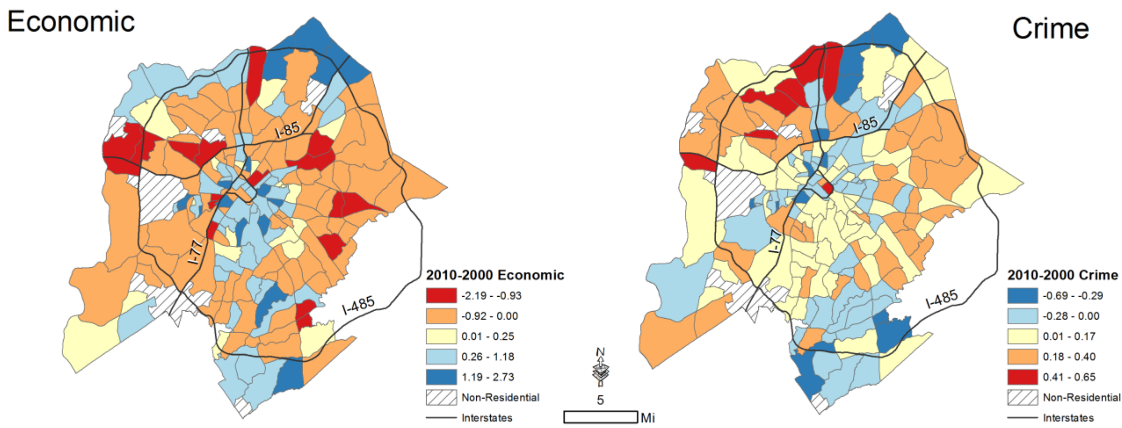

Figure 27. Spatial Distribution of Changes in Economic and Crime Dependent Variables between 2000 and 2010.

A second relationship that emerges in this longer time frame is a negative effect of crime rates on youth social indicators. While youth indicators consistently had an inverse relationship on crime rates at shorter time lags examined earlier, the reciprocal relationship did not materialize until later in the decade. In fact, by 2010, levels of crime in a neighborhood 10 years prior have a greater influence on shaping declines in youth indicators than the reverse. They also have a more significant impact than economic conditions, which are no longer significant after a decade. Crime rates continue to drive neighborhood change after 10 years; in fact the negative relationship between crime in 2000 and homeownership is the strongest with this decennial interval. On the other hand, homeownership levels in 2000 no longer exert a negative impact on crime rates 8 or 10 years later, suggesting that, while these two dimensions exhibit reciprocal relationships, the time frame in which their impacts are revealed is not equivalent.

It is striking that none of the spatial lag variables are significant in the final model (Table 11); a 10-year spatial-temporal lag appears to be too long of a time frame to capture spatial spillover effects. Finally, the last two models have the greatest amount of error covariance in dependent variables: significant covariances between economic and crime, economic and social, and social and crime variables, indicate that within these models there is a systematic unexplained variance that is not being captured. In addition, the model fit indices, while still good, fall short of those obtained for the previous two sets of equations.

One noticeable difference between the 2000-2008 model and all others is a significant, positive impact of transit access on increases in youth outcomes (Table 12). Given that neighborhoods with the highest transit access are most centrally located to the urban core, a close investigation of the data reveals that many of these neighborhoods have very small, and in some instances no juvenile populations; they are neighborhoods with newly built condominiums and apartment complexes that tend to attract young, working individuals without children. The data for 2008 represents the pinnacle of the real estate boom and consequently the height of property values for these locations, and may help to explain this finding. As was illustrated in the first analysis, neighborhood QoL in 2010 was more akin to the pre-2008 data, as 2006-2008 represented an outlier in improvements to city center neighborhoods.

Table 11. Estimated Equations for 2000-2008

(independent\dependent)	Soc 2008	Crime 2008	Econ 2008	Own 2008
Crime 2000	-0.14 (-1.66)	**0.58**** **(7.51)**	-0.09 (-1.39)	**-0.20**** **(-3.77)**
Social 2000	**0.43**** **(5.36)**	**-0.14**** **(-2.29)**	**0.22**** **(3.54)**	-0.09 (-1.83)
Economic 2000	**0.19**** **(2.10)**	-0.10 (-1.52)	**0.70**** **(10.28)**	0.07 (1.19)
%Hispanic	**-0.12**** **(-2.71)**	0.08 (1.81)	-0.03 (-0.91)	-0.05 (-1.90)
%House <1950	0.06 (0.87)	-0.02 (0.19)	-0.02 (-0.29)	0.01 (0.97)
%House 1951-1969	**-0.25**** **(-4.03)**	**0.12**** **(2.56)**	**-0.16**** **(-3.24)**	**-0.08**** **(-2.20)**
%House 1970-1999	-0.14 (-1.63)	0.05 (0.56)	**-0.14**** **(-2.19)**	-0.07 (-1.52)
Homeownership 2000	--	--	--	**0.81** **(21.21)**
Transit Access	**0.18**** **(2.88)**	-0.06 (-0.77)	0.07 (1.34)	--
Retail Access	--	0.01 (0.56)	-0.03 (-0.98)	--
Employment Density		0.08 (1.51)	0.07 (1.71)	-0.00 (-0.01)
LagCrime00		--		
LagSocial00				
LagEcon00	**0.26**** **(3.48)**		--	
LagOwn00				--
R-Squared	0.73	0.78	0.85	0.90
Error Covariance	Econ08 and Crime08 (-0.08, t=-5.15**); Econ08 and Soc08 (-0.07, t=3.84**); Crime08 and Soc08 (-0.09, t=-4.40**)			
Model Fit Indices				
Chi-Square	19.06; 13 df; *p*=0.12			
RMSEA (90% C.I.)	(0.00; 0.10)			
CFI\GFI	1.00\0.99			

Table 12. Estimated Equations for 2000-2010

(independent\dependent)	Soc 2010	Crime 2010	Econ 2010	Own 2010
Crime 2000	**-0.31** (-3.61)**	**0.60** (7.92)**	-0.11 (-1.76)	**-0.20** (-3.58)**
Social 2000	**0.34** (3.51)**	**-0.22** (-3.05)**	**0.23** (3.82)**	-0.09 (-1.48)
Economic 2000	0.16 (1.58)	-0.03 (-0.88)	**0.70** (10.40)**	0.05 (0.79)
%Hispanic	-0.06 (-1.15)	0.04 (0.91)	-0.01 (-0.39)	-0.04 (-1.15)
%House <1950	0.02 (0.22)	0.01 (0.10)	-0.04 (-0.73)	0.03 (0.51)
%House 1951-1969	-0.12 (-1.78)	**0.16** (2.81)**	**-0.18** (-3.73)**	**-0.10** (-2.41)**
%House 1970-1999	-0.03 (-0.30)	-0.00 (-0.07)	**-0.18** (-2.90)**	-0.11 (-1.91)
Homeownership 2000	--	--	--	**0.80** (17.15)**
Transit Access	--	-0.07 (-1.05)	0.05 (0.81)	--
Retail Access	--	0.04 (0.91)	-0.01 (-0.41)	--
Employment Density	--	0.07 (1.35)	0.07 (1.54)	0.03 (0.68)
LagCrime00		--		
LagSocial00	--			
LagEcon00			--	
LagOwn00				--
R-Squared	0.62	0.79	0.85	0.85
Error Covariance	Econ10 and Crime10 (-0.08, t=-5.08**); Econ10 and Soc10 (0.06, t=4.19**); Soc10 and Crime10 (-0.08, t= -3.47**)			
Model Fit Indices				
Chi-Square	18.08; 11 df; *p*=0.07			
RMSEA (90% C.I.)	(0.00; 0.11)			
CFI\GFI	1.00\0.99			

5.3.4. Summary of Modeling Results

The main findings from the statistical modeling results are summarized below.

- Youth indicators have a negative influence on changes in crime concentrations at all temporal lags.
- High crime rates in 2000 lead to declines in youth indicators 10 years later.
- High economic conditions in 2000 lead to increases in youth indicators up to 8 years later; youth indicators have a significant positive relationship with neighborhood economic conditions at all temporal lags.
- Low homeownership levels lead to short-term (2 and 4 year) increases in crime; high crime rates lead to declines in homeownership over the longer term (4, 8 and 10 years).
- From 2000-2002, the oldest housing in Charlotte (pre-1950s) was associated with economic declines and rising crime rates. This relationship became insignificant over the course of the decade.
- First-ring suburban neighborhoods (housing constructed between 1950 and 1969) declined in all four QoL dimensions by 2010.
- Neighborhoods with a concentration of housing constructed between 1970 and 1999 are associated with economic declines in the 2008 and 2010 models.
- Spatial lag of youth indicators and homeownership is significant in the 2-year model, crime is significant at 4 years, a cross-lagged spatial effect of economic conditions on youth indicators is significant at 4 and 8 years, and finally no spatial lag variables are significant at 10 years.
- Accessibility measures offered little explanatory power on QoL changes; no supporting evidence was found for the economic decline-high transit access connection identified in the literature.

- The model for 2004 had best overall fit, and captured relationships between QoL dimensions, while longer temporal lag models had the most error covariance of dependent variables.

CHAPTER 6: DISCUSSION AND CONCLUSIONS

Neighborhood quality of life is a term that transcends economic or demographic statistics pertaining to a neighborhood's residential composition. It is an encompassing concept describing the quality of life that one may expect to receive from residing in a particular neighborhood. While the meaning of quality of life is subject to personal interpretation, and may vary across individuals, in the urban geography literature, it has come to refer to the conditions of a particular place at a period of time and forms the environment in which people seek happiness. Neighborhoods offering a high quality of life are often thought to provide access to high quality schools and employment, are safe environments low in crime, and are economically vital. Over time, the characteristics that describe a neighborhood's QoL will change. To urban planners and policy makers charged with devising strategies toward improving the lives of its residents, and ensuring that the urban environment is capable of attracting and retaining businesses, understanding the process of neighborhood change is crucial. Despite a growing popularity on the part of local governments in collecting neighborhood-level QoL indicators to assess and monitor change over time, there is a paucity of studies that have sought to understand the driving factors behind these longitudinal trends.

The purpose of this dissertation has been to contribute to the understanding of the dynamics of neighborhood QoL change. Utilizing a systematically collected set of QoL indicators for all neighborhoods in Charlotte, NC during the 2000-2010 decade as a case study, this dissertation has investigated change dynamics in the context of a rapidly changing metropolitan area featuring a 35 percent increase in population, expansive suburbanization, center city construction and neighborhood revitalization. A housing and real estate boom at the start of the decade propelled much of this growth for the first seven years, while the subsequent housing bust and economic recession provided a very different setting for neighborhood QoL dynamics to play out at the conclusion of the time span. The analyses performed in this dissertation have sought to highlight how these disparate macro-level economic conditions have impacted or shaped changes in neighborhood QoL. The conclusions are summarized in four broad sets pertaining to (1) the spatial dimension of change, (2) the significant role of housing age, (3) temporal insights, and (4) the relationships between QoL dimensions and the role of other explanatory variables.

One of the overarching objectives of this dissertation was to examine the geographic or spatial dimension of neighborhood change. Specifically, the role of spatial dependence or spatial spillovers in shaping the process of change and the transforming spatial structure of the city were investigated with three complementary analytical approaches. Results of these analyses have suggested that, in terms of the biennial process of overall QoL change, spatial spillovers appear to be very influential, particularly in the case of crime, the spread of the highest QoL neighborhoods, and for youth social indicators. The spatial Markov analysis revealed that the process of improving or declining in overall QoL is not spatially independent; the conditions of surrounding neighborhoods has a definite impact on the probability of transitioning both positively and negatively. When surrounded by neighbors of a worse or equally bad quality of life index, a neighborhood is much more likely to remain in the lowest class or to decline from higher classes. However, an increasing probability of moving to a higher class is found when surrounded by neighborhoods with higher QoL values. From a public policy perspective, findings from this analysis can be used to help guide place-based community development efforts and funding. Initiatives targeting neighborhoods individually may be best directed towards the lowest QoL neighborhood amidst a group of better neighborhoods, as these efforts can be bolstered by the positive spatial spillover effects and have the highest chance of success. Improvements to the lowest QoL neighborhoods should take a more regional approach, directing resources to groups of spatially clustered neighborhoods to help offset the negative spillovers driving the probability of improvement down.

The spatial statistics and econometrics literature has relied exclusively on neighborhood or spatial lag definitions that consist of the average value of a given number of surrounding polygons to examine spatial dependency effects. In this study, alternate specifications of that spatial lag definition were investigated namely in the form of the median, mode, and upper and lower quartile of the values of the 6 nearest neighbors within a 5 mile limit. Results of the spatial Markov analysis employing these various specifications proved telling in the story of dependency effects. The extreme ends of the quartiles exhibited amplified effects; when the upper quartile of a set of neighbors only reach class 1 or 2, the probability of declining or remaining in a lowest class was at its highest level, and similarly, when the lower quartile of neighboring values reach the highest two classes, the probability of improving or remaining high also increased. In addition to revealing the difficulty a neighborhood located amidst concentrated disadvantage faces in improving over time, or the advantage that spatial clusters of the best-off neighborhoods have, these results also shed light on the potential that broadening the standard neighborhood definition can bring to spatial dependency studies.

For the self-organizing map methodology which examined the spatial location of neighborhoods that transitioned between clusters of neighborhoods with similar QoL characteristics, two apparent spatial spillover effects were observed, specifically in the case of the highest QoL and the high crime clusters. In both instances, many of the neighborhoods that moved into the groups by the end of the decade were adjacent to neighborhoods that were already in the clusters or to other neighborhoods that also moved in.

Finally, the role of spatial spillovers in the change process was investigated in the final, statistical analysis through the incorporation of spatial-temporal lagged and cross-lagged variables in the four regression equations explaining changes in crime, youth social indicators, economic conditions, and homeownership rates, at several temporal lags. At the two year time interval, evidence of spatial spillovers were present in the youth social and homeownership models, meaning that higher homeownership levels and youth indicators in a neighborhood's surrounding area led to increased homeownership and youth indicators for a given neighborhood, two years later. However, after two years, these spatial effects disappeared for the homeownership model and for the youth model, a cross-lagged effect emerged as significant with high levels of surrounding economic conditions leading to higher social indicators for years later (or low surrounding conditions leading to declines in youth indicators). This latter result may have important implications for the concentration of wealth or poverty on youth outcomes, or at least reveals the importance of considering both the conditions of an individual's neighborhood, as well as the larger encompassing region when testing for neighborhood effects. A significant spatial spillover effect for crime was also present at the four-year temporal lag. Given the strong spatial dependency effects uncovered in the Markov analysis, it was surprising that the spatial lag variables did not have greater explanatory power in the predictive change models. It seems, however, that once the characteristics of surrounding neighborhoods are taken into consideration: the economic status of residents, the local school quality, housing age, variables that all in themselves are spatially correlated; the importance of spatial proximity alone in explaining change is significantly diminished.

Another major finding of this dissertation related to the geographic dimension of neighborhood QoL dynamics was the persistent trend in the decline in QoL of older, inner-ring suburban neighborhoods. Consistent with geographic research documenting the economic decline and changing demographics of these neighborhoods and the urban economic filtering explanations of neighborhood change, both the SOM analysis and the SEM models pointed to the decline in these neighborhoods across several QoL dimensions. While prior studies on the subject have primarily focused on residential socio-demographic shifts and housing deterioration, this dissertation has provided additional information on the QoL changes encountered in these neighborhoods. Results of the SOM analysis revealed that by 2010 a number of older, suburban neighborhoods joined a cluster of neighborhoods characterized by low incomes, high food stamp dependency, and the highest concentration of crime, while others transitioned into a group dominated by youth social problems and housing deterioration. Spatially, however, the high crime neighborhoods experienced a greater dispersion outward toward the inner-ring suburbs, suggesting a spatial evolution to the dynamics of urban crime.

In the SEM analysis, the variable representing inner-ring suburbs (the percentage of housing constructed between 1951 and 1970) provided significant explanatory power in explaining increases in crime concentrations, declines in relative economic status and youth social indicators, and drops in homeownership rates between 2000 and 2010. Notably, this variable did not become significant for all QoL dimensions until the longer time lag models, after significant transformations to the city were underway. At the start of the decade, the percentage of housing constructed prior to 1950, or the neighborhoods closest to the urban core, explained a decline in economic conditions and an increase in crime, indicating that prior the rapid population and economic growth experienced by the city of Charlotte, inner-city neighborhoods were most susceptible to urban decline. Once the housing boom took off, however, and revitalization efforts were underway in those oldest neighborhoods and new housing construction shaping the outermost suburbs, older, post war neighborhoods were left in decline, across all measured QoL dimensions.

The final SEM model which captured changes during the entire decennial time span, additionally recorded relative economic declines in neighborhoods dominated by housing constructed during the 1970-1999 time span. The standardized coefficient of this variable equaled that of the inner-ring suburbs, and should serve as a warning sign of future suburban decline which need not be necessarily confined to the inner-ring. The corresponding social problems accompanying the post war suburbs were not prevalent in the second, younger suburban group, but if trends continue on the same trajectory, these neighborhoods may be at risk for the same problems in the future. Inner-ring decline has been explained by the abundance of undesirable housing which lacks the size and amenities provided by newer housing on the fringe of the metro area, coupled with a consumer demand for larger housing units (Short et al., 2007). Recent housing and development trends, however, suggest that there may be a shift in consumer preferences underway toward higher density, or so called smart growth, new urbanism, or new suburbanism designs (Atkinson-Polombo, 2010); these are trends that have been witnessed in Charlotte's housing boom of the past decade (Zhou and Thill, 2011). These latest developments could offer important explanations for the observed economic decline in neighborhoods characterized by housing constructed between 1970 and 1999, which tend to consist of large structures on large lots that are even more inaccessible to urban amenities than the postwar suburbs.

While middle-ring suburbs exhibited the greatest vulnerability to decline throughout the decade, neighborhoods with the highest QoL scores – measured either as an aggregate index in the Markov analysis, or as characterized by the SOM analysis, proved to be the most stable neighborhoods in Charlotte between 2000 and 2010. The Markov probabilities recorded a high likelihood of remaining in either of the two top classes, probabilities that withstood, and even increased throughout the economic recession. Similarly, neighborhoods associated with the highest QoL characteristics resulted in the smallest change trajectories in the SOM analysis, further reaffirming their stability. Consistent with urban economic theories of change, neighborhoods that joined this highest QoL group were those on the outermost edge of the city limits. While the highest QoL neighborhoods were the most stable over time, median-income suburban neighborhoods – characterized by low social problems and a geographic location along the outskirts of the city – were found to be the most homogenous group of neighborhoods. Conversely, low-income neighborhoods were identified as the most heterogeneous, differing in their social problems and overall QoL characteristics. Studies that simply conflate social issues with neighborhood economic conditions may overlook such nuances. This finding lends support to theories, including the subculturalists' argument that neighborhood conditions are not merely shaped by the structural characteristics of buildings, but that social networks and residential interactions may play a large role in shaping a neighborhood's trajectory over time. This dissertation has not explored these more subjective factors, but future research that seeks to understand these dynamics would provide a nice compliment to this study.

In addition to the role of space, a number of insights into the temporal process of change were uncovered in these analyses. In particular, the dynamics of change were investigated in the context of the two contrasting economic conditions. Tests on the temporal homogeneity of the Markov analysis concluded that while a general improvement trend in overall QoL persisted through the recession period, low QoL neighborhoods that had experienced improvement during the rapidly growing period of 2006-2008, retreated back to conditions earlier in the decade. A test on the temporal dependence of the Markov process further reinforced these findings, showing that a neighborhood's future state at least dependence on its state of the past two time periods (4 years) to account for improvement and reversion back to a previous state. The vulnerability of short-term improvements to the lowest QoL neighborhoods has important policy implications – if policy measures are not sustained past the immediate improvements, there is a significant chance that a neighborhood will return to its prior state; neighborhoods have a longer term memory of their previous conditions. Given that in Charlotte, many of the lowest QoL neighborhoods did receive sustained, targeted initiatives throughout the decade, these results demonstrate the overpowering influence of the larger macro-economic conditions on local neighborhood QoL.

Finally, despite the literature's suggestion that neighborhood income inequality is on the rise in metropolitan areas throughout the country, particularly those in rapidly suburbanizing areas, distribution plots of the composite QoL index illustrated a shrinking disparity in these values over time; note that this analysis does not consider spatial inequality or polarization over time. This is a result that certainly warrants further investigation.

In terms of explaining the drivers behind changes in the various dimensions that comprise a neighborhood's quality of life, this dissertation utilized the exploratory results of the SOM analysis as a guide to construct a series of models to simultaneously examine the change dynamics of 4 QoL dimensions: crime, youth social indicators, economic conditions, and homeownership. In particular, the SOM results pointed to a potential reciprocal relationship between youth social problems including high school dropout and teenage pregnancy rates, and high crime concentrations. In a confirmatory setting, the cross-lagged statistical models reiterated these findings, uncovering a persistent, significant relationship between low youth social indicators (as measured by educational achievement – high school and kindergarten test scores, and high school dropout and teenage birth rates) and a subsequent increase in neighborhood level crime concentrations (property and violent crime location quotients) at all temporal lags tested. As the length of time increased, this relationship became reciprocal, meaning that high crime rates in 2000 eventually led to a decline in these same youth indicators. Thus, a cycle of social problems becomes apparent: poor school performance or educational achievement at a neighborhood level leads to increases in crime, in as short as 2 years, and eventually, these high crime rates produce further declines in school performance and juvenile problems, seemingly locking neighborhoods in a downward spiral. These results provide some support to hypotheses that suggest that social problems will increase in high poverty, inner-city neighborhoods over time (Wilson, 1987), however, the spatial dimension of these results illustrated that such problems are not necessarily confined to inner-city, concentrations of poverty. Instead, high crime neighborhoods were shown to exhibit a dispersion pattern outward from the urban core.

A second finding reached by the structural equation models is that high youth indicators consistently led to increases in the relative economic status of neighborhoods, and that neighborhoods with a higher economic status, in turn, improved in their youth indicators. This reciprocal relationship may serve to drive spatial economic and education polarization or inequality within urban areas as families with higher economic resources select to live in neighborhoods where education is valued, and school quality is perceived to be the best, further establishing strong social capital and externalities, and subsequently increasing demand in those areas. On the other hand, those without such economic resources are constrained to areas where educational attainment is low and juvenile problems are high. Thus, it would seem that addressing educational achievement in lower-income neighborhoods would serve to tackle the entangled problems of reducing economic inequality and neighborhood crime rates. How this could be achieved and whether or not policies that strive to accomplish this are in fact effective are areas of research worth investigating further.

In terms of homeownership and the hypothesized positive relationships with QoL outcomes, the SEM analysis found that low levels of homeownership in 2000 led to increases in neighborhood crime rates both two and four years later, supporting the link between residential instability and crime in the shorter term. After 8 and 10 years, however, the relationship was no longer significant. Crime rates were found to have a significant, negative impact on homeownership rates, an effect that appeared after four years and persisted throughout the decade, substantiating the mobility inducing role of crime rates that shape the neighborhood change process. The effect of crime on influencing neighborhoods appears more durable than the reverse effect. No significant relationships between homeownership and aggregate, neighborhood-level youth social indicators, nor economic changes were uncovered at any temporal lags. It is therefore difficult to ascribe any causal effect of homeownership on neighborhood-level quality of life changes once all other factors are controlled for, with the exception of a short-term relationship with crime.

The concentration of Hispanics in 2000 led to several significant changes at the two and four year time lags including declines in youth social indicators and homeownership rates. The concentration of Hispanics never had a statistically significant relationship with rising crimes, however. No evidence was found that higher transit, retail, or employment accessibility was related to changes in a neighborhood's quality of life characteristics. This result stands in contrast to prior studies that have argued that public transit access reduces a neighborhood's economic status as the poor and auto-less are necessarily confined to locations with high access (Brueckner and Rosenthal, 2009; Glaeser et al., 2008). One reason for this discrepancy may be the way in which access to public transit has been defined or measured. Whereas previous studies have measured access via a dummy variable indicating whether more than 10 percent of the population of a Census tract relied upon public transit when traveling to work, reflecting the need for public transportation, in this study, transit access was measured as the percentage of the population within walking distance to a bus stop, which represents *potential* access afforded to a neighborhood. Therefore, in this case, given Charlotte's downtown growth and revitalization over the past decade, the transit-economic decline relationship was not realized; possessing access to public transit does not impede the economic growth potential of a neighborhood.

Finally, the SEM analysis compared models of varying time lags, given that the majority of prior studies examine change at 10 year time intervals, corresponding with the release of decennial Census data. As this analysis showed, focusing exclusively on decennial changes may overlook critical relationships that are apparent only in the shorter term, especially in rapidly changing cities such as Charlotte. A four-year temporal lag probably best captured the relationships between QoL dimensions, and offered the best overall model fit with this dataset, while a 10-year lag revealed the changing spatial location of QoL values through the housing age variables. The latter two models resulted in the most unexplained variance of the dependent variables, but a two-year time interval is probably too short to capture meaningful changes, especially in the case of cross-lagged or dynamic models as the autoregressive parameter explains the overwhelming majority of the change variance.

6.1. Limitations of Study

The purpose of this dissertation was to contribute to the understanding on how neighborhoods evolve in terms of QoL over the course of a decade though an empirical examination of these dynamics. The way in which QoL is measured, however, is limited in its consideration of only 4 dimensions: economic, social, physical, and crime, while other conceivably important factors such as environmental quality or health are omitted. Quality of life is also only captured through the use of objectively measured variables, and so certain constructs highlighted in the literature review which may help shape a neighborhood's trajectory, such as social networks or cohesion among neighbors are not incorporated.

A second limitation of this study is that it is constrained to a single case study of Charlotte, NC, so comparisons on the neighborhood change process cannot be made across different metropolitan environments, and it is not possible to assess how generalizable the results are for all urban neighborhoods. A second geographic constraint to the dataset is that it is limited to neighborhoods within the Charlotte city limits (and its immediate sphere of influence), omitting the rapidly growing suburban cities within the greater metropolitan region.

Finally, in terms of methodology, the potential for measurement error was not accounted for in the analyses which may contribute to biased SEM results (or any regression results). Future work should investigate the sensitivity of these results to a model that can incorporate measurement error corrections. Similarly, while spatial lag effects were taken into consideration, the model was not tested for spatial error effects as the SEM framework does not easily facilitate this correction. If present, such effects may lead to inflated standard errors, and consequently a potential significant relationship may have been missed. Alternate, continuous-time, cross-lagged models may also be interesting future research areas to investigate to capture rates of change between time frames (Oud et al., 2012).

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APPENDIX A: SPATIAL MARKOV MATRIX BASED ON MODE

Spatial Markov Matrices based on Mode of Neighbors

Lag Class	t\t+1 (*i**j*)	1	2	3	4	5
1	1	0.80 (0.05)	0.19 (0.09)	0.01 (0.10)	0	0
1	2	0.41 (0.13)	0.49 (0.12)	0.11 (0.16)	0	0
1	3	0.25 (0.22)	0.31 (0.21)	0.38 (0.20)	0	0.06 (0.24)
1	4	0	0	1 (0.00)	0	0
1	5	0	0	1 (0.00)	0	0
2	1	0.72 (0.08)	0.25 (0.18)	0.04 (0.20)	0	0
2	2	0.21 (0.18)	0.56 (0.12)	0.21 (0.16)	0.02	0.02
2	3	0.03 (0.17)	0.13 (0.15)	0.70 (0.09)	0.10 (0.15)	0.05 (0.15)
2	4	0	0	0	0.90 (0.10)	0.10 (0.30)
2	5	0	0.09	0.20 (0.40)	0.20 (0.40)	0.60 (0.28)
3	1	0.60 (0.28)	0	0.20 (0.40)	0.20 (0.40)	0
3	2	0.25 (0.12)	0.55 (0.09)	0.21 (0.12)	0.10 (0.12)	0
3	3	0.02 (0.14)	0.23 (0.11)	0.54 (0.08)	0.22 (0.11)	0
3	4	0.02 (0.14)	0.05 (0.15)	0.33 (0.13)	0.57 (0.10)	0.02 (0.14)
3	5	0	0	0	0.14 (0.25)	0.86 (0.10)
4	1	0.50 (0.25)	0.38 (0.28)	0.12 (0.34)	0	0
4	2	0.38 (0.28)	0.38 (0.28)	0.13 (0.34)	0.13 (0.34)	0
4	3	0	0.21	0.62	0.17	0

			(0.17)	(0.11)	(0.17)	
4	4	0	0.02 (0.14)	0.16 (0.12)	0.62 (0.08)	0.21 (0.12)
4	5	0	0	0.03 (0.17)	0.19 (0.15)	0.78 (0.08)
5	1	0.25 (0.43)	0.75 (0.25)	0	0	0
5	2	0.25 (0.31)	0.75 (0.18)	0	0	0
5	3	0	0.08 (0.27)	0.58 (0.19)	0.33 (0.24)	0
5	4	0	0	0.10 (0.13)	0.62 (0.09)	0.28 (0.12)
5	5	0	0	0.01 (0.10)	0.16 (0.09)	0.83 (0.04)