House Prices and Household Behavior: Essays in Household Valuations, Price Cointegration, Residential Location Choice, and Neighborhood Resiliency

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Abstract

Residential property values have only recently recovered from the effects of the Great Recession and the housing bubble and burst. During this period, cities were not collecting as much tax revenue as predicted because of depressed housing prices and the global economy suffered greatly because of it.

Economists and others have studied the causes of the instability in property values in recent years from many angles. Their research has been influential in explaining what happened to the housing market during that time. Yet, what is missing is a detailed level analysis of how the spatial structure of our cities may contribute to this instability or stability in residential property values and a better understanding of their local dynamics.

While economists are likely correct in their macroeconomic focus, there is still room for research on the role that local factors may have played or will play in the determination of residential property values. Even within metropolitan areas, there may have been a difference in magnitude of property value fluctuation.

Therefore, this study focuses on the extent to which the urban form may contribute to overall economic stability as seen through the stability of residential property values. This research builds on past research by 1) incorporating more detailed and accurate neighborhood measures, 2) contributing to the literature by conducting cointegration at a very local level and 3) assessing the impact that neighborhood, demographic and economic attributes at the local level may have on the long-term stability of property values in our urban areas.

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Chapter 1: Introduction

The housing boom and bust of the early 21st century in the United States and elsewhere impacted economies around the world, contributing to adverse economic conditions for communities across multiple scales. Severe economic fallout from volatility in the housing market also led some countries into economic recession as many communities struggled with unpredictable property tax revenues, loss of employment and other social problems.

While valuable research exists regarding the residential housing bubble and subsequent burst, many of these studies focus exclusively on the macroeconomic factors that contributed to fluctuations in housing prices.

Although it is certainly true that macroeconomic conditions were the leading causes of the housing crisis in the United States, there is a lack of research that seeks to understand the determinants of spatial and temporal differences in house prices across different neighborhoods within metropolitan areas.

Therefore, this research utilized several essays that together provide a measured insight into some of the demographic, economic, and neighborhood factors impacting local house prices and household choice dynamics over space and time. Hopefully, this will produce a greater understanding of local house price dynamics while also recognizing the crucial role that macroeconomic conditions play in the housing market. Thus, the overall goal of this project was to understand the extent that local demographic, economic and neighborhood measures impact the local spatial and temporal dynamics of house prices as well as improve our understanding of household choice behavior.

Motivation for this research originates from the idea that local processes play an important role in determining the spatial and temporal dynamics of house values within a metropolitan area and that some of the volatility in house prices can be understood by investigating their relationship to local neighborhood and household attributes.

Through advancing understanding of the spatial and temporal patterns of house price dynamics, planning organizations may gain the opportunity to mitigate some of the neighborhood effects of volatility in house prices and reduce the effect of macroeconomic forces on house prices that were experienced in recent years.

Opportunities to establish neighborhoods that are more resilient to price volatility through incorporating efficient and stable urban designs for residential neighborhoods may also present themselves through these research results. With an improved understanding regarding the types of neighborhoods and households that are most susceptible to experiencing the brunt of macroeconomic shocks to house prices and determining which neighborhoods are more stable in the face of house price risk and volatility, we can better understand the variation of house prices within metropolitan areas. In addition, we can highlight neighborhoods and attributes that may serve as stabilizing forces for communities.

This can serve as valuable information for many categories of urban policy analysis. Differences in house price volatility/stability within metropolitan areas may arise due to many factors including initial neighborhood house prices, demographic attributes, local economic opportunities, and neighborhood accessibility attributes.

However, issues of volatility and stability in housing markets are difficult to assess. Therefore, this research proposes several statistical approaches to assist in identifying the local spatial and temporal dynamics of house prices and household behavior.

Through the utilization of several unique datasets, each chapter of this research project sheds light on an aspect of the spatial and temporal patterns of house prices and household decision making behavior. Through incorporating data from the American Community Survey, various neighborhood attributes from the Atlanta Regional Commission, data on household residential location choice, macroeconomic indicators, and residential transaction histories, this research examined questions related to the housing market and household decisions at a finer scale than much of past research has been able to do.

This allowed for investigations into the temporal stability of household preferences, the level of cointegration between neighborhood house prices and macroeconomic indicators along with several other important facets of local housing markets.

The overall research objective for this project was how can we better understand household decision making processes and to what extent can local spatial and temporal dynamics in residential property values be explained by local demographic, economic and neighborhood attributes? We also wish to better understand the housing market more generally in the region through the use of several applied research objectives. This broad objective was achieved through several chapters, described below.

Chapter 5 is titled *Understanding Home Ownership in Metropolitan Atlanta.* The purpose of this chapter was to understand the determinants of homeownership in the region. In other words, who is more likely to own a home? This chapter provides a basis for later chapters that focus on house prices and household decisions.

Chapter 6 is titled *Understanding Housing Affordability in Metropolitan Atlanta.* This is another overview chapter that describes the housing situation in the region, focusing on affordability. This chapter investigates the extent to which households in metropolitan Atlanta can afford the homes they are in.

Chapter 7 is titled *Understanding the Determinants of House Prices in Metropolitan Atlanta: 1995-2013*. The goal of this chapter was to implement hedonic housing models to understand the relationship between structure/neighborhood attributes and house prices. In addition, we also attempted to construct yearly house price indices at the neighborhood level from sales transaction data. The attempted outcome of this chapter was yearly house price indices by year at the neighborhood level in our study region. Given computational and data constraints, house price indices and results from this chapter were not as accurate as we hoped for. Thus, we have obtained house price indices from other sources in order to complete other chapters. This chapter is also a descriptive discussion on the spatial and temporal patterns of house prices in the region. This chapter sought to analyze the

trends of house prices through the years and comment on significant changes in the housing market in Atlanta during our study time period of the boom and bust phenomenon in prices.

Chapter 8 is titled *Understanding the Determinants of House Price Changes during the Housing Boom and Housing Bust: Metropolitan Atlanta: 2000-2013*. This chapter investigates the changes in neighborhood house prices through the housing boom and housing bust period in the region. This chapter also investigates the relationship between neighborhood attributes and changes in neighborhood house prices. This is done for an overall increasing period in house prices during the housing boom as well as for the period of overall price declines during the housing bust. We sought to investigate the impact of neighborhood attributes on the severity of price changes for both of these time periods. For example, are house prices more stable in high income neighborhoods during the housing bust? These are the types of questions this chapter sought to investigate.

Chapter 9 is titled *The Dynamic Causal Relationship between Neighborhood House Values, Local Employment Opportunities and Metropolitan Area Level Economic Indicators: Metropolitan Atlanta 1990-2017*. This chapter investigated the dynamic causal relationship between house prices with local and metropolitan area level economic indicators. In other words, this chapter sought to investigate the extent to which neighborhood level house prices are linked through time with macroeconomic conditions. Given these results, this chapter then sought to investigate the patterns related to the demographic attributes of neighborhoods that are not temporally linked to macroeconomic indicators. The first goal of this chapter was to understand the level and dynamics of cointegration between neighborhood house values and local employment opportunities through time.

This chapter also sought to investigate the relationship between neighborhood house values and metropolitan area economic indices such as employment, Case-Shiller house price index, the number of building permits and housing starts, metropolitan area GDP measures, income, population, labor force participants among others.

It is important to identify the neighborhoods where house prices are not cointegrated in the long run with metropolitan area level economic fundamentals to investigate patterns of neighborhoods in a metropolitan area that are not linked to broader economic trends.

This allowed for an understanding of if there are certain kinds of neighborhoods in certain parts of the metropolitan area where house values do not move with metropolitan area level economic indicators through time. Thus, this chapter's goals were to investigate the dynamic causal relationship between housing prices, the availability of local employment opportunities and macroeconomic indicators and fundamentals across neighborhoods within a metropolitan area.

Chapter 2: Literature Review

Neighborhoods possess different attributes when it comes to economic opportunities, demographic attributes, land use patterns, accessibility to services, and other urban amenities. It has been mostly assumed that modifications to neighborhood development and composition are a suitable mechanism to spur economic development and a reliable way to increase surrounding property values as these neighborhood attributes play an important role in nearby house values. This concept has been at the center of local economic development policies for decades.

For example, research from the field of transportation economics has often led policy makers to believe that new development projects and the resulting changes in neighborhood composition that follows will increase land values and housing prices as those neighborhoods become more connected to the surrounding region through increased accessibility to amenities and employment opportunities.

This research incorporates several papers to further test some of these assumptions in order to understand the role of neighborhood changes and economic growth patterns on neighborhood house values while providing more details on the reliability of these common assumptions.

Since this research cannot cover all the facets of house prices and household behavior, chapter literature reviews provide a more detailed review of those specific methods and research findings. Also, because of the detailed nature of the methods used in this research, the length of the methodology section is limited. Detailed methodology sections for each chapter are included under each chapter heading.

Valuation of Amenities and the Temporal Stability of Prices

An important aspect to understanding house prices is understanding how households value certain structural and neighborhood amenities associated with a house. The valuation of structure and neighborhood amenities can vary across neighborhoods and across household types. Through understanding how these attributes are valued, we can better understand the dynamics of house prices and valuations in the region. Traditional modeling techniques for house prices allow us to understand the valuation of different attributes of the house and neighborhood where the total price is viewed as the valuation of a bundle of structural and neighborhood attributes.

Classic urban economic theory suggests that improving neighborhood amenities by investing in services has the potential to drive up bids for land and thus residential property values, there are situations where amenities are not valued in the same way or to the same extent across households or household types.

While there are certainly differences in valuations, several studies have shown that proximity to a variety of services influence residential real estate values in some way (Mikelbank 2004; Anderson et al. 2010; Armstrong and Rodriguez 2006). In addition, while there is variation in the results of the hedonic housing literature, studies typically demonstrate that prices are devalued as accessibility to what are perceived as valued goods and services decreases (Shin et al. 1994; Vichiensan and Miyamoto 2010; Du and Mulley 2006). Of course, this relationship may be different with regards to different neighborhoods based on household compositions as well as across different parts of the price distribution.

Literature has been quite limited concerning the impact of neighborhood attributes on housing costs across a variety of different household composition types. This lack of research is likely present for a variety of reasons, one of which is that it is exceptionally difficult to obtain household level information such as the presence of children, income and other demographic attributes that include neighborhood information along with detailed temporal information.

When these types of questions have been investigated, it has typically incorporated publicly available data at an aggregated level. However, recently there have been some exceptions to this trend where household level data was incorporated (Bayer et al. 2004), showing that heterogeneous households value housing and neighborhood characteristics differently.

This project is thus able to demonstrate how neighborhood level attributes play a role in the temporal stability of residential property values and specifically the local spatial heterogeneity in the temporal trend of this relationship within a metropolitan area.

This may mean that areas with low property values stay low and areas with high property values stay high during periods of broader housing market volatility because they both possess some neighborhood attributes that serve to stabilize house prices in the area. Likewise, neighborhoods with different neighborhood attributes may experience greater fluctuation in their property values during periods of price volatility. Understanding this relationship provides insight into how households value attributes during different periods in the broader market.

Each chapter of this research contains its own detailed literature review as a complete review of the literature regarding the spatial and temporal dynamics of house prices is of course not feasible. Therefore, an introductory literature review simply provides an overview of hedonic modeling, cointegration methods, and household behavior commonly used in the urban planning literature as well as some findings from this research area to provide basic foundational knowledge for the following chapters.

Research has shown that housing price variations can largely be explained by characteristics of the surrounding residential environment along with structural attributes (Visser et al. 2008; Smith and Gihring 2006). Findings also show that environmental factors contribute more to land values and residential property prices compared to family or property characteristics. There is a plethora of literature discussing the interaction between neighborhood attributes and residential property values. Few studies have looked at the impact of changes in neighborhood attributes over time and have a limited understanding when it comes to accurately measuring neighborhood composition.

While there has been little research directly related to local measures of economic stability in past literature, the hedonic house price studies that do exist for specific regions often provide sufficient insight into the theoretical background and methodology required for this research as well as yield results that can serve as useful guidelines for this research. In particular, these studies provided useful information in terms of what variables should be included in a model.

Also, these studies provide valuable insight into the many econometric methods used in property value research while providing opportunities for improvement through the utilization of more detailed datasets. This section discusses some of the prevailing methods being used in these studies as well as introduces some relevant results from previous research. Referenced studies provide valuable insight into the econometric methods used in property value research along with providing opportunities for improvement through the utilization of more detailed datasets. Overall, this section discusses the prevailing methods used in these studies as well as introduces some relevant results from previous applications.

Hedonic Modeling Findings

Zheng and Yang (2007) used the housing transaction database from the Beijing Construction Committee along with a residence survey about commute time to demonstrate a negative commuting time house price gradient where the values of travel time was approximately half of the wage rate using classic hedonic modeling approaches.

Hedonic models have also been used to demonstrate that increased proximity to bus transit lines can have a negative impact on property values (Cao and Hough 2008; Des Rosiers et al. 2010). Results from this large amount of hedonic house price studies demonstrate the difficulty in creating policy and designing cities for residential property value stability because we often see discrepancies in results for valuations of neighborhood attributes for different time periods, different regions or different specifications.

This is one reason why this research project focuses on creating a framework for studying the temporal stability of residential property values so that cities can incorporate these methods using their unique situations and data. There is also recognition that whatever results we gain from our research study will be a demonstration of how to manage these studies and the results may not be applicable to other cities or time periods as all housing markets possess unique local dynamics.

Hess and Almeida (2007) incorporated hedonic models to investigate the effects of a light rail station on home values in Buffalo, New York. The results from this study showed an increasingly dynamic effect on house values where proximity effects were positive in high-income station areas and negative in low-income station areas, highlighting the need to allow for spatial heterogeneity in models of residential property values. Often, the impacts of neighborhood attributes on property values vary across the study area as well as temporally, therefore methods must be used to account for this.

Anderson et al. (2010) found a very minor effect on house prices from a new high-speed railway line in Taiwan while Pan and Zhang (208) found a significant premium resulting from proximity to a

metro station in Shanghai. Using spatial hedonic price functions, Armstrong and Rodriguez (2006) found evidence of capitalization of accessibility to commuter rail stations in Eastern Massachusetts. While in this study, proximity to stations has a positive effect on property values; proximity to commuter rail right-of-way shows a significant negative effect on property values, suggesting that for every 1,000 feet from the commuter rail right-of-way, property values are between $732 and $2,897 higher.

One trend in this research area is that proximity to a transport station often increases land values, but proximity to a rail line decreases land values (Armstrong and Rodriguez 2006; Mayor et al. 2008). This highlights the difference between the household valuations of accessibility as opposed to the common devaluation from households regarding proximity to infrastructure. When looking at the pattern of these various effects across a city, we can gain insight into how households value certain types of neighborhood attributes and structural amenities as seen through the hedonic function.

Vichiensan and Miyamoto (2010) incorporated hedonic models to show that urban railway in Bangkok contributes to land and property values. Wenjie et al. (2010) used similar methods to demonstrate that accessibility indices are important determinants of residential property prices in Beijing. Debrezion et al. (2007) found that effects on land values from railway stations typically takes place at short distances. Also, commuter railway stations have a consistently higher positive impact on the property value compared to light and heavy railway/metro stations. The railway impact lessons when other accessibility variables such as roads and highways are included.

Conversely, Haider and Miller (2000) showed that accessibility factors were not strong determinants of housing values in Toronto. This highlights one of the main challenges when looking at how neighborhood attributes influence economic stability over time; one must account for new residential and commercial development along with demographic changes throughout the time period. Practically, this is a difficult situation to accurately assess as residential property values are typically changing quicker than changes in neighborhood attributes which tend to experience slower adjustments. Ryan (1999) proposed potential reasons as to why there is such a variety of outcomes in this literature, such as the delineation of the study area often significantly influencing the results. Debrezion et al. (2007) found that variations in results can generally be attributed to the nature of data, particularly spatial characteristics, temporal effects, and the methodology employed.

Modeling Approaches

Hedonic price models are a long-established method in the literature for the estimation of residential property values as well as the estimation of demand for characteristics (Rosen 1974). The term hedonic regression is most commonly used in economic and real estate research and can be described as a regression model that is used to estimate demand or prices of properties as a combination of independent variables. The concept behind hedonic price modeling is similar to that of any regression model, to disentangle such attributes of a good from one another for the purpose of estimating the price of a property. In hedonic modeling, the price of a house is a function of various attributes which are typically categorized as structural, neighborhood and accessibility/locational attributes (Anderson et al. 2010). In this study, our hedonic model must

include many variables related to residential property values such as past values of the house, values of neighbor's houses, structural attributes (rooms, kitchen, lot size etc.), and several other attributes in order to attempt to get an accurate estimation of residential property values in our study area. Of course, this presents a significant problem because there may be an infinite number of things that have an impact on the value of a home. There is no way to include all the relevant variables in a hedonic housing model. This of course creates a level of caution in our interpretation of the effects of neighborhood attributes and properly identifying these impacts (Ding and Knaap 2003; Liao and Wang 2012).

There are many variations of this classical approach that are currently being used, and these remain the prevalent method to assess the relationship between neighborhood attributes and residential property values. However, there are several drawbacks to the way this method has been used in previous studies and hedonic model specifications are becoming more sophisticated in order to deal with some of these shortcomings. These new approaches include the use of Bayesian estimation techniques (Wheeler et al. 2014), the incorporation of spatiotemporal clusters (Fotheringham et al. 2015) and moving window approaches (Paez et al. 2008), among others. The hedonic approach can also be used to assess the spatial heterogeneity of the impact of independent variables in residential property prices across household types (Des Rosiers et al. 2010; Liao and Wang 2012). Model comparison techniques are often used to determine the most appropriate model by comparing several different specifications.

Spatial dependence is a phenomenon often anticipated in the modeling of spatial data. In the context of housing research, it is reasonable to assume that the value of one house depends not just on the attributes of that house, but also on the other houses in a specified distance in proximity to that house. The market value of a house is thus determined by its structural and neighborhood attributes along with nearby house's market values either in a defined neighborhood (neighborhood effects) or based on distance (adjacency effects), often a combination of both (Shin et al. 1994).

In recent years, the hedonic model has been transformed to incorporate spatial and temporal dependency along with spatial heterogeneity into model specifications. Several studies have established that there is strong autocorrelation in housing models and it has therefore become necessary to incorporate spatial effects into hedonic housing models (Jeanty et al. 2010). This makes it impossible to use ordinary least square estimation in hedonic studies as residential property values often experience spatial autocorrelation, causing estimated to be biased and inconsistent (Chalermpong and Wattana 2009). Many of these spatial models can be understood under the name of spatial autoregressive models (SAR) where spatial effects are incorporated into the model in a variety of ways such as the spatial lag model, the spatial error model and spatial mixed model. It is also often seen where the independent variables possess a spatial lag if we cannot get the same information for a property; spatial lag models are often referred to as spatial autoregressive models in the literature (Osland 2010). In the spatial error model, the serial correlation enters through the error term in that the spatial effect is present in the error term but not in the specified function of the model. While the spatial error model is perhaps more common in many applications, the spatial lag model dominates the hedonic housing literature (Shin et al. 1994).

Variations of these models are often used when researching property values as these values typically possess both spatial and temporal clustering and dependence. The existence of spatial dependency

in residential property values leads us to use these models because the spatial dependence violates the normal assumption of uncorrelated error terms. Spatial heterogeneity in the impact of neighborhood attributes on residential property values will also lead to heteroskedastic error terms, making OLS estimates biased and inconsistent.

Researchers using housing models commonly incorporate a spatial lag model or a spatial autoregressive error model in order to account for these issues (Osland 2010). This has now become the dominant approach in the literature for estimating residential property values and the effects of neighborhood amenities through hedonic modeling (Bourassa et al. 2007; Wilhelmsson 2004; Case et al. 2004). It is necessary to utilize a methodology that considers temporal and spatial effects in hedonic modeling when the data consists of observations of property transactions and their respective prices over time as it is likely that most residential properties do not experience a transaction more than once in a given year (Dube and Legros 2011).

There are also many issues concerning missing data problems common in real estate transaction and structure data. This is due to the fact that the data tends to be maintained and collected at the county level with no standardization across counties in terms of what and how data is collected. This leads to a common problem of missing data that has spatial patterns, making multiple imputation of the missing data difficult and not practical. Therefore, estimating house price indices for small geographic areas is quite a computationally intensive task that requires sufficient sales histories in small geographic areas. Without this, it can be incredibly difficult to establish accurate neighborhood level price indices.

Sustainability in residential property values and the overall economic sustainability of neighborhoods has been an active area of research in recent years. Residential property is a large purchase for most households and residential property values may give us more information about the economic sustainability of areas as it can be used as a proxy for neighborhood level economic sustainability. However, most studies view this kind of economic sustainability in a decidedly macroeconomic way in that they look at the stability of housing markets across countries (Duca et al. 2010), states and regions (Holly et al. 2010), and related to national macroeconomic conditions (Liu et al. 2011). Few studies have investigated this phenomenon from the perspective of urban geography and the role that the urban form as measured through neighborhood attributes may play in this type of local economic temporal sustainability.

As stated previously, this project agrees with past literature regarding house value stability in that macroeconomic measures are likely to be strong determinants of residential property value changes over time, especially during the housing boom and bust of the early 21st century. However, opportunities remain within this literature to investigate the role that urban structure and the form of our metropolitan areas may play in the spatial and temporal dynamics of residential property values at the local level within large metropolitan areas. At this scale, we may find significant differences in the stabilizing effects between neighborhoods.

That being said, there has been research that has made the temporal stability of house values a central part of their goals. Mark (1983) investigated the stability of coefficients in house price equations over time. Vandell and Zerbst (1984) incorporated ridge regression techniques to estimate the effects of school desegregation on house values over time.

Price Cointegration

Cointegration refers to the idea that two or more series move together through time; i.e. that they are temporally linked. In other words, the ratio between two or more time series remains stable so that as one time series increases, another will increase at the same rate (Enders 2010). Essentially, testing two or more time series for cointegration is testing for the extent that two (or more) time series structured variables move together – the extent to which they are cointegrated through time.

This process can involve any relationship that is thought to exist in equilibrium among a set of nonstationary variables and implies that their stochastic trends are linked if there is a statistical determination of cointegration. For example, there is some evidence that there is an equilibrium between access to the labor/employment market and residential property prices (Ball and Kirwan 1977; Osland and Thorsen 2005), allowing us to proceed with local tests of cointegration with these types of time series variables.

Beenstock and Felsenstein (2010) integrated spatial econometrics with panel cointegration tests to design a methodology that utilized spatial data that are temporally non-stationary; taking spatial dependence into account when attempting to understand a cointegrating relationship on a spatial panel dataset. Mikhed and Zencik (2009) investigated the relationship between house prices in the United States and a variety of economic fundamentals using these standard unit root and cointegration tests.

While graphs and plots of the relationship between house prices and other factors can provide us with a glimpse into the moving trends and house price changes, it is preferable to utilize a more formal understanding of whether changes in other factors explain movements in house prices over time. Chowdhury and Malik (2004) found housing prices are cointegrated with rising employment in Australia across different regions. Chang et al. (2013) investigated the dynamic causal relationship accounting for spatial dependence across several regions in South Africa to find that there is a cointegrating relationship between economic growth and housing activity with varying significant relationships across several regions. As expected, it is commonly thought that there is a significant cointegrating relationship between house prices and real per capita incomes (Holly et al. 2010), though this is not always the case as the opposite dynamic has also been discovered (Gallin 206).

Overall, this research has incorporated hedonic real estate, discrete choice, and time series models to better understand household behavior and house prices in the Atlanta Metropolitan Statistical Area.

Chapter 3: Study Area and Data

The study area for this project was the 2010 defined Census Bureau Metropolitan Statistical Area Atlanta-Sandy Springs-Roswell consisting of 29 counties. Motivation for choosing this metropolitan area for our case studies consists of several reasons. These include researcher familiarity with the region along with the fact that the metropolitan Atlanta region provides us with a good representation of a complex, diverse, and multinucleated metropolitan area that has experienced substantial growth in residential property development and neighborhood changes through the years.

This region currently has a population of more than 5.8 million people along with a diverse labor and housing market encompassing many different employment sectors and household/neighborhood compositions and attributes.

This metropolitan area also experienced significant changes and shocks to housing prices over the last 20 years. There is also a plethora of data available for this region, providing us with the ability to conduct a complex and interesting application and case study for our research goals and objectives.

Another reason for selecting this study area is that macroeconomic variables related to the real estate market and other economic indicators at the level of metropolitan areas are only available for the largest of metropolitan areas in the United States. This made smaller metropolitan areas and smaller cities unsuitable case studies for these research goals.

Several datasets were utilized for this research project with each being incorporated in different ways for each chapter and objective. One of the datasets used is property transaction histories along with structural property information. This data was obtained for all of the 29 counties in our study area from CoreLogic Inc. through an academic grant council process.

This dataset includes the transaction history for all residential properties, assessor's parcel number, number of full bathrooms, number of half bathrooms, square footage of living space, census block of property, total square footage of the structure, the presence of air conditioning, exterior wall material, the presence of a fireplace, interior floor type, foundation type, garage capacity, heat type, style, topography type along with several other variables.

There are approximately 1.7 million residential properties in our study area that are initially incorporated in the analysis. The property transaction data was available from 1995-2012, though transaction histories for the earlier years are slightly more sparse.

Other data that was used for this project includes county business patterns data from the United States Census Bureau at both the county level (to describe employment opportunities) and aggregated to the metropolitan area as a measure of employment opportunities for our cointegration analysis.

We also use a variety of metropolitan area level economic indicators for this project including yearly unemployment rate for the metropolitan area for 1990-2017 from the Bureau of Labor Statistics. For the cointegration analysis, the yearly house price index for our metropolitan area is obtained from Case-Shiller and the number of housing starts by metropolitan area is obtained from the Census Bureau.

The Bureau of Economic Analysis provides data on GDP and GDP per capita along with data on metropolitan level income and population growth. The years available and the structure of all these datasets indicate that each of our chapters utilizes different elements of these datasets as well as different years of the data to develop conclusions. The Bureau of Economic Analysis provides data on GDP and GDP per capita along with data on metropolitan level income and population growth. The years available and the structure of all these datasets indicate that each of our chapters utilizes different elements of these datasets as well as different years of the data to develop conclusions.

In some cases, this is done to fit within our chapter objectives while in other situations this is done out of necessity as the years available for all of these datasets do not always match with our stated goals. This research also incorporated public ACS data and a variety of data from the Atlanta Regional Commission including land use, transportation and elevation statistics. Additional data used in this project includes data from the Atlanta Regional Commission on travel behavior and a variety of other data used throughout this project.

As we can see below in Figure 1, it appears as though home prices in the region follow a similar trend to the national situation. However, Atlanta experienced a peak in prices slightly later than other metropolitan areas that had more severe housing issues (California's Central Valley, Las Vegas and others). While Atlanta did not experience the severity of a boom and bust process as many of these other regions, it appears as though it experienced a much more significant boom and bust process compared to other Southern cities outside of Florida.

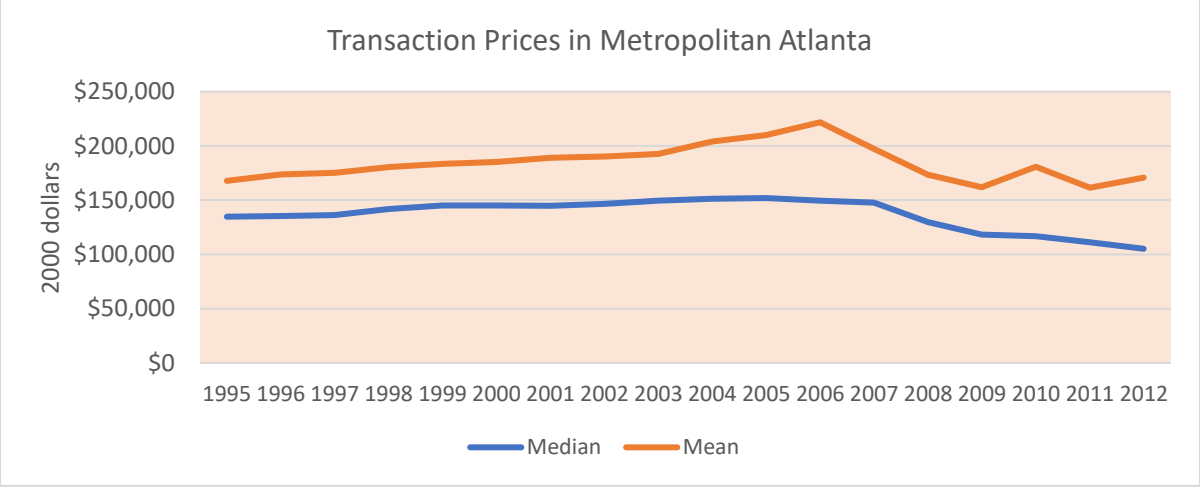


Figure 1: Transactions in Metropolitan Atlanta

Source: Real Estate Transaction Data Obtained from CoreLogic Incorporated through an Academic Grant Council Application

Limitations of Property Transaction Data

While the CoreLogic Inc. data used in this study was incorporated for some of the goals, data limitations as well as computational limitations made some of our original goals for this project impossible.

Much of the original goals of this research was dependent on the creation of good, accurate neighborhood level house price indices created from sales transaction history data from CoreLogic Inc. Unfortunately, as we can see from Figure 2, Figure 3, Figure 4, Figure 5, and Figure 6 below highlighting price data and transaction locations, there was significant spatial patterns in the missing data from CoreLogic Inc.

Not only that, but in terms of available data for each structure, there was significant discrepancies in available variables. Multiple imputation was used extensively, and some model specifications were developed to achieve these goals.

However, the amount of imputation necessary along with the number of transactions that could be incorporated into the model given computational constraints made any neighborhood level price indices indefensible. As other chapters relied in these indices, this also impacted the entire project.

To move forward, neighborhood level home price indices were incorporated that are not as local as originally planned. That being said, I was lucky to obtain/discover zip code level house price indices from the Federal Housing Finance Agency. This was a benefit in some ways as it provided many more years of data which improved our ability to perform a suitable analysis for Chapter 9.

Residential Property Transactions

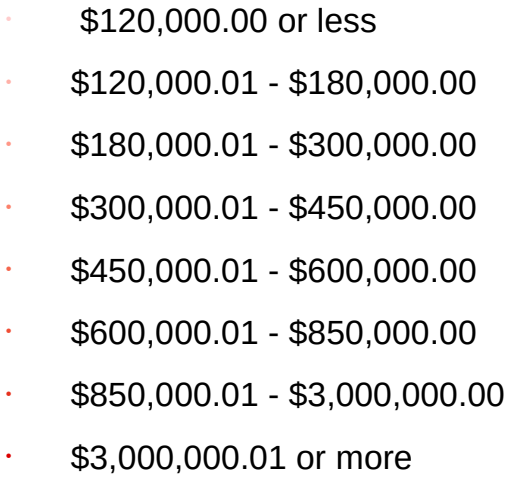


Figure 2: Transaction Price

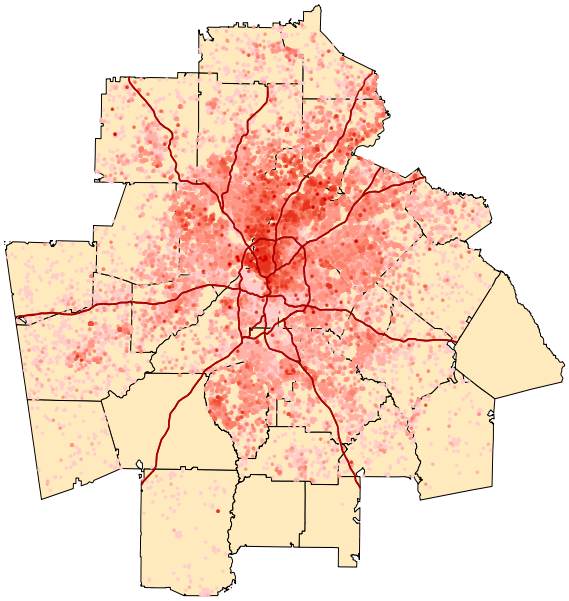


Figure 3: 1995 Transactions

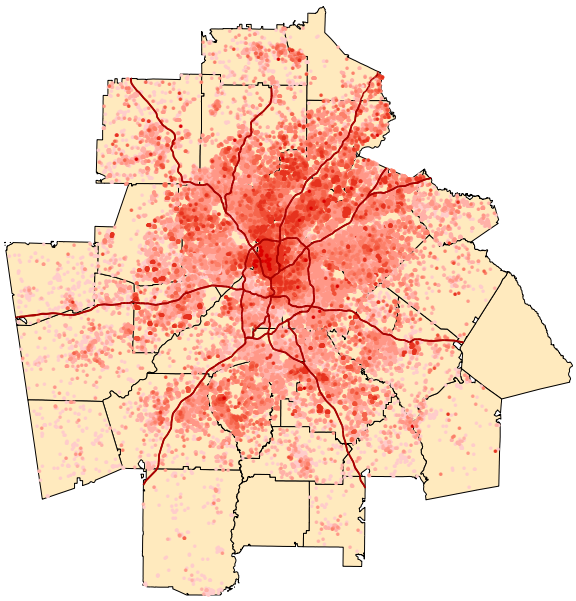


Figure 4: 2000 Transactions

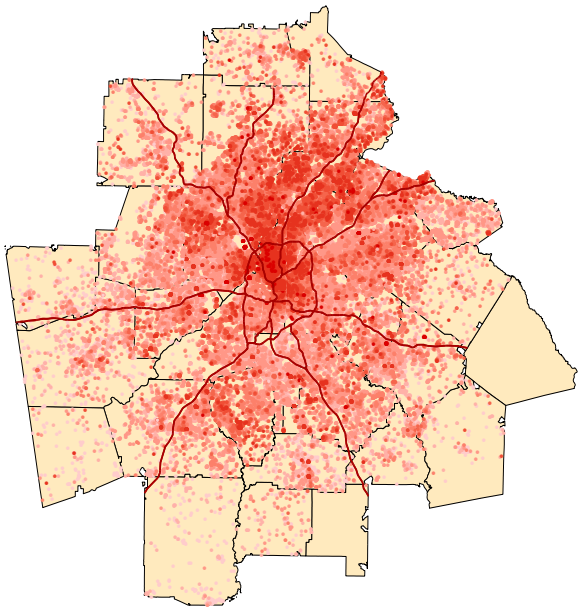


Figure 5: 2007 Transactions

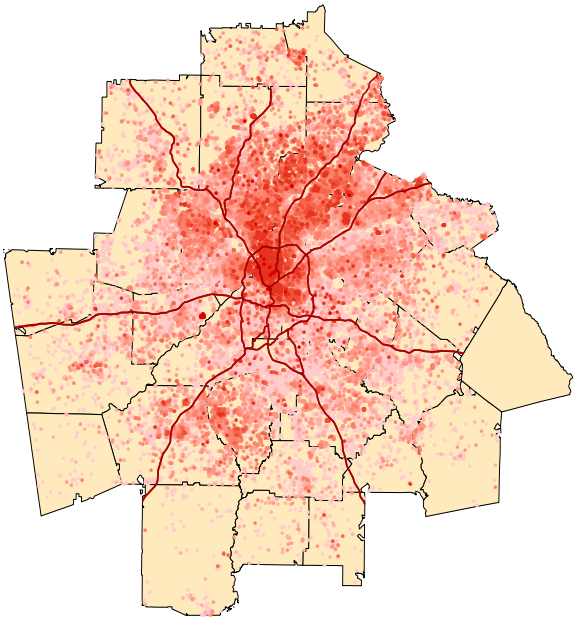


Figure 6: 2012 Transactions

Chapter 4: Methodology

For Chapter 5 titled *Understanding Home Ownership in Metropolitan Atlanta,* we implement a binomial logit model using data from the American Community Survey to understand the determinants of house tenure in the region. We incorporate the usual variables into the model including income, race, and marital status from the American Community Survey. High rates of homeownership are traditionally associated with positive economic effects and externalities. For this reason, public authorities have encouraged homeownership through a variety of taxation and subsidy policies.

For Chapter 6 titled *Understanding Housing Affordability in Metropolitan Atlanta,* the goal was to understand the current housing situation in the area in terms of affordability, crowding and general availability of housing for various groups of households. This was accomplished through the use of data from the American Community Survey to establish tables and charts highlighting the extent of the affordability issue in metropolitan Atlanta.

For Chapter 7 titled *Understanding the Determinants of House Prices in Metropolitan Atlanta: 1995-2013,* we used the property structural attributes and transaction data from CoreLogic Inc. to estimate a hedonic house price model. This data covers all 29 counties in our study area and there are approximately 1.7 million properties in the study area. For our hedonic model in this chapter, a much smaller sample was used. Even then, some multiple imputation needed to be conducted on missing variables.

It is important to state that for modeling purposes, we are only interested in sale transactions with a corresponding price. There are often records in this type of data referring to other types of transactions such as the property moving into a trust or being transferred to children and it is certainly possible that there are properties that did not experience a transaction during this time period. Regardless, based on a review of the literature and in my consultation with economists from CoreLogic Inc., we believe that a sample of this data is sufficient for the estimation of metropolitan level hedonic housing price models and allows us to come close to meeting some of our objectives.

This chapter established an understanding of the determinants of house prices in metropolitan Atlanta. Model results also highlight temporal impacts on prices corresponding to the housing boom and bust in the area.

For Chapter 8 titled *Understanding the Determinants of House Price Changes during the Housing Boom and Housing Bust: Metropolitan Atlanta: 2000-2013,* we investigate whether neighborhoods with certain demographic attributes face the same level of house price volatility during macroeconomic price shifts as neighborhoods with different attributes that may serve to assist in providing a level of stability. That is, is the volatility in house prices related to neighborhood characteristics and if so, does this relationship differ between periods of housing boom versus periods where an overall housing bust was experienced?

Models are estimated where in one case, the dependent variable is the percent increase in the housing price index for a neighborhood and the independent variables include neighborhood

attributes such as demographic and economic attributes of the area and proximity to amenities. This is the case for the model investigating 2000-2007. For 2008-2013, the dependent variable is percent decrease in the home price index by neighborhood. Zip code house price indices are obtained from the Federal Housing Finance Agency.

This represents a local level investigation into the role of certain types of neighborhood attributes as stabilizing forces during periods of change in residential property values. These models are then compared to understand if neighborhood attributes might have played a similar role in similar areas for stabilizing property values during the housing boom as well as the housing bust.

That is, are certain areas contributing more to residential property value stability when the overall metropolitan area is rising in value and are certain areas and neighborhood attributes contributing more to residential property value stability while the overall metropolitan area is experiencing price declines?

In other words, is the stabilizing effect of neighborhood attributes on residential property values dependent on if macro prices are increasing or decreasing? Was this effect different during the housing boom as opposed to the housing bust? Is house price volatility systematically related to neighborhood accessibility or socioeconomic characteristics? In other words, this part of the chapter investigates the relationship between neighborhood attributes and the magnitude of home price increases/declines.

For Chapter 9 titled *The Dynamic Causal Relationship between Neighborhood House Values, Local Employment Opportunities and Metropolitan Area Level Economic Indicators: Metropolitan Atlanta 1990-2017,* we used cointegration techniques and methods to investigate the dynamic causal relationship between neighborhood house values, local employment opportunities and a variety of metropolitan area level economic indicators.

These methods are used to investigate the relationship between neighborhood house prices and local employment along with the potential cointegrating relationship between local house prices and macroeconomic indicators at the metropolitan area level.

Thus, the results from this chapter produce several maps of t values at the neighborhood level for us that indicate the significance of cointegration between local house prices at the neighborhood level and these various economic factors. These maps then allow us to conduct clustering analysis on these values to understand the areas where house prices move along with these economic indicators through time and those areas where this is not the case.

In order to accomplish this, we attach county level employment numbers by year to each neighborhood within the county which already contains house prices for that year. We then also attach metropolitan level employment numbers, yearly unemployment rate, Case-Shiller home price index, housing starts, GDP, income, civilian labor force, per capita GDP and population to each neighborhood.

Thus, for these factors, all the neighborhoods will have the same values attached to them. We then use the Augmented Dickey-Fuller test for stationarity followed by a Johansen test for cointegration.

This chapter required a yearly general house price index for each neighborhood for each year between 1990 and 2017 and was obtained from the Federal Housing Finance Agency for zip codes.

The investigation of outlier neighborhoods allows us to determine if there is a spatial pattern in the neighborhoods that do not integrate with these various factors over time.

A panel test for cointegration formalizes this goal to look at the extent to which house prices move together with these variables through time. The Johansen test are used to test for statistical significance of these tests for cointegration with lags chosen according to recommendation (Enders 2010) and AIC criteria.

Chapter 5: Understanding Home Ownership in Metropolitan Atlanta

Abstract

The promotion of homeownership is common in the United States as high levels of homeownership are often viewed as having a strong relationship to many preferable societal outcomes. Given that a home is often the most expensive purchase that households make and their most valuable asset, governments often identify homeownership rates as a strong measure of the overall health of an economy.

Policy makers often see homeownership as an essential component of healthy neighborhoods. For these reasons, homeownership is often encouraged through the tax code and various subsidy-based policies.

This has been particularly true in the United States where the promotion of homeownership through subsidies and favorable taxation policies has been a political issue for decades given that homeownership tends to be something that wealthier people participate in. While homeownership is typically seen as a societal good, it can also promote forced savings for a household given that it is the most valuable asset most households have.

The purpose of this study was to analyze the determinants of homeownership so that we can further understand the drivers of being a homeowner versus not being a homeowner. This is accomplished through the investigation of housing tenure in the Atlanta Metropolitan Statistical Area.

A logit model of housing tenure choice is estimated using data from the American Community Survey. Results show that higher incomes, age, and the presence of children in the household possess a positive influence on homeownership, amongst other things discussed later in the chapter. As one might expect, we also see differences in the likelihood of homeownership across racial groups across household income ranges.

Introduction/Literature Review

The rate of homeownership varies significantly across major metropolitan areas in the United States. Overall, the Atlanta Metropolitan Statistical Area has been characterized by a homeownership rate that has been in the mid to high 60s in recent years, though fell to a recent low of 60 percent in 2013.

These values for homeownership in the Atlanta area are relatively close to the nation as a whole. The homeownership rate in 2014 was 63 percent. As we can see from Figure 7, Philadelphia had a higher homeownership rate than Atlanta while Los Angeles had a lower homeownership rate.

The process of purchasing and owning a home is popular for many reasons. The idea that owning a home and high levels of homeownership being good for society is a prevalent thought in U.S. society. It has often been argued that homeownership contributes to better environments that can lead to better educational outcomes for children (Green and White 1997; Kim and Sherraden 2011),

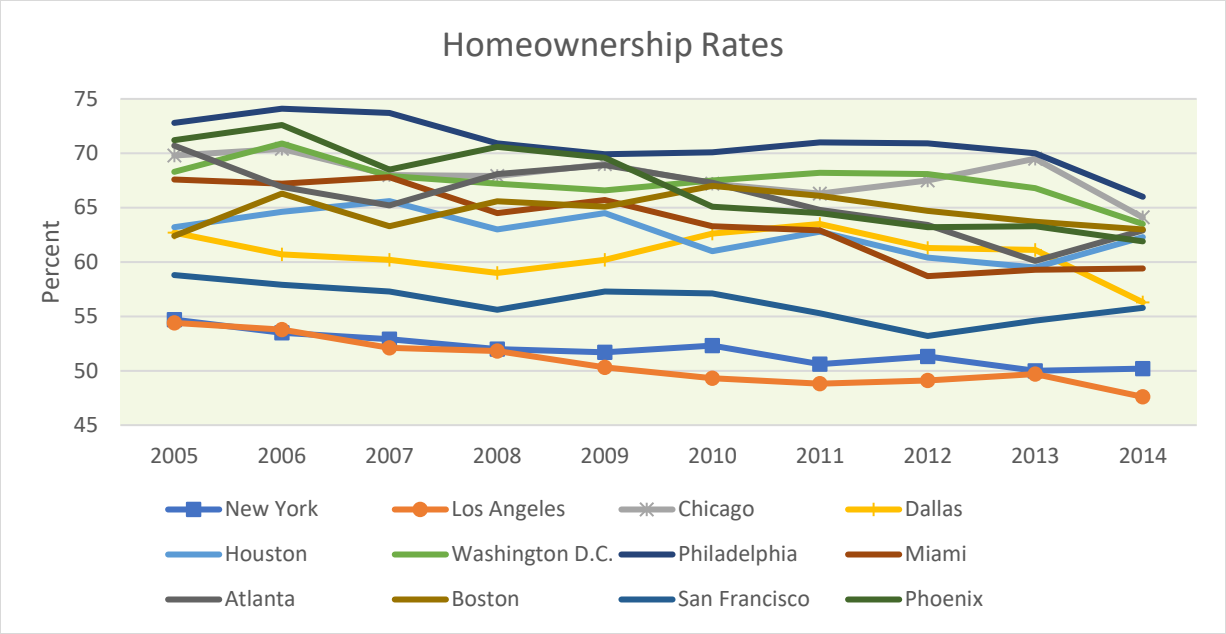


Figure 7: Homeownership Rates in Major U.S. Cities

Source: American Community Survey, United States Census Bureau

including increased school performance and decreased behavioral problems (Haurin et al. 2002), though Barker and Miller (2009) have shown that this relationship is quite weak.

It has also been argued that homeowners maintain their properties at a higher level than renters, contributing to improved neighborhood quality (Rossi and Weber 1996; DiPasquale and Glaeser 1999). Homeownership also contributes to increased levels of political engagement (Engelhardt et al. 2010; Fischel 2001). Homeownership has also been associated with improved neighborhoods (Coulson and Li 2013; Rohe and Stewart 1996) and a better overall life satisfaction and health (Lindbland and Quercia 2015; Zumbro 2014; Rohe and Stegman 1994). Hilber and Mayer (2009) demonstrated that homeownership often leads people to be more supportive of local spending on services such as their local public schools.

Dietz and Haurin (2003) and Barker and Miller (2009) collected results from many studies to discuss some of the main benefits of homeownership including improved child outcomes and self-esteem, health, political engagement, labor force participation and increased household wealth.

As we have previously discussed, homes are often the largest purchase households make in their lives. Therefore, buying a home can contribute to a forced savings and homeownership becoming beneficial for household wealth accumulation. Studies have shown that this wealth accumulation benefit found with homeownership is particularly beneficial to lower income households (Turner and Luea 2009).

Alternatively, homeownership can also lead to some negative consequences for some households. For example, homeownership involves lengthy, expensive transactions. Therefore, owning a home can limit economic opportunities for households by limiting economic mobility for homeowners (Haurin and Gill 2002). This can serve to trap households in a particular location and may

contribute to overall unemployment figures due to limits placed on a household's economic mobility (Oswald 1996). In addition, Shiller (2007) discussed the negative consequences of mortgage defaults and the rise in house prices as outcomes of a societal dependence on homeownership.

Given that homeownership is related to both positive and negative societal outcomes, it is important to understand that the benefits of homeownership change as societal changes take place. For example, a reduction in stable employment norms in society leading to a desire for households to move more often.

That being said, public authorities often lean toward a positive view of homeownership as evidenced by the implementation of extensive subsidy and tax policies that promote homeownership in the United States.

Most studies that investigate the housing tenure choice behavior of households model the likelihood of being a homeowner as a function of demographic/economic attributes. Some of the earliest work in this field was Carliner (1974) and Li (1977). Evidence from these studies and others often shows that differences in income, wealth and poverty levels across regions explains a significant amount of the variation in homeownership levels (Winter and Heylen 2014).

Particularly relevant to the social dynamics of our study area, there has been significant research regarding the differences in the likelihood of being a homeowner across racial groups (Skaburskis 1996; Hilber and Liu 2008). While most of these studies have demonstrated significant differences in the likelihood of homeownership across racial groups, other studies have highlighted that this racial difference in homeownership can be attributed to wealth differences across racial groups (Painter et al. 2001). As one would expect, there is a lot of discrepancy in the research on homeownership. For example, while most research finds that white households are significantly more likely to own than black households, Goodman (1990) found that only white demand is higher than black demand.

The often-discussed mortgage interest deduction has been shown to have a significant impact on the levels of homeownership (Hilber and Turner 2014; Green and Vandell 1999). However, some have also argued that a large portion of the benefits of these taxation and subsidy-based policies benefit the wealthy to a greater extent (Heylen 2013).

There has been a plethora of research over the years that has implemented models of housing tenure choice which has shed light on the main factors that tend to influence the likelihood of homeownership. For example, stable income increases the likelihood of homeownership for households (Robsta et al. 1999; Haurin et al. 1994; Bourassa and Hoesli 2008; Henderson and Ioanides 1983) along with the family/life-cycle (Arimah 1997).

The general affordability of housing in a region also has a major impact on tenure choice (Goodman 1988), with local subsidies and taxation benefits playing a significant role in homeownership as well (Glaeser and Shapiro 2002). A potential way to shed additional light on the factors influencing homeownership include research that investigates not just the propensity for homeownership, but the likelihood of transitioning from to owning a home from other housing situations (living with parents, renting, or public housing (Salvo and Ermisch 1997).

It has also been shown that one of the major constraints on home ownership is the inability to come up with a down payment (Brueckner 1986; Bourass and Yin 2008), including the ability of young people to enter into homeownership across countries and how this is impacted by varying subsidy approaches (Bourassa and Yin 2006).

Study Area/Data

The study area for this chapter is the same as the overall research project, the Atlanta Metropolitan Statistical Area. However, this chapter incorporates PUMS data from the U.S. Census Bureau's American Community Survey. Therefore, the household and person sample used in this research is sampled using PUMAs and thus there is a small discrepancy in terms of accurately corresponding to the 29 counties that comprise the Atlanta Metropolitan Statistical Area.

For this chapter, we merge the person and household ACS files together to obtain a dataset for each sampled householder and a variety of attributes including homeownership status, household income, age, education, and race. In addition, it must also be noted that the American Community Survey is a weighted survey. In this case, since we are investigating at the household level (including person attributes for the householder), we use the household weights during our model specification phase.

Methodology/Literature Review

This section provides a background explanation and discussion for the methods used in this chapter. Following the work of Ray and Garcia (2012) along with many other studies previously cited in this chapter, this study implements a binomial logit model to understand the likelihood of homeownership versus non-homeownership and the relationship to household demographics.

Classic models of tenure choice typically incorporate a sample of households and attempt to model the overall attainment of homeownership. However, recent move models can provide additional insight when studying the transition to homeownership from other living conditions.

In this study, we model household tenure choice behavior using American Community Survey data with particular attention placed to income and demographic related variables. We use several past studies as a guide when selecting variables that may be of interest from the ACS (Raya and Garcia 2012; Bourassa and Peng 2011).

For example, income is tied to both household wealth and to the life-cycle. It has been regularly shown that life-cycle plays a significant role in the likelihood of homeownership (Bourassa 2000), in that older households tend to be more settled with more money for a down payment (Bourassa 1995). The presence of children is also related to this and is often shown to be a strong determinant of homeownership as it provides insight into the stability of a household (Carliner 1974).

Logit models are a common technique used to model outcome variables that are binary or multinomial. Using logistic regression, the log odds of homeownership are modeled as a combination of the independent variables. As is typical in discrete choice modeling, we also

calculate odds ratios which are the odds that homeownership occurs compared to the odds that it does not occur.

Logistic regression models are fit using maximum likelihood. Results of these models estimate conditional means in terms of log odds. Through transformation, results can be displayed as odds ratios or as probabilities. Unlike the typical goodness of fit measure used in other models, we must use McFadden's pseudo R-squared in the case of discrete choice models. Another approach to assessing the goodness of fit in a binary logit model is to simply investigate the percent of outcomes that the model accurately predicts.

Table 1 below highlights the variables used in our models. This specification was developed through a combination to stepwise variable selection, intuition and the minimization of AIC as shown in Table 2. We establish several specifications after investigating the data and the results are presented below in Table 3. Final model selection is based partly on theoretical assumptions and partly on AIC criteria.

We expect to discover results that are mostly consistent with other studies. Namely, we expect that income will have a positive influence on homeownership. Given our knowledge of the region, we also expect that there will be significant differences in the attainment of homeownership across racial categories. We also expect marriage and the presence of children in the household to have a positive influence on the probability of homeownership, consistent with much of past literature.

Results

The table below presents several model specifications and their associated coefficients. Model results were compared using a variety of diagnostics that are typically used in logistic regression with final model selection using AIC criteria. Several model specifications were explored to determine the most appropriate specification and the results can be found in Table 3. Ultimately, in conjunction with our exploratory methods of model specification choice, we also incorporated stepwise variable selection methods to highlight the final model choice.

Overall, as we can see from the model results, it appears as though the specification of model specification 6 is the most appropriate and we thus proceed with that in our interpretation and further analysis.

We find that all of the variables are statistically significant at the 5 percent level. However, in discrete choice models, only the signs of the coefficients are easily interpretable. The information they provide remains limited to the way (positively or negatively) the probability varies.

The table above presents several model specifications and their associated coefficients. Model results were compared using a variety of diagnostics that are typically used in logistic regression with final model selection using AIC criteria.

Table 1: Description of Variables

Variable	Description	Mean/SD	Count
Homeownership	A measure of whether the housing unit is owned. 1=housing unit is owned either with a mortgage or without a mortgage		1=1,344,950 0=809,040
Household Income	Household Income	80,996/84779	59,000
Citizenship	Citizenship of Householder. 1=U.S. Citizen		1=1,991,980 0=162,010
Married	Marital Status of Householder. 1=Married		1=1,094,400, 0=1,059,590
Race	Race of Householder		
1	White Householder		1,293,271
2	Black Householder		669,788
3	Other Householder		190,931
Number of People in Household	Number of People in Household	2.57/1.492	
Number of Vehicles in Household	Number of Vehicles in Household	1.8468/1.030785	
Number of Children in Household	Number of Children in Household	0.5843/1.017224	
Number of Persons in Family	Number of Persons in Family	3.1483/1.330026	
Age of Householder	Age of Householder	49.78/15.79	
Sex of householder	Sex of Householder. 1=Male		1=1,063,647, 0=1,090,343
Educational Attainment of Householder	Educational Attainment of Householder		18.6/3.5
1	No schooling completed		18,425
2	Nursery school, preschool		552
3	Kindergarten		348
4	Grade 1		1,325
5	Grade 2		1,582
6	Grade 3		2,997
7	Grade 4		3,297
8	Grade 5		3,679
9	Grade 6		20,010
10	Grade 7		9,325
11	Grade 8		17,792
12	Grade 9		27,608
13	Grade 10		32,844
14	Grade 11		44,294
15	12th grade - no diploma		29,516
16	Regular high school diploma		398,085
17	GED or alternative credential		71,162

Table 1 Continued

Variable	Description	Mean/SD	Count
18	Some college, but less than 1 year		113,258
19	1 or more years of college credit, no degree		346,897
20	Associate degree		158,028
21	Bachelor's degree		523,115
22	Master's degree		234,817
23	Professional degree beyond a bachelor's degree		57,950
24	Doctorate degree		37,084

Source: American Community Survey, U.S. Census Bureau

Table 2: Stepwise Variable Selection

Stepwise	Deviance	AIC
none	1205800	1205830
Sex	1205863	1205891
Household Income:Race	1207688	1207714
Number People in Family	1208601	1208629
Number of Children	1208754	1208782
Citizenship	1212087	1212115
Number of Persons	1212450	1212478
Marital Status	1213433	1213461
Educational Attainment	1214967	1214995
Vehicles	1281709	1281737
Age	1313966	1313994

Table 3: Regression Results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	-5.5880000	-5.6860000	-5.6970000	-5.8500000	-5.6970000	-5.6390000	-5.7340000
	0.0194500	0.0153300	0.0154700	0.0159900	0.0154700	0.0197200	1.692e-02*
Age	0.0616300	0.0550900	0.0552000	0.0554600	0.0552000	0.0617600	0.0535100
	0.0002015	0.0001262	0.0001264	0.0001270	0.0001264	0.0002016	0.0001582
Marital Status	0.5101000	0.7962000	0.7934000	0.7902000	0.7934000	0.5032000	0.7906000
	0.0057260	0.0042690	0.0042710	0.0042950	0.0042710	0.0057350	0.0042970
Household Income	0.0000081	0.0000068	0.0000071	0.0000069	0.0000071	0.0000089	0.0000068
	0.0000001	0.0000000	0.0000000	0.0000000	0.0000000	0.0000001	0.0000000
Citizenship	0.6544000	0.5993000	0.5847000	0.6247000	0.5847000	0.6361000	0.6201000
	0.0080960	0.0070560	0.0070310	0.0071000	0.0070310	0.0080600	0.0071300
newracebl ack	-0.7722000	-0.6151000	-0.6424000	-0.4270000	-0.6424000	-0.7756000	-0.7100000
	0.0051320	0.0038180	0.0061170	0.0079290	0.0061170	0.0088530	0.0169900
newraceo ther	-0.0162900	-0.0348000	0.1894000	-0.1008000	0.1894000	0.3544000	-0.3819000
	0.0078500	0.0065810	0.0093900	0.0141000	0.0093900	0.0117300	0.0277900
Sex	-0.0377400	-0.1099000	-0.1098000	-0.1142000	-0.1098000	-0.0390200	-0.1153000
	0.0049180	0.0036410	0.0036410	0.0036450	0.0036410	0.0049180	0.0036460
NP(Number of Persons)	-0.6064000	-0.1144000	-0.1153000	-0.0826500	-0.1153000	-0.5994000	-0.0891100
	0.0075140	0.0014650	0.0014650	0.0019200	0.0014650	0.0075130	0.0019420

Table 3 Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Number of Children	0.1716000					0.1709000	
	0.0031420					0.0031450	
Education	0.0645300	0.0752000	0.0755600	0.0780900	0.0755600	0.0656300	0.0783500
	0.0006875	0.0005568	0.0005567	0.0005594	0.0005567	0.0006864	0.0005596
Vehicle	0.7810000	0.7470000	0.7434000	0.7409000	0.7434000	0.7760000	0.7405000
	0.0030380	0.0023910	0.0023990	0.0024040	0.0023990	0.0030470	0.0024040
NPF	0.4110000					0.4030000	
	0.0077200					0.0077190	
AGE*newraceblack			0.0000005	0.0000016			0.0050420
			0.0000001	0.0000001			0.0002689
AGE*newraceother			-0.0000032	-0.0000034			0.0053750
			0.0000001	0.0000001			0.0004822
HINC*newraceblack					0.0000005	0.0000002	0.0000018
					0.0000001	0.0000001	0.0000001
HINC*newraceother					-0.0000032	-0.0000051	-0.0000033
					0.0000001	0.0000001	0.0000001
Newraceblack*NP				-0.1146000			-0.1034000
				0.0026350			0.0026990

Table 3 Continued

Newraceother*NP				0.0972900			0.1084000
				0.0038700			0.0039570
AIC	1207714	2020768	2019499	2016130	2019499	120580	2015720
McFadden Pseudo R squared	0.576446	0.291294	0.291741	0.292924	0.291741	0.577108	0.293069
Observations	20575	20575	20575	20575	20575	20575	20575

Several model specifications were explored to determine the most appropriate specification and the results can be found in Table 3. Ultimately, in conjunction with our exploratory methods of model specification choice, we also incorporated stepwise variable selection methods to highlight the final model choice.

Overall, as we can see from the model results, it appears as though the specification of model specification 6 is the most appropriate and we thus proceed with that in our interpretation and further analysis. This specification was developed through a combination to stepwise variable selection, intuition and the minimization of AIC as shown in Table 2.

We find that all of the variables are statistically significant at the 5 percent level. However, in discrete choice models, only the signs of the coefficients are easily interpretable. The information they provide remains limited to the way (positively or negatively) the probability varies.

We can compare different model specifications to understand model fit. In the table, we also provide several indices of model fit such as the AIC and pseudo R-squared. For this model, the McFadden's Pseudo R-Squared is quite high.

Overall, we do not find many surprises in the results and the variables we have included in our analysis appear to influence the probability of homeownership in relatively predictable ways. For example, increasing income has a positive influence on the probability of homeownership, while being a male householder has a slight negative influence on homeownership in the Atlanta MSA.

It appears as though the influence of age also follows an expected pattern. That is, younger householders have a lower likelihood of being a homeowner than older householders. Also, as expected, marriage and children tend to have a positive influence on homeownership. Overall, it appears as though income, age and being married seem to have the strongest influence on homeownership in the metropolitan Atlanta region.

In order to provide some of the basic though rather cumbersome interpretations of these results, for every one unit change in age, the log odds of homeownership (versus non-homeownership) increases by 0.0617600. For a one unit increase in household income, the log odds of being a homeowner increases by 0.0000089. The race variables in the model have a slightly different interpretation. For example, a black householder versus a white householder changes the log odds of homeownership by -0.77560000.

As we can see from the model results, the interaction term is significant which indicates that the slopes for homeownership on the race categories are significantly different for different levels of income. It may be true that the oldest age groups may be expected to have lower probability of homeowner status because of specific needs though this is not typically the case in the United States where wealth concentrates in the older age groups.

Not surprisingly, marriage and the presence of children also have a positive influence on homeownership. These variables provide some indications about the stability of the household's housing demand that logically increase the likelihood of homeownership. Moreover, the presence of dependent children could involve higher requirements in terms of, amongst others, space or dwelling characteristics and thus encourage homeownership.

One measure of model fit is the significance of the overall model. To test this, we attempt to understand whether a model with independent variables fits significantly better than a model with only the intercept (a null model). As we can determine from Table 4, our model performs better than no model. The chi-square with an associated p-value of less than 0.001 tells us that our model as a whole fits significantly better than an empty model. This is often called a likelihood ratio test, which we can see the results of below.

Table 5 below highlights the odds ratios. Interpretation here is highly dependent on how the variables were coded. However, these odds ratios provide for a slightly clearer interpretation compared to the coefficients above. For example, a one unit increase in household income increases the odds of being a homeowner versus not being a homeowner by a factor of 1.00000892.

While this still provides insight into the differences across racial categories, more work into the predicted probabilities could be done for a more in depth investigation.

As demonstrated in Figure 8, it is also common practice to calculate predicted probabilities to better understand our model. For example, we can calculate the predicted probability of homeownership for different race categories, holding other variables at their means.

In this study, we see that the predicted probability is 0.8596433 for white householders, 0.7412535 for black householders and 0.8388206 for householders of other races. This appears to be relatively high, likely because of mean household income in the area.

Calculating these predicted probabilities at the median or removing very high income households would provide more reasonable probabilities that align with the actual homeownership rate. That being said, it still provides useful interpretation for understanding the differences between racial groups.

We highlight this with a plot showing the predicted probabilities and 95 percent confidence intervals. Unsurprisingly given the region of study, we see that white householders/households are more likely than black householders/households to be homeowners.

However, a surprising result is that other householders/households are more likely to be homeowners at lower incomes than white householders/households. My guess is that, compared to other metropolitan areas of similar size, there is likely a strong relationship between other householders/households and relatively recent immigrant status.

Table 4: Likelihood Ratio and Wald Tests

Likelihood Ratio Test					
	DF	LogLik	DF	Chisq	Pr(>Chisq)
Model 1	15	-602900			
Model 2	1	-15986153	-14	30766506	0.0000000
Wald Test					
					0.0000000

Table 5: Odds Ratios

	Odds Ratio	2.50%	97.50%
Intercept	0.003555979	0.003421079	0.00369604
Household Income	1.00000892	1.000008791	1.00000905
Citizenship	1.889016377	1.859415628	1.91909948
Marital Status	1.654042198	1.635553056	1.67273805
Number of People	0.549139513	0.541107317	0.55727964
Vehicles	2.172709827	2.159783064	2.18573124
Number of Children	1.186317553	1.179028867	1.19365183
Educational Attainment	1.067836727	1.066401246	1.06927446
newraceblack	0.460445166	0.452522697	0.46850198
newraceother	1.425391431	1.392978051	1.45853531
Age	1.063705994	1.063285954	1.06412667
Number of People in Family	1.496279819	1.473825203	1.51910396
Sex	0.961728595	0.952501377	0.97104297
HHIncome:newraceblack	1.000000156	0.999999944	1.00000037
HHIncome:newraceother	0.99999488	0.999994648	0.99999511

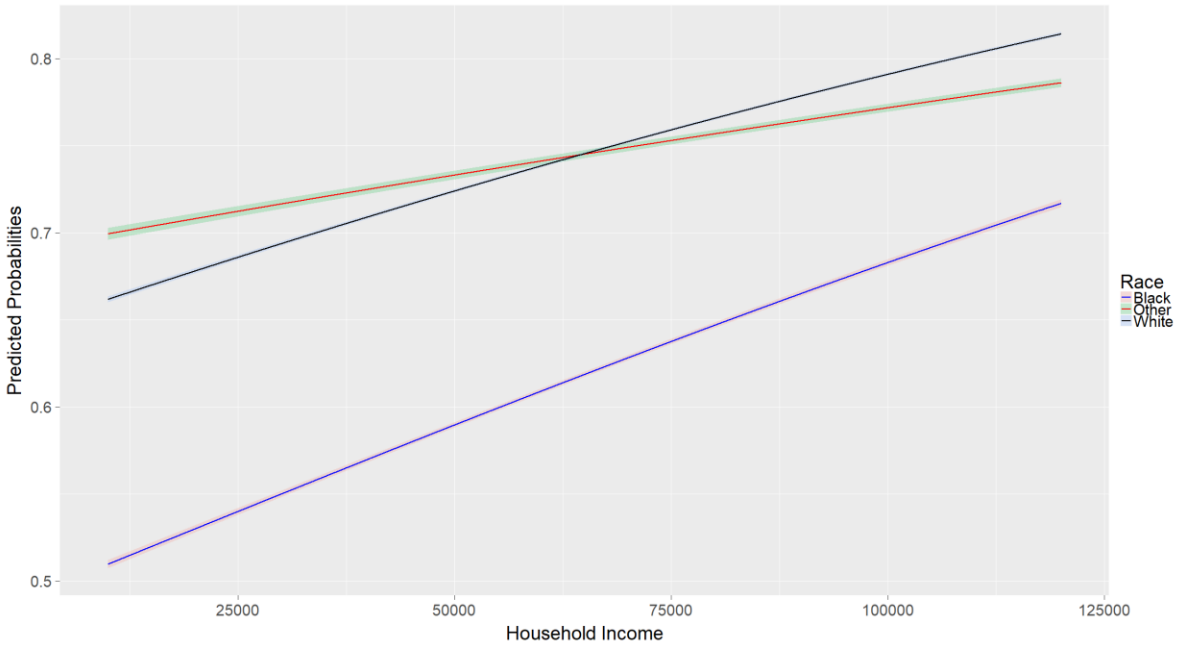


Figure 8: Predicted Probabilities

Marginal Effects

Again, as is typical in discrete choice models, we calculate marginal effects found in Table 6. The marginal effects identify the change in homeownership probability in the case of a marginal change in one parameter (all of things being equal).

For example, how does a change in income impact the probability of homeownership? For dummy variables, the marginal effect is calculated for a discrete change from 0 to 1. For continuous variables, the marginal effect is calculated at the means.

This is the average change in probability when a variable increases by one unit. For example, the average marginal effects for the sex variable demonstrates the extent to which the probability of homeownership changes as the sex variable changes from 0 to 1 while holding all other variables at their means. For example, the table below shows that the average marginal effect for sex is -0.0052.

This is telling us that for two hypothetical householders in the Atlanta MSA with average values in the rest of the variables in the model, the predicted probability of homeownership is 0.0052 less for male householders than for female householders.

The value of 0.0082 would suggest that a one unit increase in age will produce a 0.0082 increase in the probability of homeownership for an otherwise average household. A visualization of the marginal effects can be found in Figure 9.

Table 6: Marginal Effects

Factor	Average Marginal Effect	SE	z	p	lower	upper
Age	0.0082	0	346.0747	0	0.0082	0.0083
Marital Status	0.0671	0.0008	88.7443	0	0.0656	0.0686
Household Income	0	0	164.7395	0	0	0
Citizenship	0.0848	0.0011	79.6481	0	0.0827	0.0869
Black	-0.1078	0.0008	-142.0607	0	-0.1093	-0.1063
Other	-0.0003	0.0011	-0.3038	0.7613	-0.0024	0.0017
Sex	-0.0052	0.0007	-7.935	0	-0.0065	-0.0039
Number of Children	0.0228	0.0004	54.5028	0	0.022	0.0236
Number of Persons	-0.0799	0.001	-80.4058	0	-0.0819	-0.078
Number of Persons in Family	0.0537	0.001	52.388	0	0.0517	0.0557
Educational Attainment	0.0087	0.0001	96.7462	0	0.0086	0.0089
Vehicles	0.1034	0.0004	277.1755	0	0.1027	0.1042

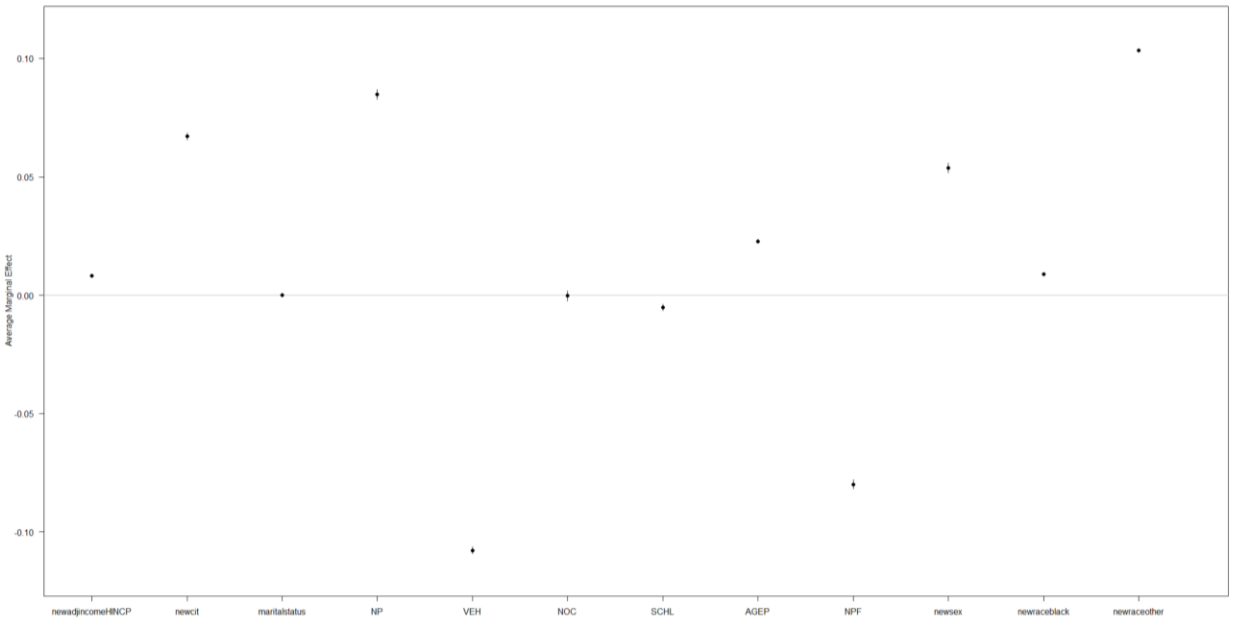


Figure 9: Average Marginal Effects

ROC (receiver operating characteristic) curves (Figure 10) are a common tool used to visualize the performance of a binary model. In this case, we are understanding homeownership versus non-homeownership. This compares the model's predictions to the true homeownership status in the area.

It plots the true positive rate against the false positive rate. The more accurate the model, the closer the curve follows the left-hand and top border.

The area under the curve demonstrates the frequency in which a random draw from the predicted response probabilities for homeownership is greater than a random draw from our predicted response probabilities on non-homeownership records. In this study, we have discovered that our model accurately predicts the result more than 60 percent of the time.

Limits of Study/Future Research

There are many limits to this study. It does a relatively elementary job of advancing our understanding of homeownership in the region. However, it does provide some background information for later chapters and assists in understanding the issues and determinants surrounding homeownership in the region. With additional data, time and resources it may be possible to investigate homeownership in a more detailed way. In particular, understanding the transition to homeownership from various other forms of living would provide a more detailed investigation. In addition, the predicted probabilities and marginal effects from this research could be investigated and discussed at a much more in-depth level.

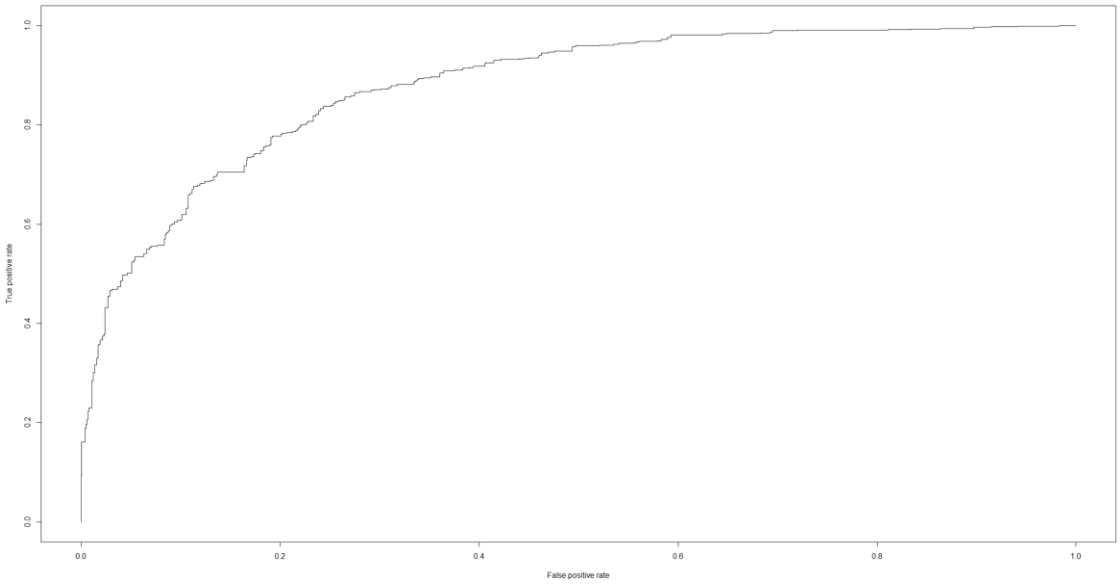


Figure 10: ROC Plot

Conclusion

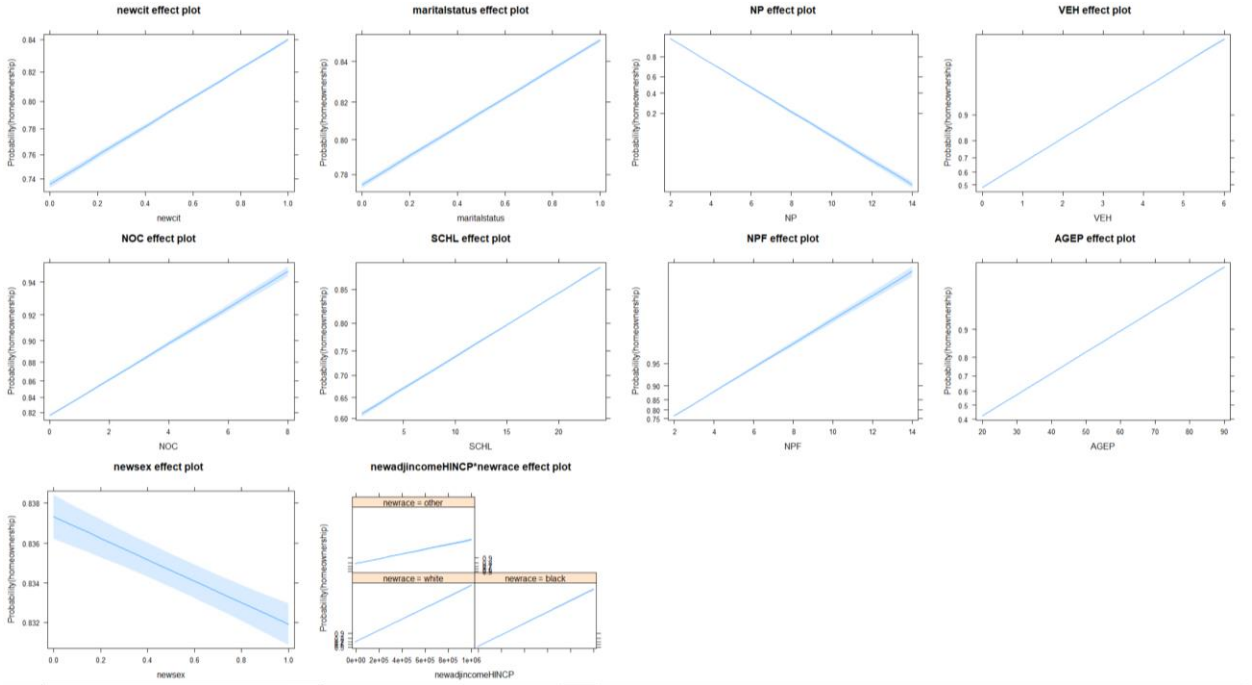
This paper proposed an econometric model of housing tenure for the Atlanta Metropolitan Statistical Area. While the issues of housing tenure choice have been at the center of discussion in numerous studies, this research presents insight into the field of housing tenure choice in the Atlanta Metropolitan Statistical Area as a reference and guide for later chapters.

A brief review of the literature shows that many authors focus on the roles that mortgage accessibility, risk, uncertainty and transaction costs play in the attainment of homeownership. In addition, homeownership was modeled as a function of household's demographic attributes and income as in past studies.

We have hypothesized that the underlying significance of these variables are relevant regarding the determinants of homeownership. Consequently, the model developed in this paper included variables related to income, life-cycle variables which are relevant in regards to the stability of the household and the down payment constraint.

Logistic regression was the employed method in this paper, which is the most popular and effective way of modeling a binary response. For this paper, we wondered how certain variables influenced a household to be a homeowner. This has allowed us to understand the determinants of homeownership in the Atlanta metropolitan area. Future research can involve a deeper investigation into the role of transition into homeownership from other housing situations.

Appendix A: Predicted Probabilities



Chapter 6: Understanding Housing Affordability in Metropolitan Atlanta

Abstract

This study assessed the housing situation in Metropolitan Atlanta and the need for affordable housing. Through analyzing the households that are burdened by their housing costs, the community can better understand what may be required to alleviate this burden. All data used in this report came from the American Community Survey 2015 public use microdata sample, an anonymized set of records about individual people and housing units. A substantial portion of Metropolitan Atlanta households were burdened by housing costs, with renter households being particularly vulnerable. Some key findings from the study are presented below along with further discussion regarding the extent that renter households remain significantly burdened by housing costs and potential alleviation policies.

Introduction

The extent to which housing is affordable significantly impacts a household's economic well-being. As money spent on housing is the largest monthly expense for most households, the availability of affordable housing significantly impacts the amount of money left over for other goods and services.

Housing affordability often becomes an issue in areas where prices rise rapidly, forcing people to spend a larger portion of their income on housing unexpectedly. For those households that own a home, the purchase was likely the most expensive they have made in their lives. For renters, the rent payment is likely their largest bill.

Therefore, understanding the housing market is crucial for understanding the broader economy. While expensive housing can be seen as a sign of wealth for a community, a lack of affordable housing can lead to difficulty in recruiting workers and increases in traffic congestion and commute times as households seek affordable living arrangements. It also impedes households in the community from becoming financially secure. Households that suffer from unaffordable housing conditions may also move more often, leading to instability in the household and worse outcomes for the members of the household. Affordable housing also frees up money for the household to spend on other necessities.

Affordable housing is also an issue when we look at differences between metropolitan areas. Unaffordable housing can lead to companies rethinking their location decisions and a city that has affordable, quality housing may have a greater ability to attract employees.

An affordable assessment to understand households that are burdened by housing costs is important for identifying those with the most immediate need. Analyzing the number of households that are burdened by their housing costs, and the additional units that may be necessary to alleviate this burden, can also inform long-term housing planning policies.

This report assesses 1) the attributes of housing units in Metropolitan Atlanta, 2) households experiencing cost-burdened housing across several groups (including owners with a mortgage, owners without a mortgage and renters), 3) the degree of overcrowding in housing units, 4) the

income and age groups experiencing the most severe issues of housing affordability,[1] and 5) the availability of affordable housing across income groups.

Background/Data

Affordable housing is typically defined in terms of the percentage of income spent on housing-related costs. The conventional approach, introduced in the United States National Housing Act of 1937, assumes 30 percent of household income can be devoted to housing-related costs before the household is cost-burdened. In this report, additional categories are analyzed above the 30 percent threshold to investigate how severely households are burdened.

The data for this study come from the 2015 American Community Survey (ACS) 1-year Public Use Microdata Samples (PUMS), a set of records about individual people and housing units.[2] The national survey includes approximately 3 million households every year, collected from housing units and group quarters in every county of the United States.[3]

Demographic information for each household comes from the householder, the number-one person in the household[4] and typically the person in whose name the housing unit is rented or owned. No distinction is made between a family householder and a nonfamily householder, so the demographics of the householder are assumed to be those of the household for purposes of this report as is common.

As housing affordability is the main focus of this report, the American Community Survey variables of interest are household income, monthly owner costs and gross monthly rent. Monthly owner costs are calculated from questions in the American Community Survey about mortgage, second mortgage/home equity loans, real estate taxes, homeowner's insurance, condo fees, mobile home costs, and utilities (electricity, gas, water, sewer and other utilities).

Monthly gross rent costs are calculated from questions in the American Community Survey about contract rent and utilities. This information is used with monthly household income figures to determine the percent of income that each household spends on housing and, thus, housing affordability.

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[1] The researchers also investigated housing burden across racial categories and did not find any interesting patterns. Thus, the decision was made to not include this output in the initial report. This information can be included in subsequent versions if requested.

[2] Please note that the American Community Survey is a survey and thus numbers presented in this report have associated margins of error. If interested in these margins of error, please contact the author for values and further explanation.

[3] All data based on samples, such as the American Community Survey, include a range of uncertainty. It is important to note that the values in this report are estimates. The 2010-2014 ACS PUMS data are the most current available at the time of this writing.

[4] According to the survey, "Person 1 is the person living or staying here in whose name this house or apartment is owned, being bought, or rented. If there is no such person, start with the name of any adult living or staying here." https://www2.census.gov/programs-surveys/acs/methodology/questionnaires/2015/quest15.pdf

Metropolitan Atlanta

Metropolitan Atlanta contains a similar percentage of renter households as the nation as a whole. In Metropolitan Atlanta, the poverty rate is approximately 12.5 percent. The American Community Survey data represents approximately 2.4 million housing units containing a population of nearly 6 million people.

Occupied housing units number over 2.15 million for an occupancy rate of near 90 percent in the metropolitan area. Building of housing units has declined in recent years; just 53,747 housing units were constructed in the metropolitan area since 2010. This may reflect increased housing stock in counties outside the metropolitan area with lower housing costs.

Overall, 71.8 percent of the housing stock in Metropolitan Atlanta was built prior to 2000 (Figure 11). Housing units are also relatively large, with 70 percent containing three or fewer bedrooms and 73.2 percent having a total of six or fewer rooms (Figure 12). Single-family detached homes predominate, making up 67.2 percent of housing units, a value comparable to other large sunbelt metropolitan areas (Figure 13).

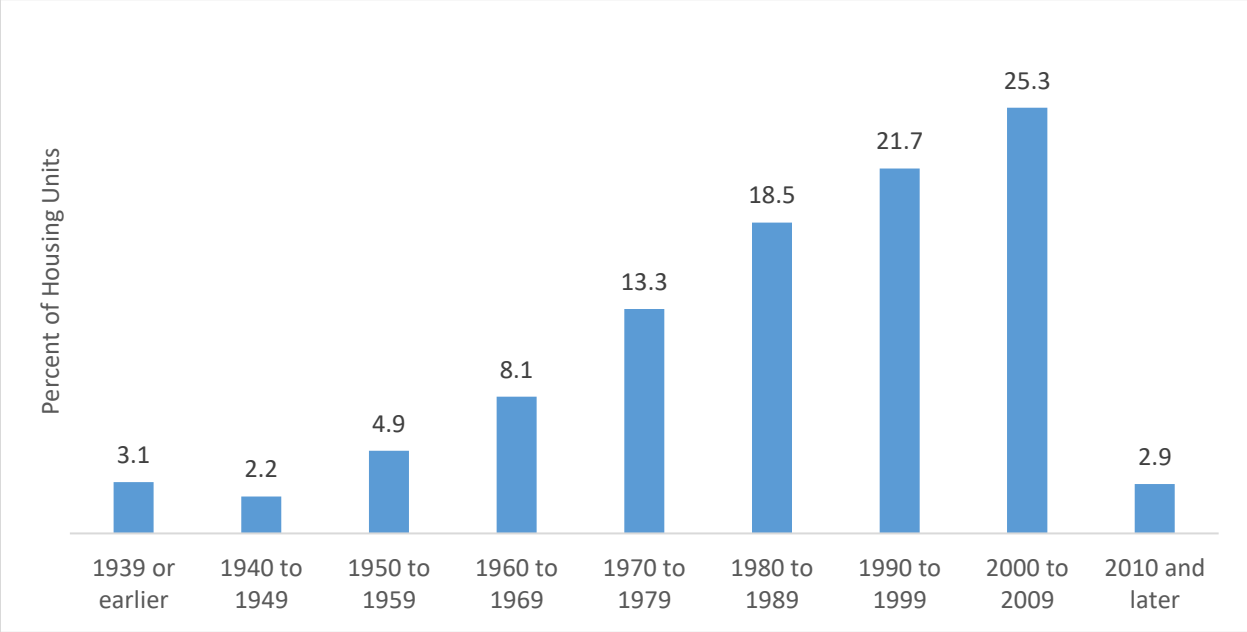


Figure 11: Percent of Metropolitan Atlanta Housing Units by Year Built

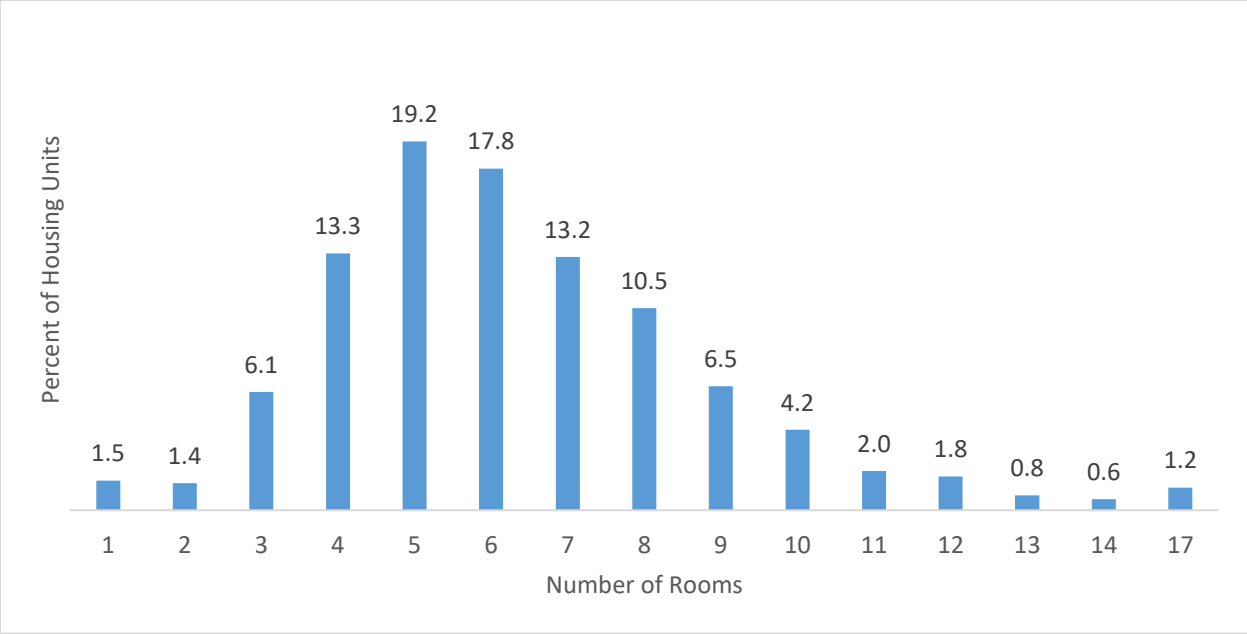


Figure 12: Percent of Metropolitan Atlanta Housing Units by Number of Rooms

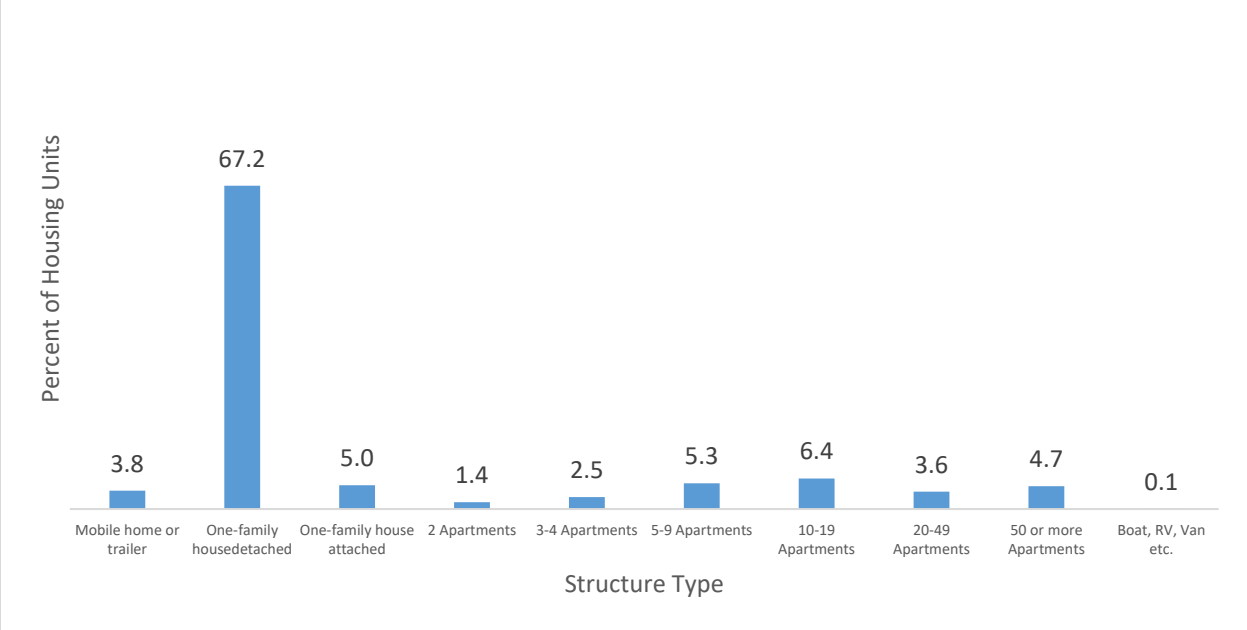


Figure 13: Percent of Metropolitan Atlanta Housing Units by Structure Type

Household Characteristics

Household size in Metropolitan Atlanta tends to be average, with most containing fewer than three people (Figure 14). Household income categories are defined by percentages of the median annual household income of $59,074 (Table 7).

Given its purpose, this report focuses on establishing detailed income categories for low income households. For example, low income households are defined as those with household income between 51 percent and 80 percent of the county's median household income.

As shown in Table 8, these income categories are converted to monthly income ranges for each category. Housing affordability ranges (Table 9) determine the monthly housing costs that each income category can comfortably afford. As an example, the highest monthly income for those in the extremely low income group is $1,476.86. Therefore, the most any household in this income group could comfortably afford is $444 in monthly housing costs (30 percent of its monthly income). Other affordability ranges correspond to housing costs above this threshold.

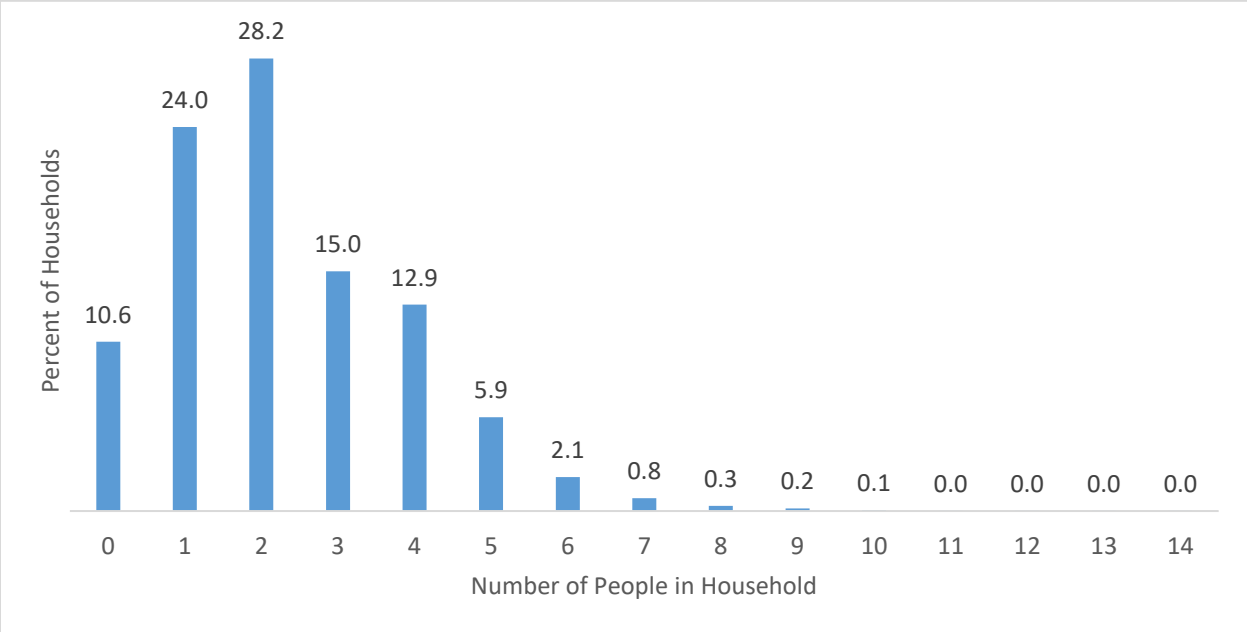


Figure 14: Percent of Households by Size

Table 7: Annual Household Income Categories

Income Category (Percent of Median Income)	Lower	Upper
Extremely Low Income (0%-30%)	$0	$17,722.37
Very Low Income (31%-50%)	$17,722.38	$29,537.29
Low Income (51%-80%)	$29,537.30	$47,259.66
Moderate Income (81%-120%)	$47,259.67	$70,889.49
High Income (Over 120%)	$70,889.50	n/a

Table 8: Monthly Income Categories

Income Category (Percent of Median Income)	Lower	Upper
Extremely Low Income (0%-30%)	$0	$1,476.86
Very Low Income (31%-50%)	$1,476.87	$2,461.44
Low Income (51%-80%)	$2,461.45	$3,938.31
Moderate Income (81%-120%)	$3,938.32	$5,907.46
High Income (Over 120%)	$5,907.47	n/a

Table 9: Affordable Monthly Housing Costs

Income Category	Lower	Upper
Extremely Low Income	$0	$444
Very Low Income	$445	$738
Low Income	$739	$1,181
Moderate Income	$1,182	$1,772
High Income	$1,773	n/a

Ownership and Renting

Approximately 45.0 percent of Metropolitan Atlanta housing units are owned with a mortgage, 17.4 percent are owned without a mortgage, 36.1 percent are rented, and 1.5 percent are occupied without payment of rent (Figure 15).

Occupied rental units total approximately 777,520 (Figure 16). As expected, renter households are much more likely to be lower income than households that own their home (Figure 17). The majority of renter households in the metropolitan area are classified as either extremely low income, very low income or low income.

Thus, as is typical in other communities, affordable housing policies in Metropolitan Atlanta should pay special attention to rental units and renter households. While Metropolitan Atlanta's occupancy rate is slightly higher than for the nation as a whole, there are approximately 254,537 vacant housing units in the county, of which 21.1 percent are for rent (Figure 18).

Other vacant housing units may be rented but not occupied,[5] for sale, sold but not occupied, for seasonal use only, for migrant workers, or vacant for other reasons.



Figure 15: Percent of Occupied Units

[5] These are vacant units rented but not yet occupied, such as cases where money has been paid or agreed upon, but the renter has not yet moved in (https://www2.census.gov/programs-surveys/acs/tech_docs/subject_definitions/2014_ACSSubjectDefinitions.pdf).

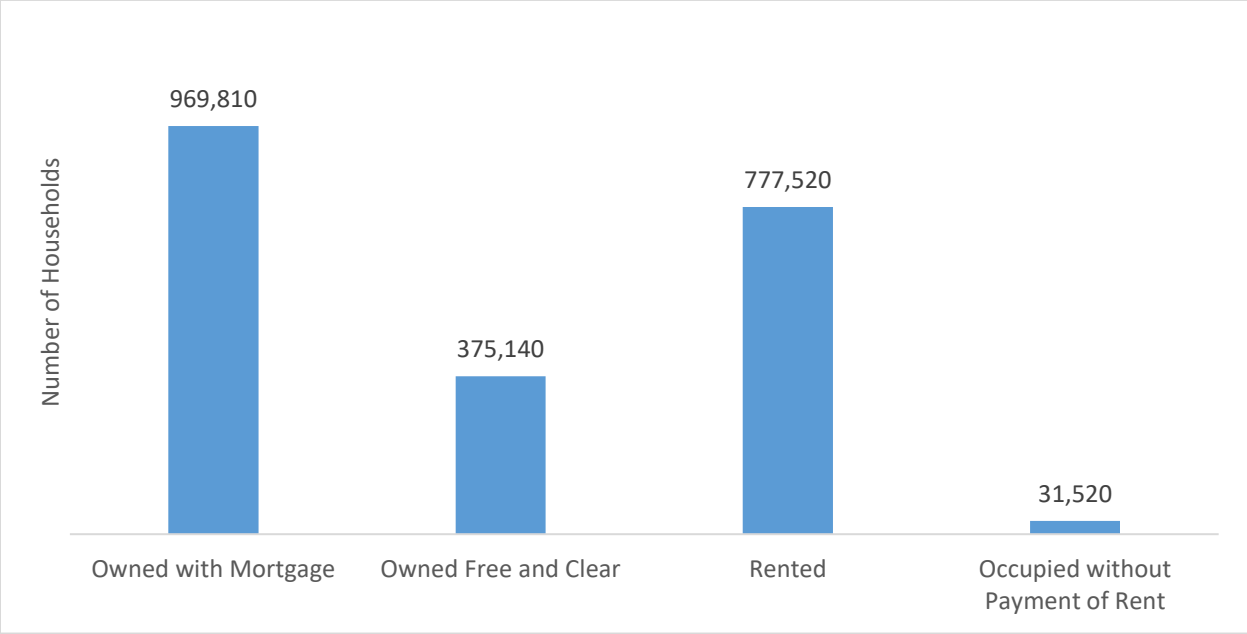


Figure 16: Tenure - All Housing Units

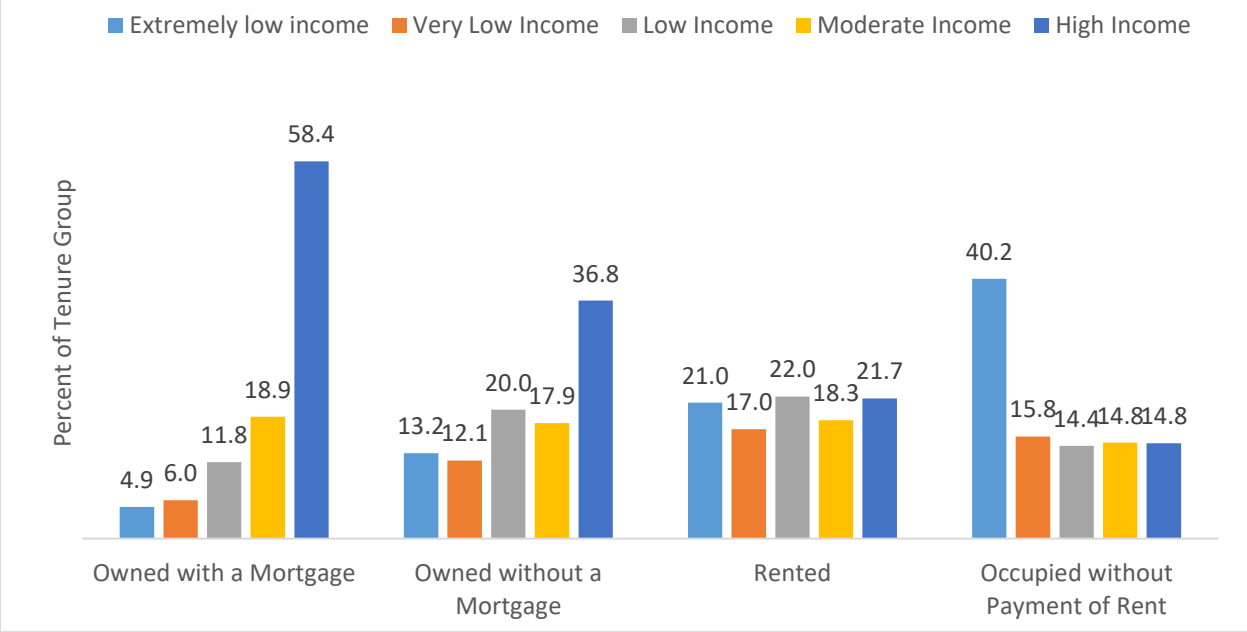


Figure 17: Income Category by Tenure

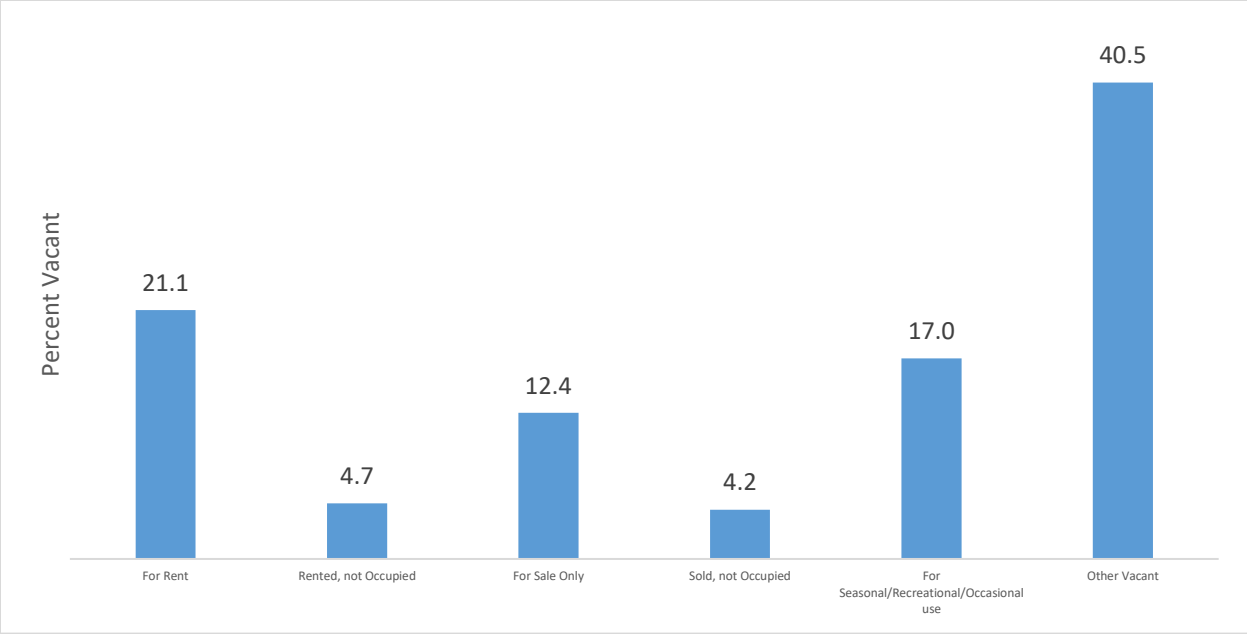


Figure 18: Percent Vacancy Category

Home Values and Rent

Property value in the American Community Survey refers to the respondent's estimate of how much the property (house and lot) would sell for if it were for sale. This includes only specific owner-occupied housing units that are single-family houses on less than 10 acres without a business or medical office on the property. It also excludes houses on 10 or more acres and housing units in multi-unit structures. As we can see in Figure 19, approximately 18.7 percent of homes were estimated to be worth less than $100,000.

Figure 20 highlights the percent of renters in each gross rent category. The median gross rent paid was $998, whereas the median selected monthly owner costs were $1,137. The ACS data indicate the median property value for Metropolitan Atlanta was approximately $180,000.

Overcrowding

Overcrowding issues in housing are typically defined in terms of persons-per-room. Following current literature on this topic, this report uses a standard of more than one person per room to define a household as overcrowded, and more than 1.5 persons per room as severely overcrowded.



Figure 19: Percent of Single-family, Owner-Occupied Units by Property Value

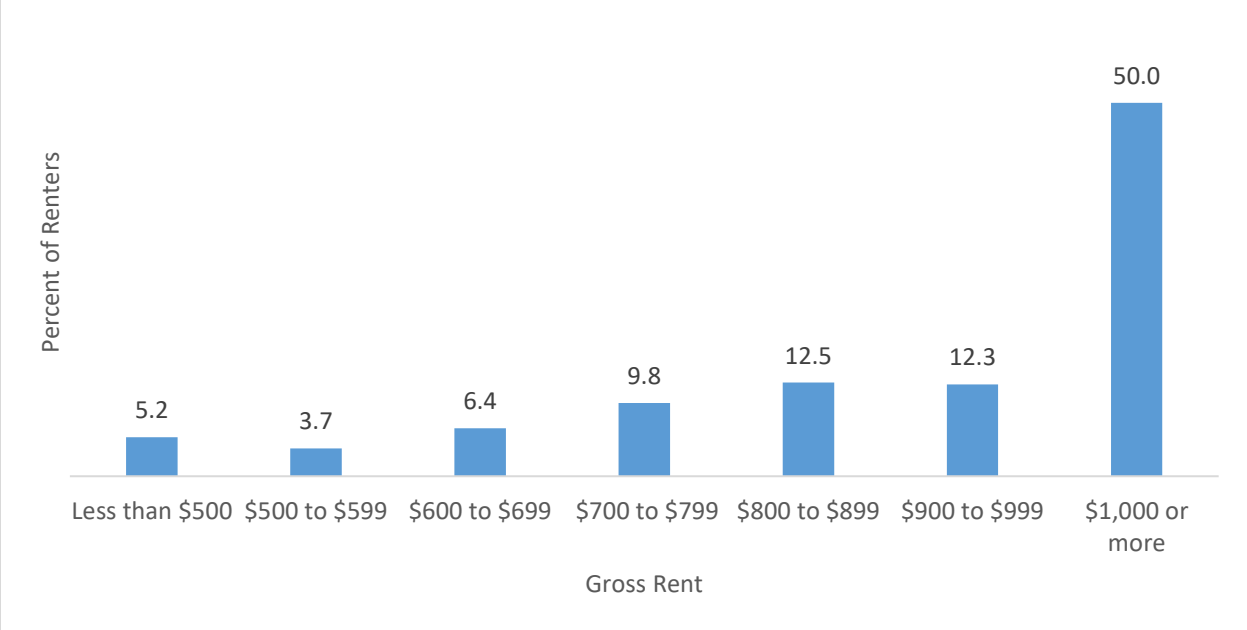


Figure 20: Percent of Renters by Gross Rent Paid

This overcrowding standard comes from a report prepared for the U.S. Department of Housing and Urban Development.[6] As Table 10 shows, overcrowding is not very common in Metropolitan Atlanta. This measure may lead one to believe that housing is relatively affordable in the county, as more expensive communities typically experience higher levels of overcrowding. However, even without significant overcrowding problems, some affordability issues remain.

Housing Affordability

The largest group of occupied housing units in Metropolitan Atlanta is owned with a mortgage, followed by rented, owners without a mortgage and units occupied without the payment of rent. Several measures were developed to determine if a household is burdened by housing costs and if so, the extent of the burden. If the household spends 30 percent or less of their household income on housing-related costs, they are considered unburdened by housing costs. Households are burdened if they spend more than 30 percent, but less than 35 percent, on housing-related costs. Severely burdened households spend 35 percent or more, but less than 50 percent. Those spending more than 50 percent of household income on housing costs are considered extremely burdened (Table 11). While spending over 30 percent on housing costs is defined as "unaffordable," extremely burdened households are the most vulnerable group and are often targeted for housing affordability programs.

Large differences exist between Metropolitan Atlanta owners and renters in terms of housing affordability. The median share of income owners spent on housing is 17.6 percent versus 29.5 percent for renters. For households that are owned with a mortgage, less than 27 percent experience cost-burdened housing of any kind, with less than 11.4 percent being extremely burdened (Figure 21). The situation is even better for owners without a mortgage. Only 11 percent of these households are cost burdened, and only 5.8 percent experience extreme burden (Figure 22).

Table 10: Percent of Overcrowded Housing, by Tenure

Tenure	Not Overcrowded	Overcrowded	Severely Overcrowded
Owned with Mortgage	98.9	0.8	0.3
Owned Free and Clear	98.6	1.1	0.3
Rented	95.8	3.0	1.3
Occupied without Payment of Rent	94.3	2.7	3.0

[6] U.S. Department of Housing and Urban Development, "Measuring Overcrowding in Housing," September 2007, http://www.census.gov/programs-surveys/ahs/research/publications/Measuring_Overcrowding_in_Hsg.html.

Table 11: Housing Affordability Definitions

Housing Affordability	Percent of Household Income Spent on Housing
Not Burdened	Less than or equal to 30%
Burdened	Greater than 30% and less than 35%
Severely Burdened	Greater than or equal to 35% and less than 50%
Extremely Burdened	Greater than or equal to 50 percent

Source: Schwartz and Wilson (2008)

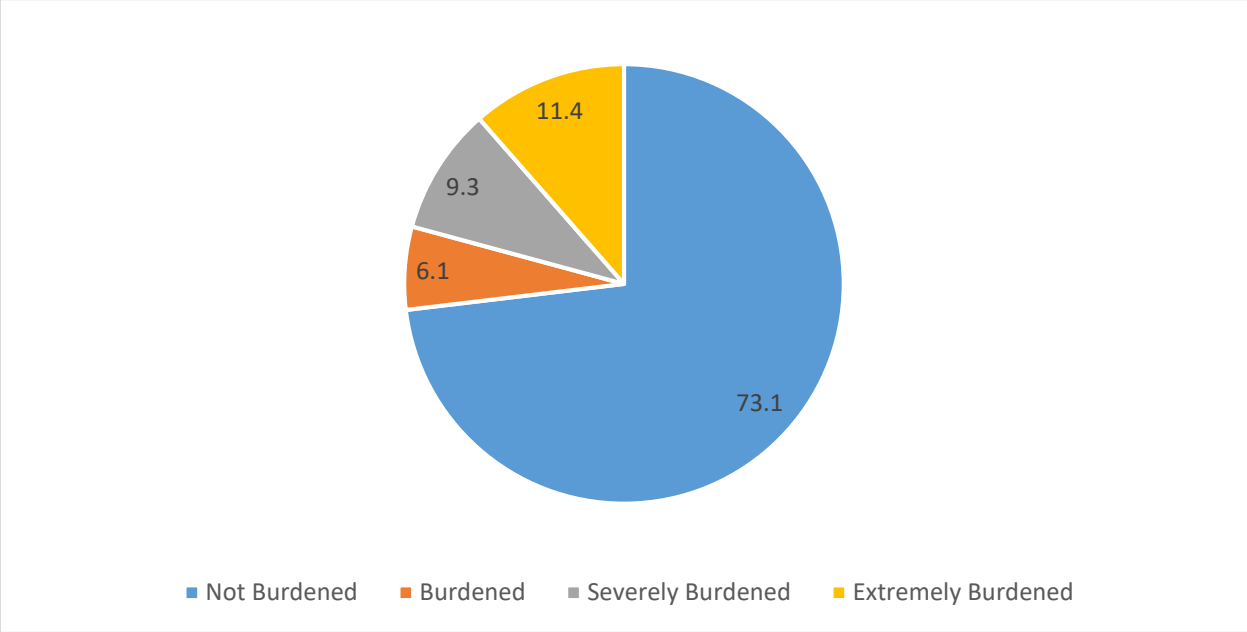


Figure 21: Housing Affordability (Owners with Mortgage)

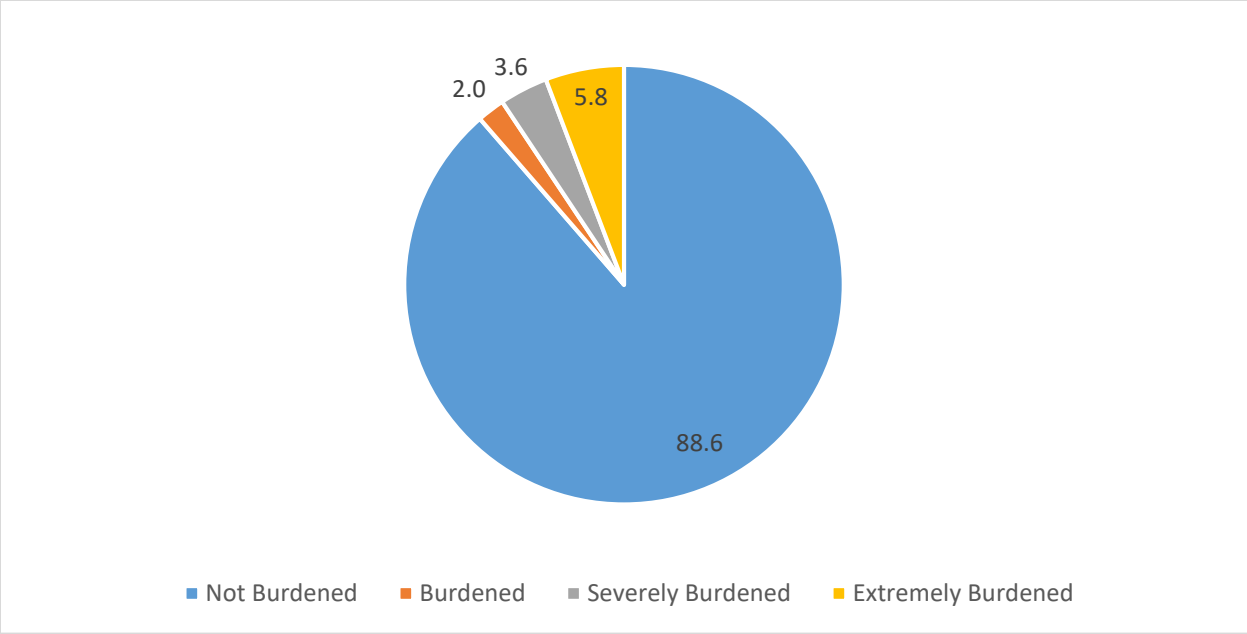


Figure 22: Housing Affordability (Owners without a Mortgage)

For renter households, the situation is notably less favorable. Approximately 49 percent experience cost-burdened housing of some kind, and nearly 26 percent are extremely burdened, spending half or more of their income on housing-related costs (Figure 23).

Regarding the age of the householder, younger (under 25) households have a higher share of housing cost burden (Figure 24 and Figure 25). Unsurprisingly, those with lower incomes experience more housing cost burden compared to those with high income for both owners and renters (Figure 26 and Figure 27).

Figure 28 demonstrates that there is not an obvious trend of burdened households across property values. Overall, while renter households comprise the largest percentage of occupied housing units, they also have the highest levels of cost burdened households. Levels of burden for households remain high when only including non-student households in the analysis. Regardless, it is clear that renter households experience significant housing cost burden.

Assessing Metropolitan Atlanta's Need for Affordable Housing Units

Given that many Metropolitan Atlanta residents are renters, and that they experience more housing cost burden, we decided to further investigate why renters are so vulnerable when it comes to housing costs, as well as policy initiatives that might be undertaken to address this. Figure 29 shows the approximate number of units in Metropolitan Atlanta in each affordability category along with the number of households in the respective income categories (also refer to Appendix B).

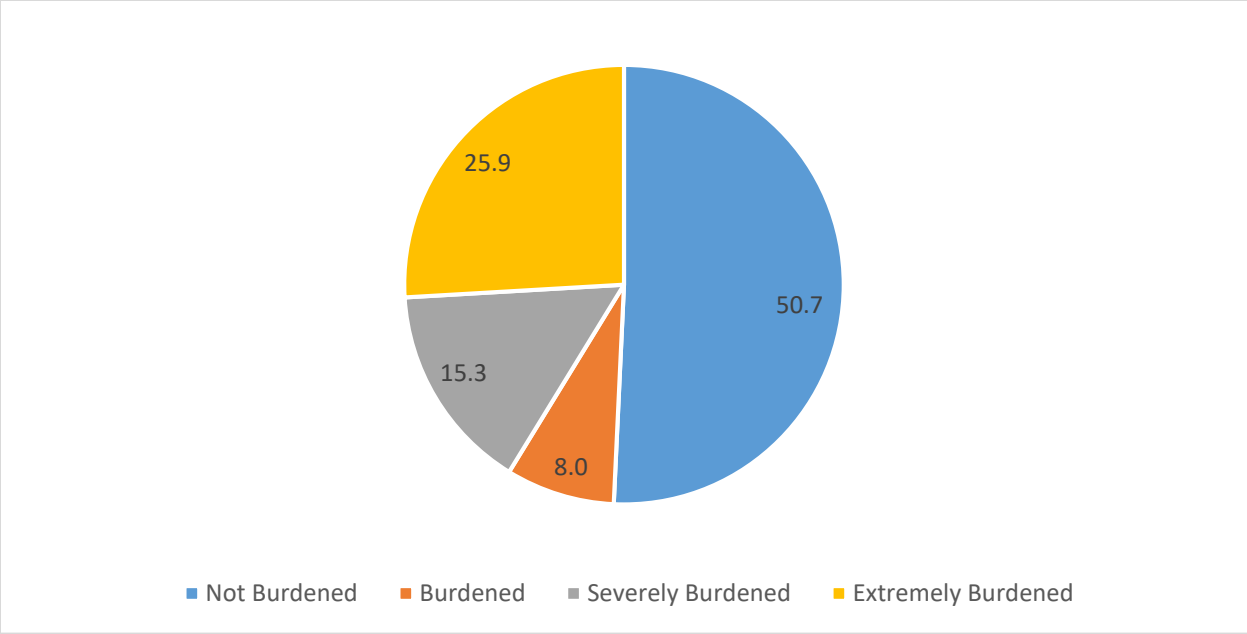


Figure 23: Housing Affordability (All Renters)

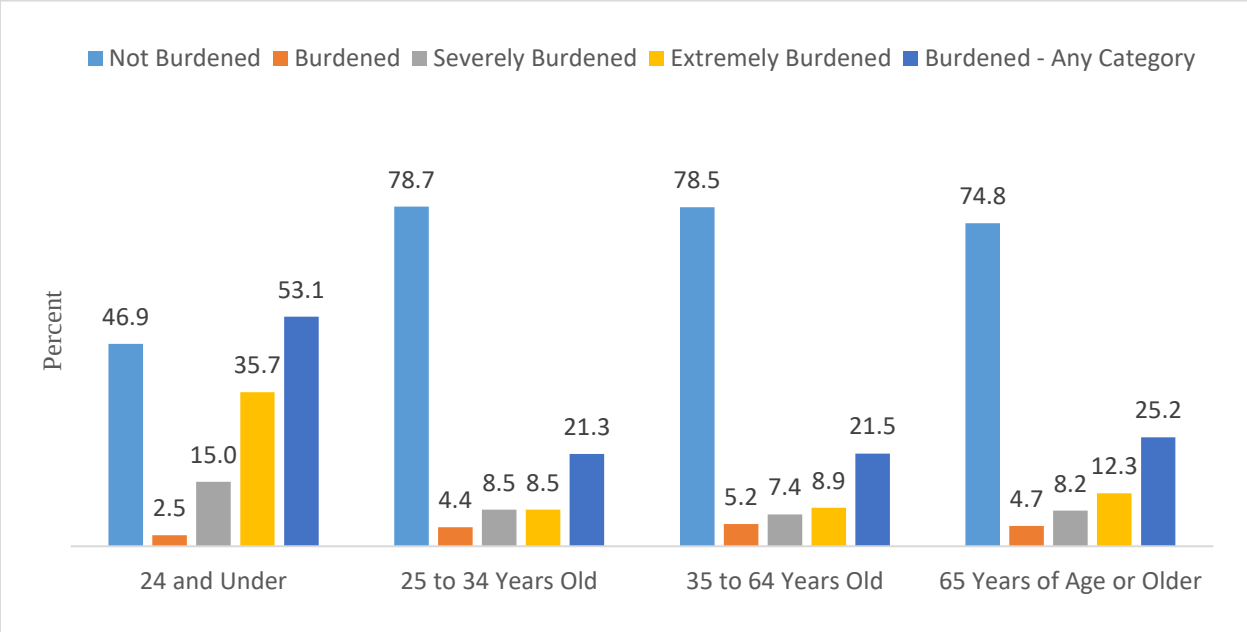


Figure 24: Owner Burden by Age

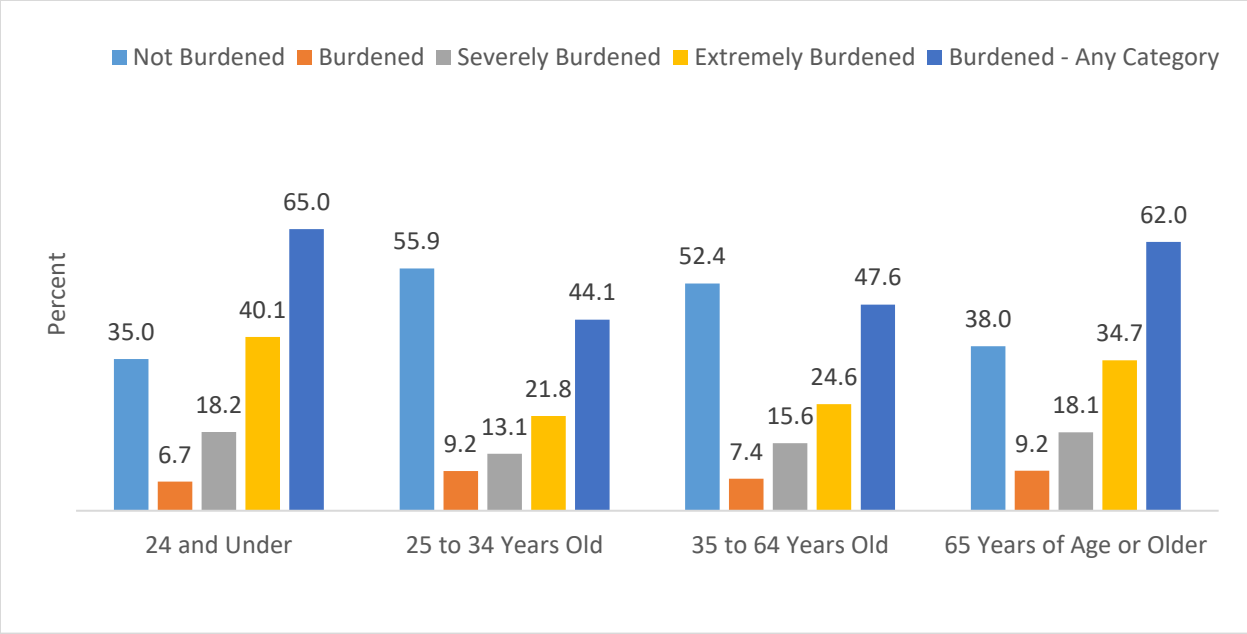


Figure 25: Renter Burden by Age

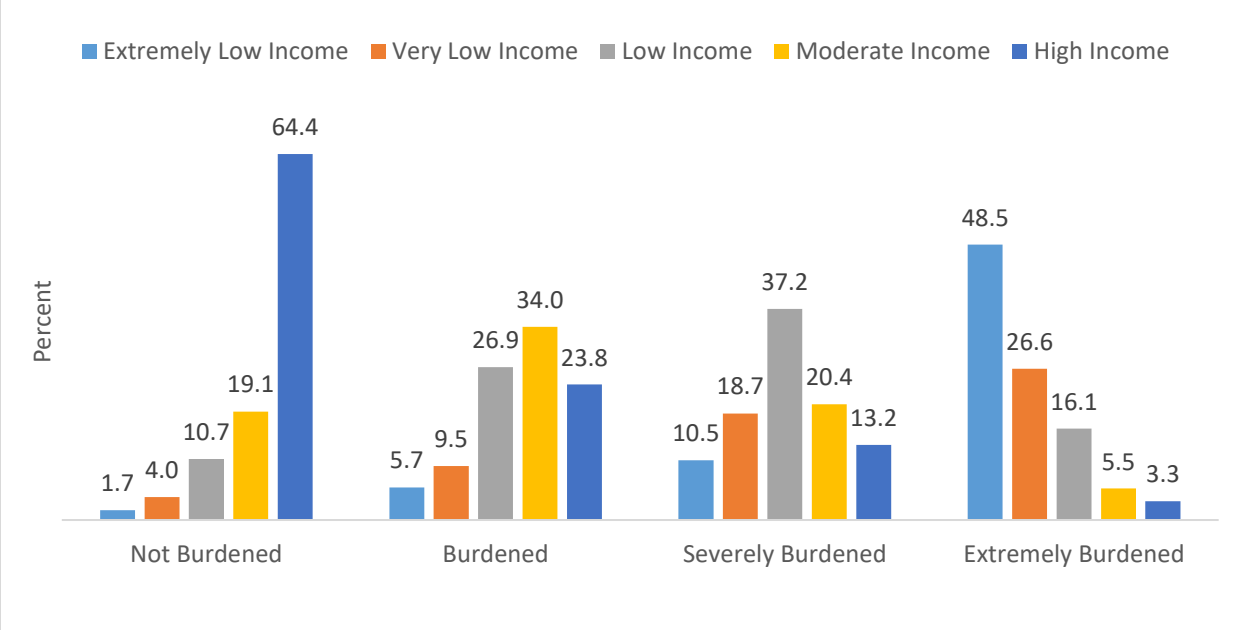


Figure 26: Owner Burden by Income Category

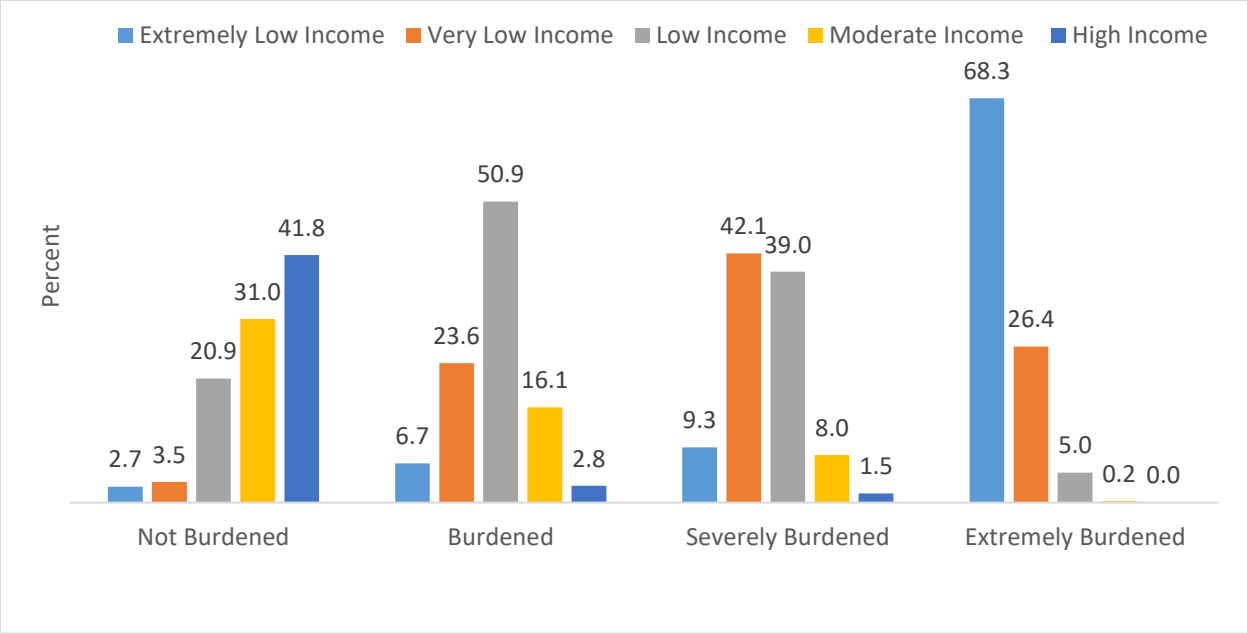


Figure 27: Renter Burden by Income Category

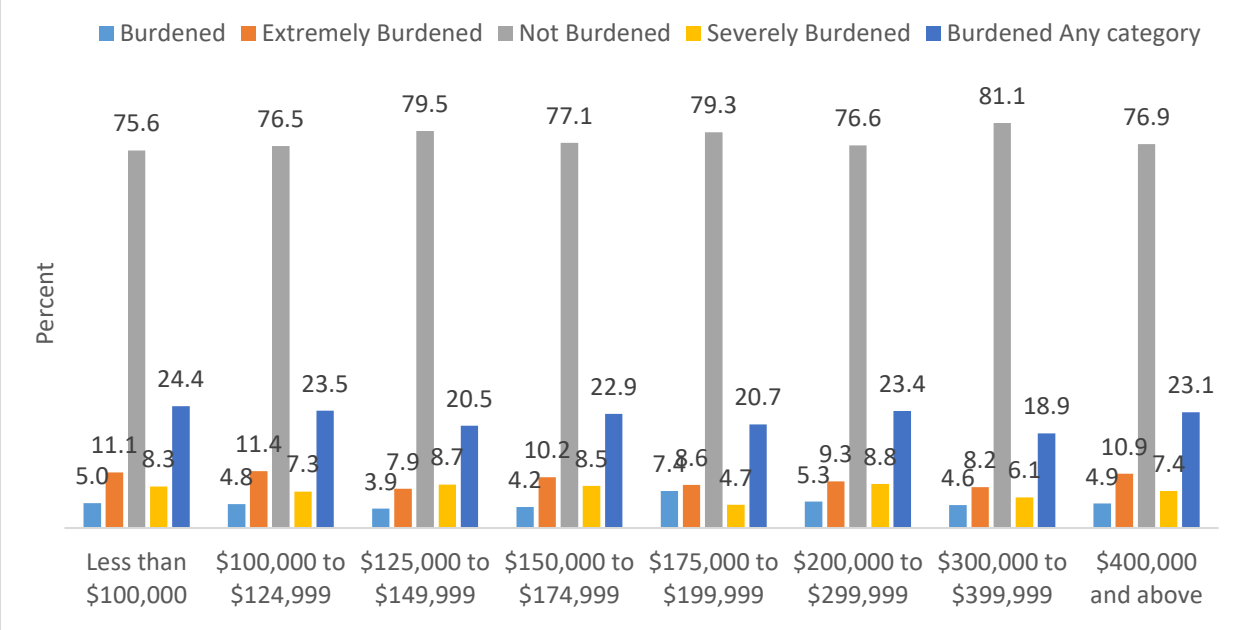


Figure 28: Owner Burden by Property Value

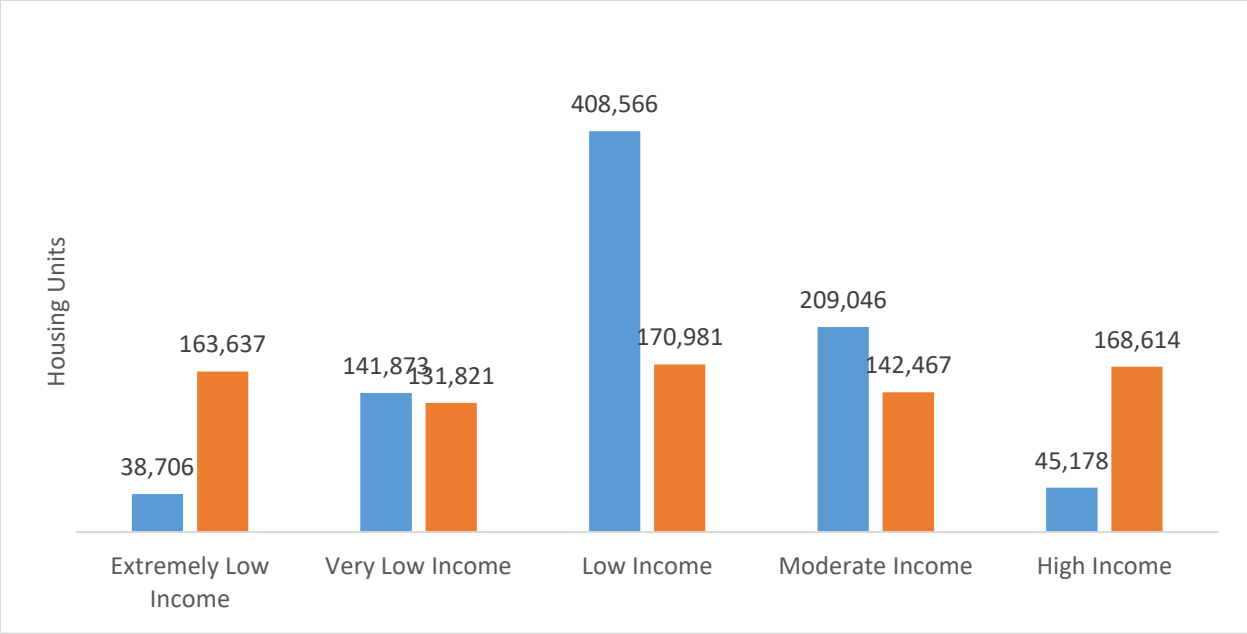


Figure 29: Affordable Rental Units vs. Renter Households by Income Category

For example, there are approximately 163,637 renter households in the extremely low income category, though only 38,706 units (33,151 occupied and 4,740 for rent) are affordable for households in this category. Overall, there are more renter households than units in their respective affordability range for extremely low income households, very low income households, and high income households. Alternatively, there are more affordable units than renter households in the low income and moderate income household categories.

Of course, there could be many reasons for these discrepancies. To be frugal, many households may prefer to live in housing units that fit into affordability categories below their own. It may not be attractive for developers to produce housing that is affordable for extremely low income households. To explore this discrepancy further, we looked at renter households by income category to see the affordability range of housing they were occupying (Table 12). This shows that the lack of affordable housing for extremely low and very low income renters is not due to moderate and high income households occupying these units in large numbers. Rather, there are not enough units for these low income households. As we can see from Figure 30, many extremely low income households occupy units that are unaffordable for them, with many occupying units that are in the affordability range for low or moderate income households. There is a similar pattern for very low income renter households (Figure 31). These patterns demonstrate the extent to which households in certain income groups are occupying units in their affordability range and the extent to which they overspend or underspend on their housing costs relative to norms (Figure 32, Figure 33, and Figure 34).

Table 12: Occupancy & Affordability of Rental Units by Income Group

Affordability, Vacancy	Extremely Low Income	Very Low Income	Low Income	Moderate Income	High Income	Vacant
Extremely Low Income, Occupied	24,970	3,888	2,049	1,716	528	0
Extremely Low Income, For Rent	0	0	0	0	0	4,740
Extremely Low Income, Rented (Not Occupied)	0	0	0	0	0	815
Very Low Income, Occupied	41,996	31,147	26,219	12,277	5,271	0
Very Low Income, For Rent	0	0	0	0	0	21,693
Very Low Income, Rented (Not Occupied)	0	0	0	0	0	3,270
Low Income, Occupied	70,424	75,140	105,118	81,039	55,239	0
Low Income, For Rent	0	0	0	0	0	18,689
Low Income, Rented (Not Occupied)	0	0	0	0	0	2,917
Moderate Income, Occupied	22,989	19,269	34,387	41,261	80,147	0
Moderate Income, For Rent	0	0	0	0	0	7,497
Moderate Income, Rented (Not Occupied)	0	0	0	0	0	3,496
High Income, Occupied	3,258	2,377	3,208	6,174	27,429	0
High Income, For Rent	0	0	0	0	0	1,195
High Income, Rented (Not Occupied)	0	0	0	0	0	1,537
Total	**163,637**	**131,821**	**170,981**	**142,467**	**168,614**	**65,849**

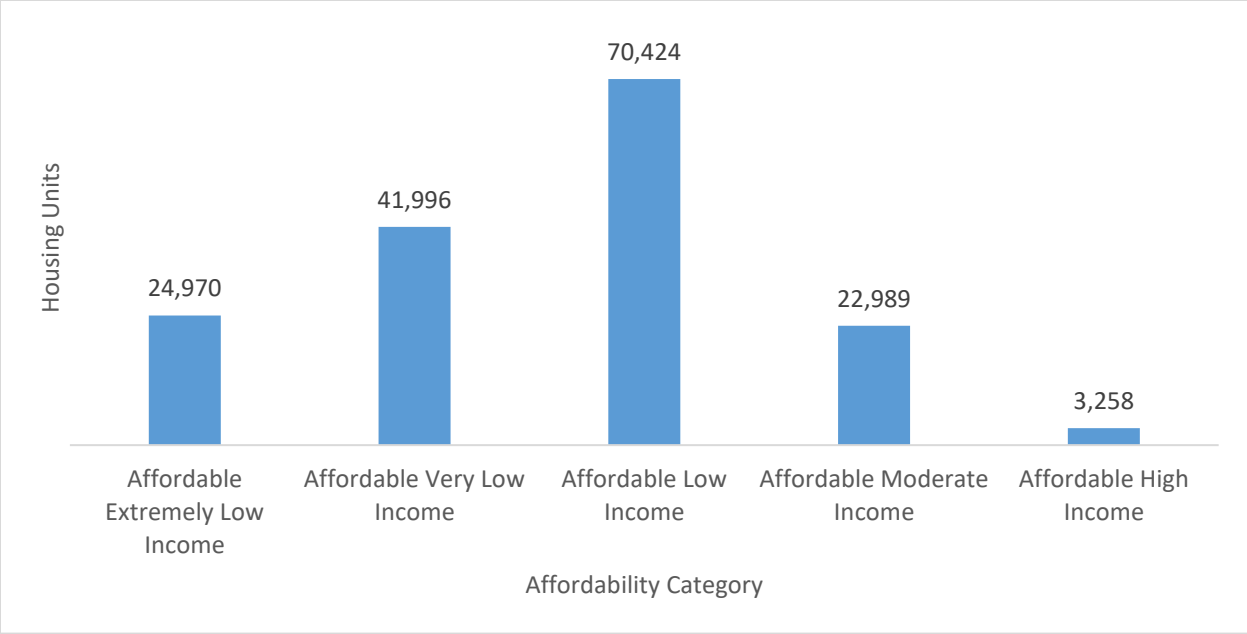


Figure 30: Units Occupied by Extremely Low Income Renters

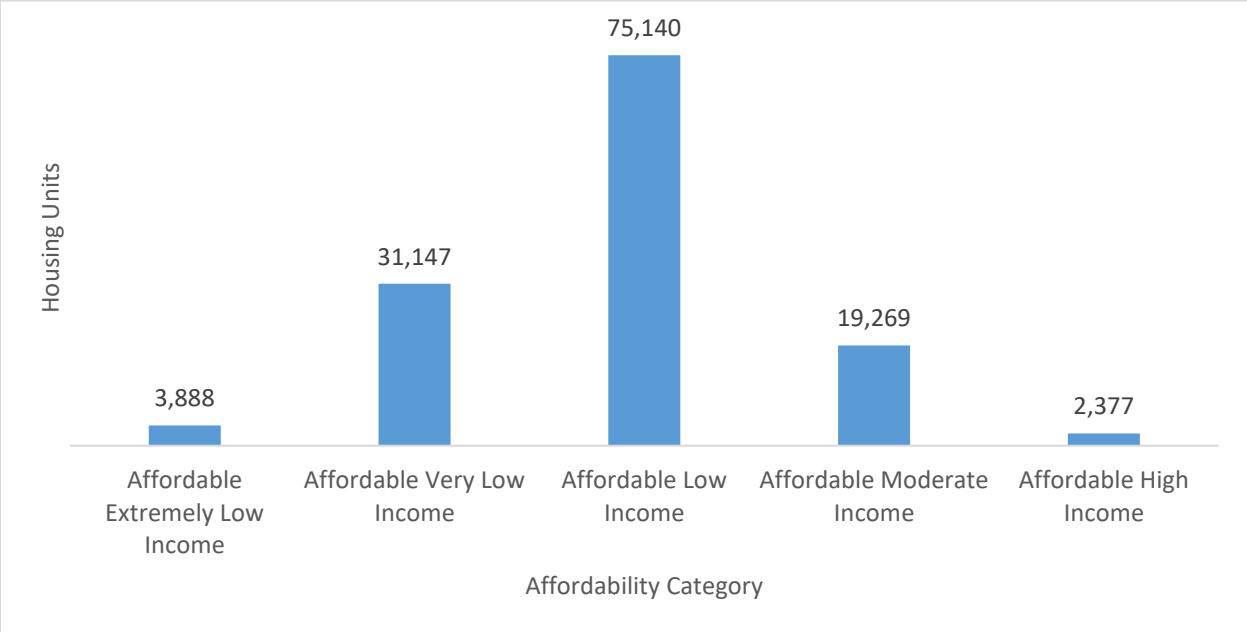


Figure 31: Units Occupied by Very Low Income Renters

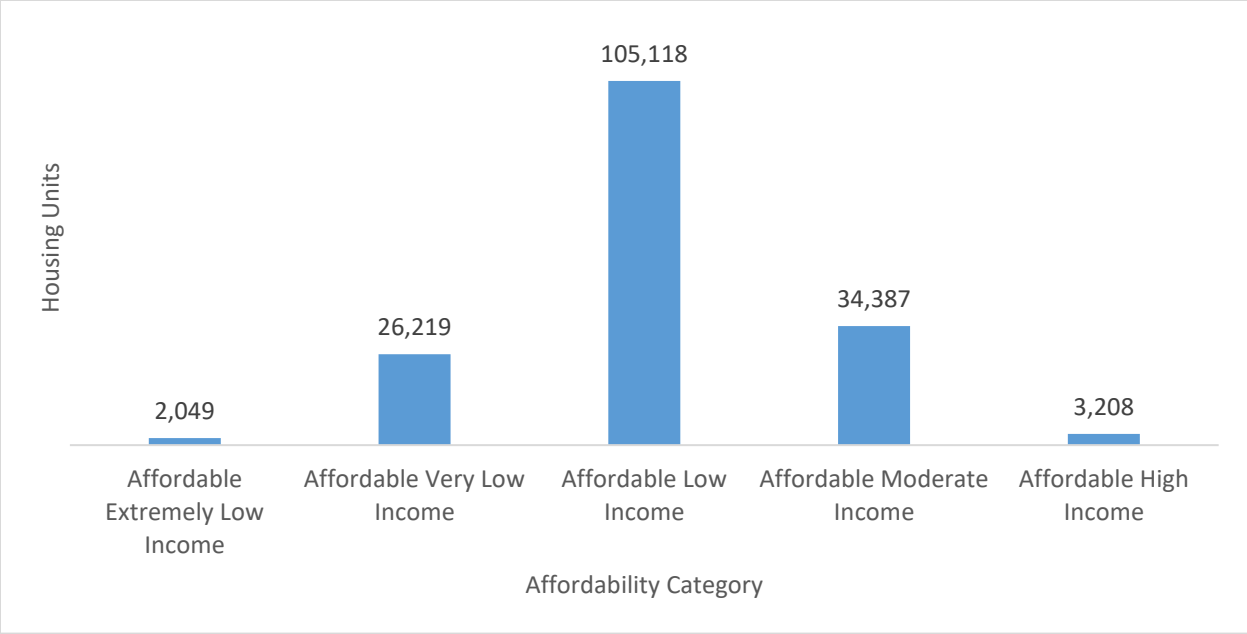


Figure 32: Units Occupied by Low Income Renters

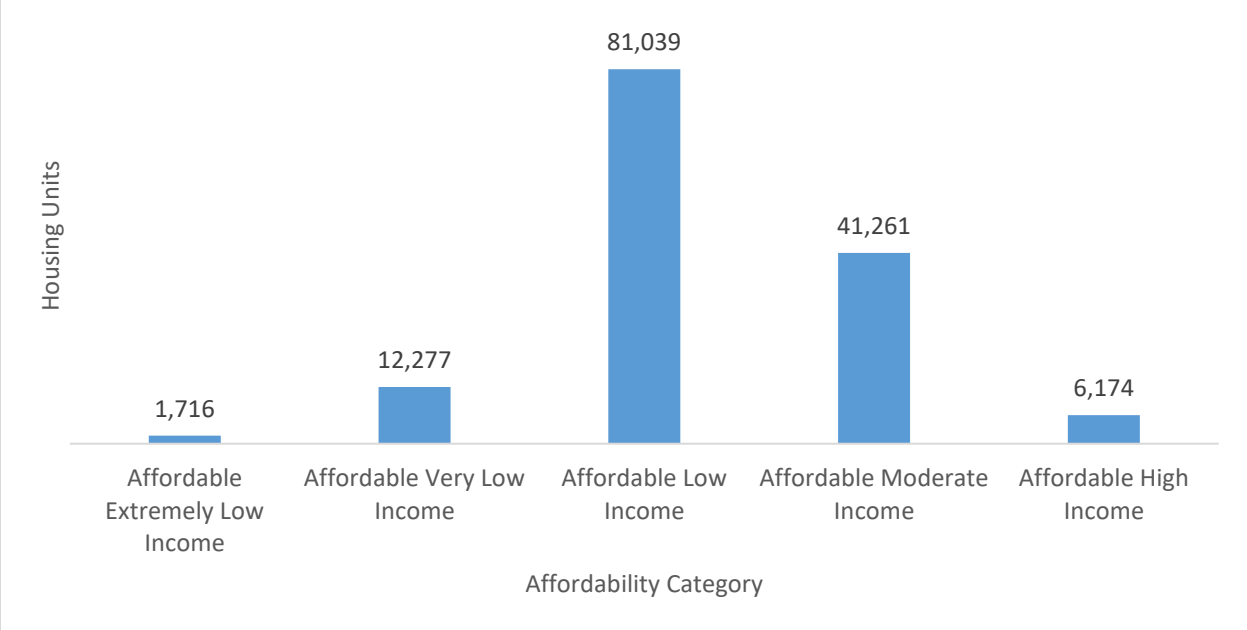


Figure 33: Units Occupied by Moderate Income Renters

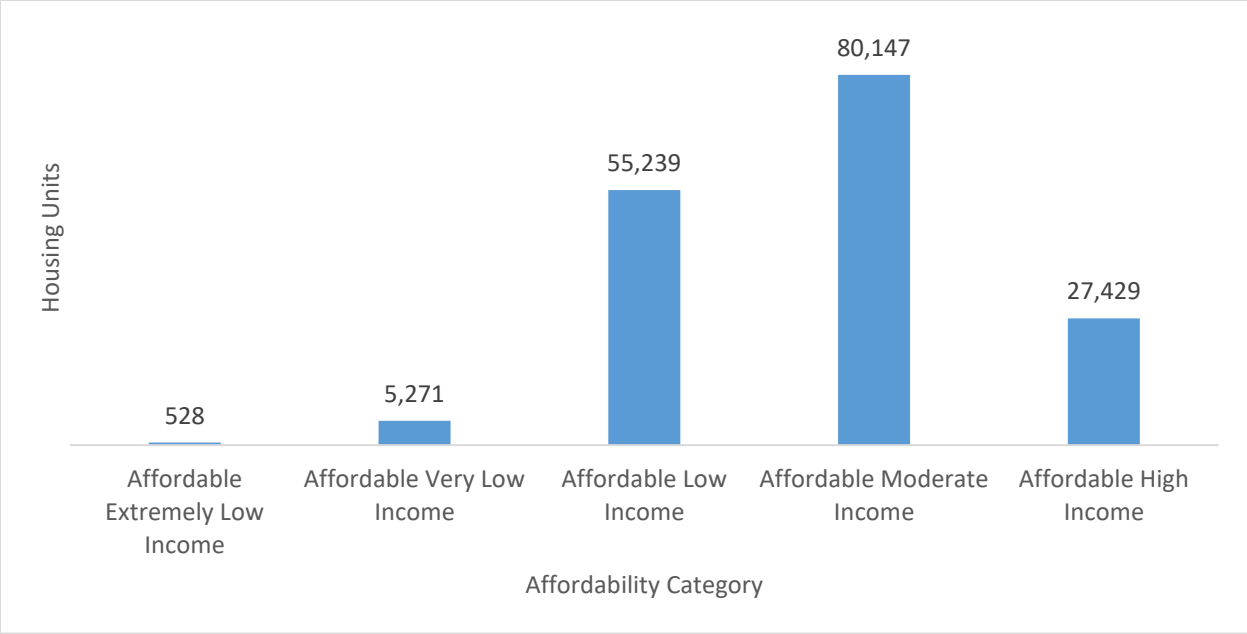


Figure 34: Units Occupied by High Income Renters

Affordability – Tract Level Price to Income Ratio

While most of this study investigated affordability issues for the metropolitan area as a whole, Figure 35 below highlights the median sales prices of homes in a census tract as a percentage of the median income in that census tract. This helps us to understand the regions of the metropolitan area where the relationship between prices and income is not affordable. As discussed previously, the areas where prices are more than 300 percent of income are generally considered to be unaffordable.

Limits of Study/Future Research

This study provided broad estimates regarding the affordability and suitability of housing in the metropolitan Atlanta area. Again, the estimates provided in this chapter have associated margins of error and do not correspond to the actual exact number of housing units. Please contact the author for these margins of error.

As highlighted in Table 11 previously, it is common practice in the affordability literature to use approximately 30 percent of income on housing costs as a measure of affordability. However, the standards for affordability may be changing and of course vary across metropolitan areas.

Additionally, improvements to this study could be made by matching actual sales data with household records to obtain more accurate estimates.

There are many potential approaches to looking into the affordability issue in greater detail given that the issues of housing affordability are so important for communities. For example, future research should include comparing affordability across different cities as we have started to highlight in Table 13. As one would expect, we see that Dallas and Nashville have similar levels of cost burden placed on households for their housing costs. Tampa, Miami and San Francisco households appear to experience slightly higher levels of housing cost burden. A more detailed comparison is necessary to fully understand the housing cost burden placed on households across metropolitan areas.

Conclusion

This study assessed households in Metropolitan Atlanta to determine the extent to which they are financially burdened by their housing costs. The analysis reveals that many local households are unable to afford the homes they occupy, and that renters face significant challenges in meeting their monthly housing costs.

As renters make up a large portion of burdened households in the country, further investigation was conducted to study the units that households occupy as well as the number of vacant units available for each income group.

This analysis discovered that a large percentage of renters in metropolitan Atlanta are burdened by housing costs. Thus, we conclude that Metropolitan Atlanta has an affordable housing challenge.

If Metropolitan Atlanta is to remain a place that is home to a wide range of household types, policies to encourage expansion of the supply of affordable housing may be needed. When many households are experiencing housing costs burden, spending half or more of their income on housing, even the most frugal of households will have difficulty becoming financially secure. Figure 35 highlights the spatial distribution of the affordability issue. Overall, it seems clear that Metropolitan Atlanta has an affordable housing problem.

Table 13: Comparing Households Across MSAs

City	Not Burdened	Burdened	Severely Burdened	Extremely Burdened
Atlanta - Own with Mortgage	73.1	6.2	9.3	11.4
Atlanta - Own without Mortgage	88.6	2	3.6	5.8
Atlanta - Rent	50.7	8	15.4	25.9
Nashville - Own with Mortgage	75.6	5.6	9.1	9.7
Nashville - Own without Mortgage	90.1	2	2.7	5.2
Nashville - Rent	52.9	7.6	15.5	24
Tampa - Own with Mortgage	69.2	7.7	11.1	12
Tampa - Own without Mortgage	85.1	2.8	4.1	8
Tampa - Rent	45.9	8.8	16.5	28.8
Miami - Own with Mortgage	58	8	13.9	20.1
Miami - Own without Mortgage	76.3	4.2	7.3	12.2
Miami - Rent	36.1	8.5	18.6	36.8
Dallas - Own with Mortgage	73.2	6.4	10.4	10
Dallas - Own without Mortgage	86.6	2.7	4.5	6.2
Dallas - Rent	52.8	8.7	15.2	23.3
San Francisco - Own with Mortgage	63.6	8.5	12.6	15.3
San Francisco - Own without Mortgage	85.8	3.1	3.6	7.5
San Francisco - Rent	52.3	8.2	14.8	24.7

Source: American Community Survey

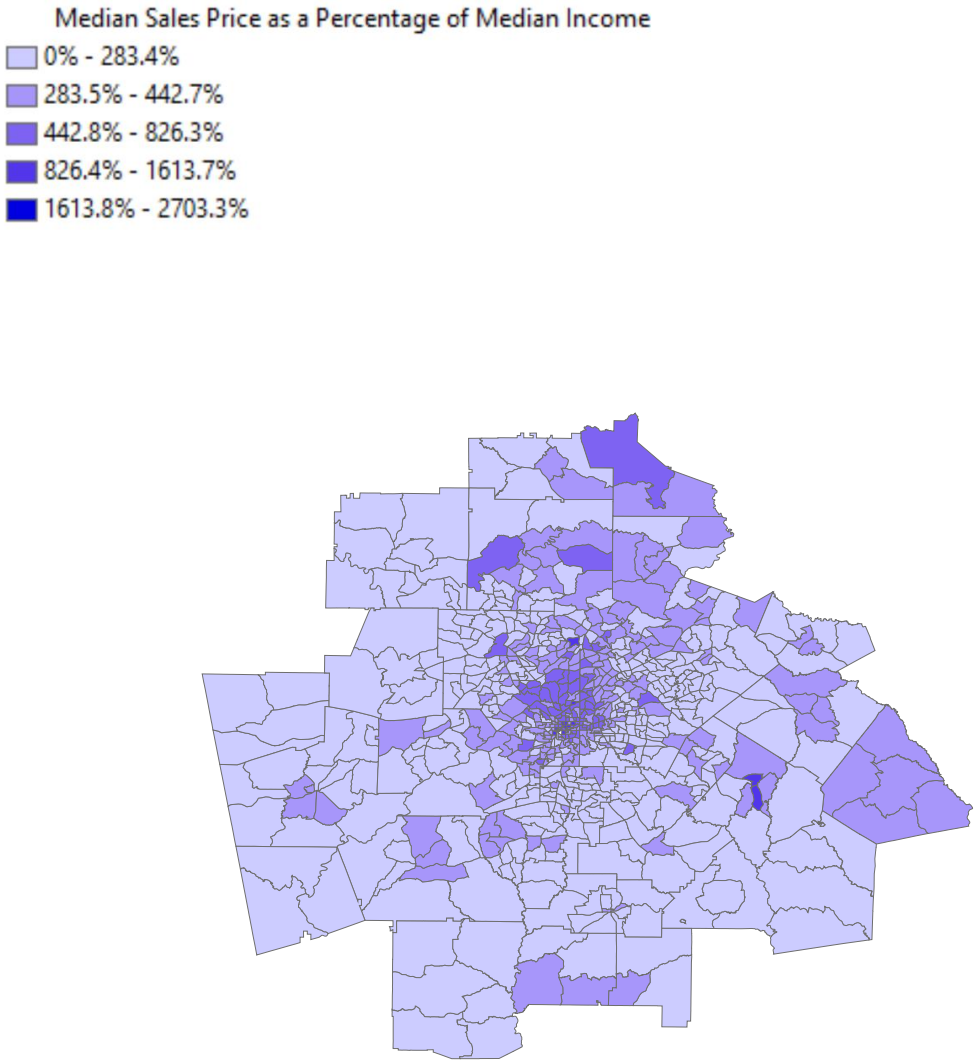


Figure 35: Median Sales Price as a Percentage of Median Income

Appendix B: Rental Units by Affordability Category

Rental Unit Type	Number of Units
Affordable - Extremely Low Income – Occupied	33,151
Affordable - Extremely Low Income - For Rent	4,740
Affordable – Extremely Low Income – Rented, Not Occupied	815
Affordable - Very Low Income – Occupied	116,910
Affordable - Very Low Income - For Rent	21,693
Affordable - Very Low Income - Rented, Not Occupied	3,270
Affordable - Low Income – Occupied	386,960
Affordable - Low Income - For Rent	18,689
Affordable - Low Income - Rented, Not Occupied	2,917
Affordable - Moderate Income – Occupied	198,053
Affordable - Moderate Income - For Rent	7,497
Affordable - Moderate Income - Rented, Not Occupied	3,496
Affordable - High Income – Occupied	42,446
Affordable - High Income - For Rent	1,195
Affordable - High Income - Rented, Not Occupied	1,537

Chapter 7: Understanding the Determinants of House Prices in Metropolitan Atlanta: 1995-2012

Abstract

The recent economic recession has had a significant impact on residential real estate in the United States. This research project focused on the Atlanta Metropolitan Statistical Area and sought to understand the impact that various attributes had on residential property values in the region.

Through a variety of model specifications, we seek the most appropriate modeling approach for house values in the region and attempt to use those model results as a way of understanding house prices. We also attempted (unsuccessfully) to use model results as a way to establish very detailed neighborhood level house price indices.

Each household that buys a home places a certain amount of significance on the many different aspects of a property that provides the house with its value. These characteristics include proximity to amenities, the number of bedrooms, and square footage. Results confirm previously discovered temporal trends for house prices in the region.

Introduction

The main purpose of this chapter was to explore hedonic model specifications for house prices in the Atlanta Metropolitan Statistical Area to understand the main determinants of sales prices. This is done for the years that we have available data, 1995-2012.

Our dataset consists of several million residential property sales in the metropolitan Atlanta area. However, due to computational constraints as well as significant issues with missing data, models for this chapter were only run on a relatively small sample of this data.

OLS and spatial regression models were applied, and we expected to discover that the year of the transaction and the square footage of the property to be the most significant determinants of sales prices.

A review of the existing literature on hedonic models identifies a core set of variables that are commonly related to prices. These are generally divided between property characteristics and location characteristics. Property characteristics may include the size of the structure, the number of bedrooms, the presence of a garage along with several other variables related to the property. Location variables can include demographics of neighborhoods in addition to proximity to transportation facilities, land use, and other variables concerning the urban environment.

A hedonic house price model and any indices that result from them are typically calculated using individual level record data on residential property sales prices that includes data on the characteristics of the house along with characteristics of its location/neighborhood.

Through the imputation of this information into a statistical model that controls for factors that might impact the sales price of a house, the hedonic model can tell us how much influence certain factors have on sales prices and can be converted into an index that can track neighborhood price changes over time.

Estimation of neighborhood house price indices has a lengthy literature and there are many different estimation approaches. The two most prevalent approaches found in the literature for estimating house prices include a repeat sales approach and the hedonic approach used here.

It is important to state that for modeling purposes, we are only interested in sale transactions with a corresponding price as there are often records referring to other types of transactions such as the property moving into a trust or being transferred to children.

While home prices and home attributes vary widely, there seems to be certain characteristics that consistently contribute to the value of residential properties. Through the hedonic modeling of house prices, we can better understand how houses are valued and analyzed by potential buyers through investigating the relationship between prices and structural/neighborhood attributes.

Background/Literature Review

The real estate literature is full of hedonic models, which is simply another term for a regression model that seeks to understand the valuation of attributes as well as the demand for certain characteristics. While it is most commonly seen in the real estate literature, hedonic models can be used to understand how the attributes or characteristics of any good are valued.

The assumption is that the house of interest can be viewed as a package. This package has many different characteristics that contribute to the value of a house. Some of these attributes may be related to higher housing prices while others may be related to lower housing prices. Most studies assume that a house price is a function of this combination of characteristics that includes both attributes about the structure of the house as well as neighborhood attributes.

The concept of identifying traits that contribute to the price of a particular good was initially developed by Court (1939) after developing indices for car prices. However, Lancaster (1966) and Rosen (1974) are the two that are often credited as the founders of product differentiation based on hedonic modeling and are often cited in the housing literature. In hedonic modeling, the price of a house is a function of various attributes which are typically categorized as structural, neighborhood and accessibility/location attributes (Anderson et al. 2010; Can 1990; Palmquist 1985; Follain and Jimenez 1985; Blomquist and Worley 1981; Witte et al. 1979; Harrison and Rubinfeld 1978; Nelson 1978). Though the inclusion of local submarkets is often important as well (Bajic 1985). Of course, this presents a significant problem because there may be an infinite number of things that have an impact on the value of a home. There is no way to include all the relevant variables in a hedonic housing model.

This creates caution in our interpretation regarding the impact of accessibility and other neighborhood attributes and while we would like to convey these impacts on property values, we can only assess this impact by holding the relevant variables constant in the model. Appropriate variable inclusion is determined by using the normal model selection criteria and methodology. In practice, researchers increasingly incorporate the use of non-linear model specifications in hedonic housing studies (Ding and Knaap 2003; Liao and Wang 2012).

Existing hedonic house price studies often provide sufficient insight into the theoretical background and methodology required for this research as well as yield results that can serve as useful guidelines for model specification.

This section discusses some of the prevailing methods being used in these types of studies as well as introduces some relevant results from previous research. Referenced studies provide valuable insight into the econometric methods used in property value research along with providing opportunities for improvement through the utilization of more detailed datasets.

Zheng and Yang (2007) used the housing transaction database from the Beijing Construction Committee along with a residence survey about commute time to show a negative commuting time house price gradient where the value of travel time was about half of the wage rate using classic hedonic modeling approaches. Hedonic models have also been used to demonstrate that increased proximity to bus transit lines can have a negative impact on property values (Cao and Hough 2008; Des Rosiers et al. 2010). These results demonstrate the difficulty in establishing policy and designing cities for residential property value stability because we often see discrepancies in results for valuations of neighborhood attributes.

Hess and Almeida (2007) incorporated hedonic models to investigate the effects of a light rail station on home values in Buffalo, New York. The results from this study showed an increasingly dynamic effect on house values where proximity effects are positive in high-income station areas and negative in low-income station areas, highlighting the need to allow for spatial heterogeneity in models of residential property values.

Often, the impacts of neighborhood attributes on property values vary across study areas as well as temporally. Anderson et al. (2010) found a very minor effect on house prices from a new high-speed railway line in Taiwan while Pan and Zhang (2008) found a significant premium resulting from proximity to a metro station in Shanghai.

Using spatial hedonic functions, Armstrong and Rodriguez (2006) found evidence of capitalization of accessibility to commuter rail stations in Eastern Massachusetts. While in this study, proximity to stations has a positive effect on property values; proximity to commuter rail right-of-way shows a significant negative effect on property values, suggesting that for every 1,000 feet from the commuter rail right-of-way, property values are between $732 and $2,897 higher.

One interesting trend in this research area is that proximity to a transport station often increases land values, but proximity to a rail line decreases land values (Armstrong and Rodriguez 2006; Mayor et al. 2008). This highlights the difference between the household valuations of accessibility as opposed to the common devaluation from households of proximity to infrastructure. Unfortunately, this effect could not be investigated in this research due to limits on data availability.

When investigating these results, we gain insight into how households value certain types of neighborhood attributes and structural amenities as seen through the hedonic function. This serves to inform us regarding how the urban structure may influence property values and guides us towards potential valuation instruments for local governments.

Vichiensan and Miyamoto (2010) incorporated hedonic models to show that urban railway in Bangkok contributes to land and property values. Wenjie et al. (2010) used similar methods to

demonstrate that accessibility indices are important determinants of residential property prices in Beijing. Debrezion et al. (2007) found that effects on land values from railway stations typically takes place at short distances. Also, commuter railway stations have a consistently higher positive impact on the property value compared to light and heavy railway/metro stations. The railway impact lessons when other accessibility variables such as roads and highways are included.

Conversely, Haider and Miller (2000) showed that accessibility factors were not strong determinants of housing values in Toronto. Mark (1983) investigated the stability of coefficients in house price equations over time while Rohe and Stewart (1996) presented an original analysis of the relationship between homeownership rates and property values using a two stage least squares approach. Vandell and Zerbst (1984) incorporated ridge regression techniques to estimate the effects of school desegregation on house values over time.

Spatial dependence is a phenomenon often anticipated in the modeling of spatial data and is particularly relevant to housing data. In this context, it is reasonable to assume that the value of one house depends not just on the attributes of that house, but also on the other houses near that house. The market value of a house is thus determined by its structural and neighborhood attributes along with nearby house's market values either in a defined neighborhood (neighborhood effects) or based on distance though often a combination of both (Shin et al. 1994). In recent years, the hedonic model has been transformed to incorporate spatial and temporal dependency along with spatial heterogeneity into model specifications.

Several studies have established that there is strong autocorrelation in housing models and it is therefore necessary to incorporate spatial effects (Jeanty et al. 2010). This is because it is inappropriate to use ordinary least squares estimation in hedonic studies as residential property values often experience spatial autocorrelation, causing estimates to be biased and inconsistent (Chalermpong and Wattana 2009).

Many of these spatial models can be understood under the name of spatial autoregressive models (SAR), where spatial effects are incorporated into the model in a variety of ways such as the spatial lag model, the spatial error model and spatial mixed model. It is also often seen where the independent variables possess a spatial lag if we cannot get the same information for a property (Osland 2010).

In the spatial error model, the serial correlation enters through the error term in that the spatial effect is present in the error term but not in the specified function of the model. While the spatial error model is perhaps more common in many applications, the spatial lag model dominates the hedonic housing literature (Shin et al. 1994). Variations of these models are often used when researching property values as these values typically possess both spatial and temporal clustering and dependence.

The existence of spatial dependency in residential property values leads us to use these models because the spatial dependence or autocorrelation violates the normal assumption of uncorrelated error terms. Spatial heterogeneity in the impact of neighborhood attributes on residential property values also leads to heteroskedastic error terms, making OLS estimates biased and inconsistent. This has now become the dominant approach in the literature for estimating residential property values and the effects of neighborhood amenities through hedonic modeling (Bourassa et al. 2007;

Wilhelmsson 2004; Case et al. 2004; Osland 2010). Property values are often used as an example of where spatial effects normally need to be taken into account because regression coefficients will be biased and inconsistent if spatial relationships are ignored.

Ryan (1999) proposed potential reasons as to why there is such a variety of outcomes in this literature, such as the delineation of the study area often significantly influencing the results. Debrezion et al. (2007) found that variations in results can generally be attributed to the nature of data, particularly spatial characteristics, temporal effects, and the methodology employed. Luckily, Sirmand et al. (2005) analyzed 125 different hedonic housing price models that have been published in recent years.

The premise of the study was to understand and to identify the most common housing characteristics that were used in hedonic pricing equations as well as whether or not those particular factors had positive or negative effects in the model. This serves as a useful guide when choosing what variables to include in our own housing price hedonic model. The results of their study are presented in Table 14.

Table 14: Common Variables used in Hedonic House Price Models

Variable	Appearances	# Times Positive	# Times Negative
Lot Size	52	45	0
Ln Lot Size	12	9	0
Square Feet	69	62	4
Ln Square Feet	12	12	0
Brick	13	9	0
Age	78	7	63
# of Stories	13	4	7
# of Bathrooms	40	34	1
# of Rooms	14	10	1
Bedrooms	40	21	9
Full Baths	37	31	1
Fireplace	57	43	3
Air-conditioning	37	34	1
Basement	21	15	1
Garage	61	48	0
Deck	12	10	0
Pool	31	27	0
Distance	15	5	5
Time on Market	18	1	8
Time Trend	13	2	3

Source: Sirman et al. (2005)

Methodology

The original objective of this chapter was to incorporate residential transaction data from CoreLogic Inc. to implement several model specifications and to use those results to establish yearly house price indices for the Atlanta MSA at the tract and/or block group level.

After several unsuccessful attempts at achieving this goal, the objective of this chapter has since changed. New objectives are achieved by first implementing an OLS model of house prices in the region followed ay any appropriate spatial regression models based on findings from the OLS model.

Therefore, this chapter provides an understanding of the determinants of house prices for the metropolitan area but leaves out the detailed local level analysis originally hoped for.

The steps necessary to carry out this project involve some geocoding of the property transactions followed by defining neighbors based on a k nearest neighbor structure. This information was then used to create several spatial weight matrices based on different numbers of 'k' nearest neighbors.

This allows us to decide what spatial weight specification is most appropriate. In general, it is common to explore the spatial autocorrelation structure using several different neighbor definitions in order to appropriately choose one for the final model specification used for interpretation. This is accomplished in conjunction with carrying out Moran's I tests on the (log)price of houses to clarify the presence of spatial autocorrelation using different neighbor definitions.

OLS regressions are then run on the data and the residuals are investigated for spatial dependence. Of course, a correlation matrix was also investigated to check for multicollinearity. These checks must be conducted as some of the basic assumptions of OLS include normal distribution, lack of strong correlation amongst the independent variables and that observations should be independent of each other.

This last assumption of OLS is one of the reasons spatial regression models are so prevalent, particularly in the housing literature. In the case of house prices, it is often thought that houses with similar values cluster together or in other words, observations that are closer to each other tend to have related values. If this phenomenon does exist as is often the case with housing data, this may violate the independent of observations assumptions and we may discover meaningful spatial dependencies. Given spatial dependencies that are unaccounted for, OLS estimates thus become biased and inconsistent.

Therefore, in these situations, a spatial lag model that assumes that there are spatial dependencies amongst house prices may be more appropriate. In deciding on the type of spatial regression model to incorporate, we have used the Lagrange Multiplier diagnostic test.

Data/Study Area

As real estate transaction data often comes with a significant problem of missing data, the Amelia package was utilized for multiple imputation of missing values before models were run.

However, given our sample size shown in Table 15, the amount of multiple imputation that was required was relatively minimal. A simple random sample of the data was taken. A correlation matrix for all variables can be found in Appendix D.

Figure 36 highlights the transactions used in these models with Figure 37 highlighting the neighborhood relationships.

Additional neighborhood attributes utilized in these models were obtained from the United States Census Bureau and the Atlanta Regional Commission.

Table 16 highlights the variables that were available for model specifications along with summary statistics for these variables. As we can see, the variables from CoreLogic Inc. are relatively minimal. This is due to data limitations.

Table 15: Sample Size Used in Hedonic Model

Year of Transaction	Sample Size
1995	289
1996	346
1997	413
1998	550
1999	598
2000	659
2001	719
2002	794
2003	925
2004	1,099
2005	1,372
2006	1,552
2007	1,286
2008	991
2009	800
2010	777
2011	799
2012	1,011
Total Sample Size used in Models	14,980

Source: CoreLogic, Inc.



Figure 36: Visualizing Transactions Used in Models



Figure 37: KNN1

Table 16: Description of Variables

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Sales Price (log)	14980	11.833	0.769	6.782	15.865
Age of Structure	14980	24.2	19.27	1	179
Finished Square Footage	14980	2229.87	1092.74	9.08	11606
Bedrooms	14980	3.32	0.93	0.21	40
Full Bathrooms	14980	2.21	0.79	0.12	8
Rooms	14980	6.86	1.88	0.42	44.42
1995	14980	0.019			
1996	14980	0.023			
1997	14980	0.0275			
1998	14980	0.0367			
1999	14980	0.039			
2001	14980	0.0479			
2002	14980	0.053			
2003	14980	0.0617			
2004	14980	0.0734			
2005	14980	0.0915			
2006	14980	0.1036			
2007	14980	0.0858			
2008	14980	0.06615			
2009	14980	0.0534			
2010	14980	0.05186			
2011	14980	0.05333			
2012	14980	0.067489			
Garage	14980	0.23			
Year Structure Built	14980	1988.798	19.26976	1834	2012
Pool	14980	0.0307			
Fireplace	14980	0.7246			
Percent of Neighborhood Residential	221	40.571	21.555	6.00E-06	87.463
Percent of Neighborhood that is Owned	221	72.71	17.037	2.055	94.961
Bus Stops in Neighborhood	221	54.2	110.4122	0	676
Median Year Built for Neighborhood	221	1989.288	19.07549	1948	2005
Poverty Rate of Neighborhood	221	7.532	5.6541	0.4393	38.09524

Table 16 Continued

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Median Income of Neighborhood	221	56446.54	15984.81	13084	114674
ITP (Within Atlanta's Main Perimeter Road)	14980	0.1218291	0.3270992	0	1
Percent of Neighborhood with College Degree	221	30.26458	16.50458	0	78.2
Mean Elevation of Neighborhood (meters)	221	290.4808	36.63564	165.0984	474.1594
Distance to CBD (feet)	221	1.719E+10	15517452685	3169520	1.29E+11
Distance to Nearest Public Transportation Facility (feet)	14980	20335.75	24865.55	6.369919	204369.4
Distance to Nearest Highway (feet)	14980	19757.82	9.037438	18147.04	139628.8
Vacancy Rate of Neighborhood	14980	9.737	4.247149	4.459921	50

Source: CoreLogic Inc., United States Census Bureau, Atlanta Regional Commission

Results

Table 17 highlights the results from the full OLS model where the dependent variable is (log)price. As we can see, the F statistic is quite high, indicating that the independent variables jointly impact (log)price. In other words, we see that this model is preferable to no model at all. The R squared value of 0.56 indicates that approximately 56 percent of the variation in house prices can be explained by our independent variables.

Once again, it is important to remember that in the presence of spatial autocorrelation, the estimated regression coefficients here are biased and inconsistent.

From looking at the results, there appears to be a clear time impact here. Since the dependent variable is the log of sales price, we can interpret the coefficients in terms of percentages. Thus, for each additional full bathroom, we expect the sales price to increase by approximately 11 percent holding all other factors constant.

Perhaps the most interesting results are the year dummy variables included in the model (2000 is the reference year). We see that compared to 2000, the impact of the transaction occurring in 2007 is positive. Yet, beginning in 2008, the impact of a transaction occurring in that year has a negative impact on price.

It is also striking to see the magnitude of this impact. For example, a transaction occurring in 2011 is expected to have a price 39 percent lower compared to a transaction occurring in 2000. As stated previously, prices were of course put in constant dollars using the Consumer Price Index. Roughly speaking, the results of this model appear to correspond to the housing bubble and housing burst in the United States and the Atlanta MSA.

In Appendix A, you will find the correlation matrix for these variables. There is clearly a multicollinearity issue between square feet and bedrooms which is why we have removed it for our final OLS model found in Table 18.

In addition, we also incorporate stepwise techniques and AIC comparison to develop a more suitable model specification to use and interpret given our available variables. This helps us to identify the variables with the greatest explanatory power. The results of this OLS model can be found in Table 18.

Overall, we see that approximately 56 percent of the variation in house prices can be explained by variation in our independent variables. To further discuss the interpretation of the model, we see that a property being located ITP (inside I-285, the main ring road/perimeter in the area) corresponds to a significantly higher price than not being ITP as expected. In addition, for each additional percent of the vacancy rate in the neighborhood going up, we expect the sales price to decrease by approximately 2 percent.

Now that we have a more appropriate model free of multicollinearity, we can improve on our interpretations. We still find that the year dummies turn negative beginning with 2008. A transaction occurring in 2011 is expected to have a price that is 37 percent lower compared to a transaction occurring in 2000.

Table 17: Full OLS Model

	Estimate	Standard Er.	Statistic	P value
(Intercept)	11.724283	0.5128921	22.85916	1.05E-113
Age of Structure	-0.002493	0.0002693	-9.25705	2.38E-20
Finished Square Feet	0.0002562	6.32E-06	40.54883	0
Bedrooms	-0.000795	0.007301	-0.10885	0.913322
Full Bathrooms	0.1114032	0.0081523	13.66531	2.94E-42
Rooms	0.0368037	0.0036285	10.14308	4.26E-24
1995	-0.224002	0.0365595	-6.12704	9.18E-10
1996	-0.16229	0.0343692	-4.72198	2.36E-06
1997	-0.197836	0.0324962	-6.08798	1.17E-09
1998	-0.171867	0.0299053	-5.74704	9.26E-09
1999	0.0243251	0.0292336	0.832093	0.40537
2001	0.1065749	0.0278978	3.820189	0.000134
2002	0.1206727	0.0272733	4.424572	9.73E-06
2003	0.1238195	0.0263778	4.694079	2.70E-06
2004	0.1611155	0.0254974	6.318889	2.71E-10
2005	0.2082935	0.0245372	8.488879	2.28E-17
2006	0.2132256	0.0240772	8.855921	9.22E-19
2007	0.1774414	0.024831	7.145961	9.35E-13
2008	-0.031965	0.0260613	-1.22653	0.220018
2009	-0.236334	0.0272414	-8.67555	4.53E-18
2010	-0.270565	0.0274482	-9.85731	7.48E-23
2011	-0.369607	0.0272942	-13.5416	1.56E-41
2012	-0.349364	0.0259626	-13.4564	4.89E-41
Garage	-0.001179	0.0116739	-0.10102	0.919539
Pool	0.033274	0.025057	1.327931	0.184221
Fireplace	0.1315879	0.0102709	12.81172	2.22E-37
Percent of Neighborhood that is Residential	-0.003368	0.0003532	-9.5339	1.74E-21
Percent of Neighborhood that is Owned	-0.004302	0.0005849	-7.35546	2.00E-13
Bus Stops in Neighborhood	-0.000203	6.09E-05	-3.32796	0.000877
Median Year Built of Neighborhood	-0.000557	0.0002531	-2.20189	0.027688
Poverty Rate of Neighborhood	-0.003877	0.001629	-2.38011	0.01732
Median Income of Neighborhood	1.42E-06	8.25E-07	1.724893	0.084568

Table 17 Continued

	Estimate	Standard Er.	Statistic	P value
ITP	0.4115467	0.0200401	20.53621	1.92E-92
Percent of Neighborhood with College Degree	0.0100453	0.000689	14.57968	8.06E-48
Mean Elevation of Neighborhood	0.0013469	0.0001398	9.632547	6.75E-22
Distance to CBD	-1.54E-12	6.68E-13	-2.30228	0.021333
Distance to Nearest Public Transportation Facility	-1.10E-06	3.76E-07	-2.92422	0.003458
Distance to Nearest Highway	6.17E-07	3.18E-07	1.941213	0.052251
Number of Establishments in Neighborhood	-3.61E-06	1.04E-05	-0.34854	0.727437
Vacancy Rate of Neighborhood	-0.018252	0.0019053	-9.57985	1.12E-21
R-squared	0.56			
F Statistic	468.1****			

Note: Standard Errors are Robust SE

Table 18: OLS Model Specification based on AIC Criteria

	Estimate	Standard Er.	Statistic	P value
(Intercept)	11.71032	0.5117947	22.88089	6.47E-114
Age of Structure	-0.00246	0.0002672	-9.20515	3.86E-20
Finished Square Feet	0.0002572	6.19E-06	41.55969	0.00000
Full Bathrooms	0.1113248	0.0079498	14.0034	2.83E-44
Rooms	0.0364306	0.0031061	11.7287	1.25E-31
1995	-0.223088	0.0365461	-6.1043	1.06E-09
1996	-0.162124	0.0343609	-4.71829	2.40E-06
1997	-0.197189	0.032488	-6.0696	1.31E-09
1998	-0.171281	0.0298921	-5.72997	1.02E-08
1999	0.0248768	0.029227	0.851156	0.394696
2001	0.1067796	0.0278924	3.828266	0.00013
2002	0.1207658	0.0272708	4.428384	9.56E-06
2003	0.1238272	0.0263754	4.694804	2.69E-06
2004	0.1611185	0.0254928	6.320167	2.69E-10
2005	0.2085179	0.0245314	8.50005	2.07E-17
2006	0.2130496	0.0240742	8.849706	9.75E-19
2007	0.1774297	0.0248264	7.146823	9.29E-13
2008	-0.031993	0.0260503	-1.22812	0.21942
2009	-0.23653	0.0272348	-8.68484	4.18E-18
2010	-0.270494	0.0274419	-9.85698	7.51E-23
2011	-0.369464	0.0272881	-13.5394	1.61E-41
2012	-0.349456	0.0259586	-13.4621	4.54E-41
Fireplace	0.1317597	0.0101522	12.97848	2.61E-38
Percent of Neighborhood that is Residential	-0.003363	0.0003523	-9.54773	1.53E-21
Percent of Neighborhood that is Owned	-0.004229	0.0005538	-7.63599	2.38E-14
Bus Stops in Neighborhood	-0.000207	6.03E-05	-3.43203	0.000601
Median Year Built of Neighborhood	-0.000553	0.0002528	-2.18583	0.028843
Poverty Rate of Neighborhood	-0.003922	0.0016282	-2.40905	0.016006

Table 18 Continued

Median Income of Neighborhood	1.38E-06	8.19E-07	1.678752	0.093221
ITP	0.413032	0.019252	21.45398	1.37E-100
Percent of Neighborhood with College Degree	0.0100002	0.0006675	14.98272	2.21E-50
Mean Elevation of Neighborhood	0.0013338	0.0001374	9.707094	3.27E-22
Distance to CBD	-1.57E-12	6.59E-13	-2.37997	0.017326
Distance to Nearest Public Transportation Facility	-1.08E-06	3.70E-07	-2.90644	0.003661
Distance to Nearest Highway	6.16E-07	3.13E-07	1.964569	0.049483
Vacancy Rate of Neighborhood	-0.018055	0.0018489	-9.76568	1.84E-22
R Squared	0.56			
F Statistic	521.6***			

Note: Standard Errors are Robust SE

In addition, an increase in ten years of a structure's age is associated with a 2.5 percent increase in the house price. Unsurprisingly, we see that square feet, bathrooms, and rooms have significant positive impacts on house prices. Distance to the CBD has a significant negative impact on residential property prices.

The Moran's I results in Table 19, Table 20, Table 21, and Table 22 highlight that there is statistically significant spatial autocorrelation of house prices using several different spatial weight specifications. In other words, with each neighbor definition, we find that there is significant positive autocorrelation of house prices in our study area. To speak plainly, similar values of house prices tend to cluster together.

The interpretation of these results is that we reject the null hypothesis of a random spatial pattern for house prices and thus proceed under the assumption of spatial autocorrelation.

Moran's I statistics can be slightly difficult to compare in terms of strength. For example, a Moran's I statistic of 0.48 found in Table 19 does not necessarily signify that the strength of the spatial autocorrelation is larger than the other variables. In other words, the inference of the Moran's I value is dependent on the spatial weights incorporated and cannot necessarily be compared with other values.

Comparison across different weights can be difficult. Z values are more appropriate for the comparison of appropriate model weights. In this case, we see that perhaps a spatial weights matrix that include more neighbors may be more appropriate according to the Z values. We investigate model results incorporating multiple spatial weights matrices later in the chapter.

Table 19: Moran's I Statistic for Log(Price) k=1 Nearest Neighbor

Moran I Statistic	Expectation	Variance	P-Value	Z Score
4.764334e-01	-6.676013e-05	1.080130e-04	<.0001	45.5511

Table 20: Moran's I Statistic for Log(Price) k=2 Nearest Neighbor

Moran I Statistic	Expectation	Variance	P-Value	Z Score
4.436687e-01	-6.676013e-05	5.606259e-05	<.0001	60.2704

Table 21: Moran's I Statistic for Log(Price) k=4 Nearest Neighbor

Moran I Statistic	Expectation	Variance	P-Value	Z Score
4.126274e-01	-6.676013e-05	2.900135e-05	<.0001	76.5932

Table 22: Moran's I Statistics for Log(Price) k=10 Nearest Neighbor

Moran I Statistic	Expectation	Variance	P-Value	Z Score
3.637141e-01	-6.676013e-05	1.194464e-05	<.0001	107.1870

Table 23 highlights the Global Moran's I for residuals value from our OLS model, indicating that there is spatial autocorrelation in the residuals.

To determine the nature of the dependence, we use a Lagrange Multiplier Diagnostic for Spatial Dependence. The results of which are shown in Table 24 for knn=1. For the purpose of this research, we run both spatial lag and spatial error models and assess the results from there to determine appropriateness.

However, it appears from the Lagrange Multiplier Diagnostic for Spatial Dependence that a lag model is most appropriate. Results from a studentized Breusch-Pagan test (BP=882.36, p<.00001) also indicates that the errors are heteroskedastic as shown in Table 25.

In the Appendix, we find the results from the spatial lag (Table 26) and spatial error (Table 28) models. Through comparison models, it appears as though the spatial lag model with knn=1 may be the most appropriate model for our data.

The AIC is also lower than the linear model, indicating a better model fit. The LM test for residual autocorrelation indicates that there is no more spatial autocorrelation in the data. Table 27 and Table 29 highlight heteroskedasticity from the Breusch-Pagan test.

We can also use the log-likelihood for a comparison between the spatial lag and spatial error models. We see that the spatial error model's value (-11178.37) is worse than the spatial lag model's value (-11130.74).

As we can see from the results of this model, the general results remain similar to OLS. For example, a transaction occurring in 2011 is expected to have a price that is approximately 37 percent lower compared to a transaction occurring in 2000.

Table 23: Global Moran's I for Residuals

Observed Moran's I	Expectation	Variance	P value
0.189023	-0.000993	0.0001081	<.001

Table 24: Lagrange Multiplier for Spatial Dependence

Model	LM	df	p value
Lmerr	330.68	1	2.20E-16
Lmlag	423.34	1	2.20E-16
RLMerr	1.3627	1	0.2431
RLMlag	94.053	1	2.20E-16
SARMA	424.74	2	2.20E-16

Table 25: Studentized Breusch-Pagan Test

BP	df	p value
882.36	35	2.20E-16

Limits to Study/Future Research

One of the main drawbacks to this study is the exclusion of some variables in our model that have been shown in past research to have a strong relationship to house prices and an essential component to a hedonic house price model. The two most important variables that were not included in this study are crime rates and school quality for the neighborhoods that these houses are located in.

In the United States, local public schools can vary widely in terms of quality. In addition, school districts are often relatively homogenous in terms of class structure. When households purchase a home, the attributes of the local schools often greatly impact their decisions. For example, households may be willing to spend more money on a house in a good school district rather than less money on a house in a worse school district and instead utilize private schools. The literature often confirms this impact where it has been shown that many households place a great importance on school quality when purchasing a home (Holme 2002; Gibbons and Machin 2008; Gibbons et al. 2013), where test scores are often used as a proxy for school quality.

The reason that these variables were not included in this study was largely due to the inability to gain access to suitable data sources. However, in future research, the School Proficiency Index from the United States Department of Housing and Urban Development may be a potential path for including school quality measures in future research.

This dataset may potentially help us to understand neighborhood level school quality as it measures performance across elementary schools and seems to be available at the block group level.

Neighborhood level crime measures are a little more difficult to include in future research. This is largely due to how they are collected at the local government level. As stated previously, the fact that our metropolitan area of interest includes 29 counties can lead to some difficulties in terms of data collection. This is not to say that there is not detailed level, neighborhood crime index data out

there because obviously others have used it. However, for this study, neighborhood level crime index data that covered the entire metropolitan area could not be found.

Conclusion

This paper established several model specifications for house prices in the Atlanta MSA. Through the incorporation of several model specifications, we were able to better understand the determinants of house prices in the region as well as account for spatial autocorrelation that is common in house price research. We identified a strong temporal trend in our regression model that corresponds to what we know about the housing boom and bust period in the region.

We also identified attributes of structures/neighborhoods that contribute both positively and negatively towards house prices. Future work/limitations to this study involve a need to look at the relationship between attributes and house prices in different time periods. This involves interacting attributes with time periods corresponding to before and after the housing peak.

Appendix C: Spatial Regression Model Results

Table 26: Spatial Lag Model

term	Estimate - knn=1	std.error – knn=1	Statistic – knn=1	p.value – knn=1	Estimate – knn=10	Std.error-knn=10	Statistic – knn=10	p.value-knn=10
(Intercept)	10.2	0.505	20.2953	<2.2e-16	8.1765	0.51034	16.0217	<2.2e-16
Age of Structure	-0.00243	0.000262	-9.2772	<2.2e-17	-0.0025415	0.0002592	-9.8045	<2.2e-16
Finished Square Feet	0.000239	0.0000061	39.1013	<2.2e-18	0.0002264	6.09E-06	37.1799	<2.2e-16
Full Bathrooms	0.106	0.00779	13.5905	<2.2e-19	0.10418	0.0077103	13.5117	<2.2e-16
Rooms	0.0334	0.00305	10.9582	<2.2e-20	0.033213	0.0030199	10.9982	<2.2e-16
1995	-0.218	0.0358	-6.0816	1.19E-09	-0.21122	0.035435	-5.9608	2.51E-09
1996	-0.163	0.0337	-4.8485	0.00000124	-0.15404	0.033316	-4.6236	0.000003772
1997	-0.189	0.0318	-5.9339	2.96E-09	-0.18424	0.0315	-5.8489	4.95E-09
1998	-0.172	0.0293	-5.8733	4.27E-09	-0.16709	0.028983	-5.7652	8.16E-09
1999	0.0294	0.0286	1.0275	0.304188	0.027747	0.028338	0.9792	0.327504
2001	0.107	0.0273	3.9246	0.0000869	0.1084	0.027044	4.0083	0.00006116
2002	0.127	0.0267	4.7493	0.00000204	0.12659	0.026441	4.7875	0.000001689
2003	0.126	0.0258	4.8853	0.00000103	0.12935	0.025573	5.0582	4.23E-07
2004	0.161	0.025	6.4324	1.26E-10	0.16128	0.024717	6.5249	6.80E-11
2005	0.207	0.024	8.617	<2.2e-16	0.21199	0.023785	8.9131	<2.2e-16
2006	0.211	0.0236	8.9594	<2.2e-17	0.21489	0.023341	9.2063	<2.2e-16
2007	0.176	0.0243	7.2382	4.55E-13	0.17936	0.024071	7.4514	<2.2e-16
2008	-0.0267	0.0255	-1.0455	0.295787	-0.027931	0.025258	-1.1058	<2.2e-16
2009	-0.239	0.0267	-8.9759	<2.2e-16	-2.3041	0.026408	-8.725	<2.2e-16
2010	-0.269	0.0269	-10.0101	<2.2e-17	-0.26883	0.026609	-10.1031	<2.2e-16
2011	-0.373	0.0267	-13.9431	<2.2e-18	-0.37245	0.026458	-14.0773	<2.2e-16
2012	-0.351	0.0254	-13.8084	<2.2e-19	-0.35854	0.025169	-14.2455	<2.2e-16
Fireplace	0.119	0.00996	11.9089	<2.2e-20	0.11501	0.0098708	11.6515	<2.2e-16
Percent of Neighborhood Residential	-0.00287	0.000346	-8.301	<2.2e-21	-0.0019093	0.0003447	-5.5385	3.05E-08
Percent of Neighborhood that is Owned	-0.00369	0.000542	-6.7964	1.07E-11	-0.002733	0.0005397	-5.0635	4.12E-07

Table 26 Continued

term	Estimate - knn=1	std.error – knn=1	Statistic – knn=1	p.value – knn=1	Estimate – knn=10	Std.error-knn=10	Statistic – knn=10	p.value-knn=10
Bus Stops in Neighborhood	-0.000194	0.0000591	-3.2788	0.001042	-0.0001660 3	0.0000584 92	-2.8385	0.004532
Median Year Built of Neighborhood	-0.000465	0.000248	-1.8763	0.060614	-0.0005323 5	0.0002451 1	-2.1719	0.029865
Poverty Rate of Neighborhood	-0.00287	0.0016	-1.8014	0.071641	-0.0021578	0.0015796	-1.366	0.17192
Median Income of Neighborhood	0.0000007 44	0.0000008 03	0.9263	0.354269	-7.54E-07	7.98E-07	-0.9451	0.344588
ITP	0.369	0.019	19.477	<2.2e-16	0.30184	0.019009	15.8787	<2.2e-16
Percent of Neighborhood with College Degree	0.00914	0.000655	13.9495	<2.2e-17	0.0074044	0.0006527 2	11.344	<2.2e-16
Mean Elevation of Neighborhood	0.00109	0.000135	8.0965	6.66E-16	0.0007436 6	0.0001347 1	5.5206	3.38E-08
Distance to CBD	-1.40E-12	6.45E-13	-2.1718	0.029869	-1.42E-12	6.39E-13	-2.231	0.02568
Distance to Nearest Public Transportation Facility	-0.0000008 85	0.0000003 63	-2.4407	0.014659	-4.18E-07	3.60E-07	-1.1625	0.245045
Distance to Nearest Highway	0.0000004 54	0.0000003 07	1.4794	0.139035	1.45E-07	3.04E-07	0.4754	0.634505
Vacancy Rate of Neighborhood	-0.0152	0.00182	-8.3767	<2.2e-16	-0.0092179	0.0018151	-5.0783	<3.808e-07
Diagnostic Test	**Value**		**P value**		**Value**		**P value**	
Rho	0.11922				0.31441			
LR test value	454.29		<2.22e-16		752.97		<.001	

Table 26 Continued

Diagnostic Test	Value	P value	Value	P value
Asymptotic standard error	0.0054105		0.010985	
z value	22.035	<2.22e-16	28.622	<.001
Wald statistic	485.53	<2.22e-16	819.21	<.001
Log likelihood	-11130.74		-10981.4	
Observations	14980		14980	
Number of parameters estimated	38		38	
AIC	22337		220396	
AIC for OLS	22790		22790	
LM test for residual autocorrelation	0.41277	0.52057	59.232	<.001

Table 27: Studentized Breusch-Pagan Test

Studentized Breusch-Pagan test	Knn=1	Knn=10
BP	859.54	836.79
df	35	35
p value	2.20E-16	2.20E-16

Table 28: Spatial Error Model

term	Estimate – knn=1	std.error – knn=1	Statistic-knn=1	p.value-knn=1	Estimate – knn=10	std.error – knn=10	Statistic-knn=10	p.value-knn=10
(Intercept)	11.5	0.511	22.6084	<2.2e-16	11.586	0.51466	22.5125	<2.2e-16
Age of Structure	-0.00264	0.000274	-9.6361	<2.2e-17	-0.0029314	0.0002765 4	-10.6004	<2.2e-16
Finished Square Feet	0.000247	0.0000062 1	39.734	<2.2e-18	0.0002385 5	6.1932E-06	38.5185	<2.2e-16
Full Bathrooms	0.109	0.00789	13.764	<2.2e-19	0.10275	0.0077644	13.2329	<2.2e-16
Rooms	0.0365	0.0031	11.7782	<2.2e-20	0.040682	0.0031016	13.1162	<2.2e-16
1995	-0.21	0.0358	-5.867	4.44E-09	-0.21167	0.035213	-6.0112	1.841E-09
1996	-0.167	0.0336	4.9644	0.000000689	-0.16103	0.033019	-4.8768	0.000001078
1997	-0.197	0.0317	-6.2127	5.21E-10	-0.18484	0.031239	-5.9171	3.276E-09
1998	-0.168	0.0292	-5.7591	8.46E-09	-0.17143	0.02869	-5.9751	2.299E-09
1999	0.0249	0.0285	0.8729	0.382741	0.019379	0.028126	0.689	0.4908
2001	0.103	0.0273	3.7881	0.000152	0.10119	0.026724	3.7864	0.0001528
2002	0.129	0.0267	4.8311	0.00000136	0.12377	0.026221	4.7201	0.000002358
2003	0.132	0.0259	5.0906	0.000000357	0.12669	0.025364	4.9946	5.896E-07
2004	0.157	0.0249	6.2844	3.29E-10	0.15099	0.024533	6.1547	7.523E-10
2005	0.202	0.024	8.4174	<2.2e-16	0.20596	0.23631	8.7159	<2.2e-16
2006	0.211	0.0236	8.9476	<2.2e-16	0.20848	0.023178	8.9947	<2.2e-16
2007	0.172	0.0243	7.0682	1.57E-12	0.16991	0.023801	7.139	9.404E-13
2008	-0.0322	0.0256	-1.2585	0.208221	-0.035319	0.0251	-1.4071	0.15938
2009	-0.241	0.0266	-9.0667	<2.2e-16	-0.24059	0.026147	-9.2014	<2.2e-16
2010	-0.27	0.0268	-10.0906	<2.2e-17	-0.28302	0.02639	-10.7243	<2.2e-16
2011	-0.373	0.0268	-13.935	<2.2e-18	-0.3799	0.026233	-14.4818	<2.2e-16
2012	-0.359	0.0254	-14.1344	<2.2e-19	-0.37199	0.024992	-14.8843	<2.2e-16
Fireplace	0.127	0.0104	12.2068	<2.2e-20	0.13406	0.010573	12.6796	<2.2e-16

Table 28 Continued

term	Estimate – knn=1	std.error – knn=1	Statistic-knn=1	p.value-knn=1	Estimate – knn=10	std.error – knn=10	Statistic-knn=10	p.value-knn=10
Percent of Neighborhood Residential	-0.00333	0.000391	-8.5143	<2.2e-21	-0.002809	0.00051018	-5.5059	3.673E-08
Percent of Neighborhood that is Owned	-0.0042	0.000617	-6.8155	9.39E-12	-0.0042587	0.0008041	-5.2962	1.182E-07
Bus Stops in Neighborhood	-0.000198	0.0000672	-2.9535	0.003142	-0.00017745	0.00008718	-2.0354	0.041808
Median Year Built of Neighborhood	-0.000457	0.000252	-1.8182	0.069028	-0.00049129	0.00025089	-1.9581	0.0502129
Poverty Rate of Neighborhood	-0.00336	0.00181	-1.8575	0.063238	-0.0028104	0.0023456	-1.1981	0.2308
Median Income of Neighborhood	0.00000151	0.000000912	1.6544	0.098052	1.8582E-06	1.1879E-06	1.5643	0.1177
ITP	0.408	0.0215	18.9971	<2.2e-16	0.36469	0.028416	12.834	<2.2e-16
Percent of Neighborhood with College Degree	0.0101	0.000742	13.6613	<2.2e-16	0.0092512	0.00095175	9.7201	<2.2e-16
Mean Elevation of Neighborhood	0.00133	0.000154	8.633	<2.2e-16	0.0013464	0.00021065	6.3918	1.64E-10
Distance to CBD	-1.49E-12	7.34E-13	-2.0342	0.041935	-1.4535E-12	9.7068E-13	-1.4974	0.1342833

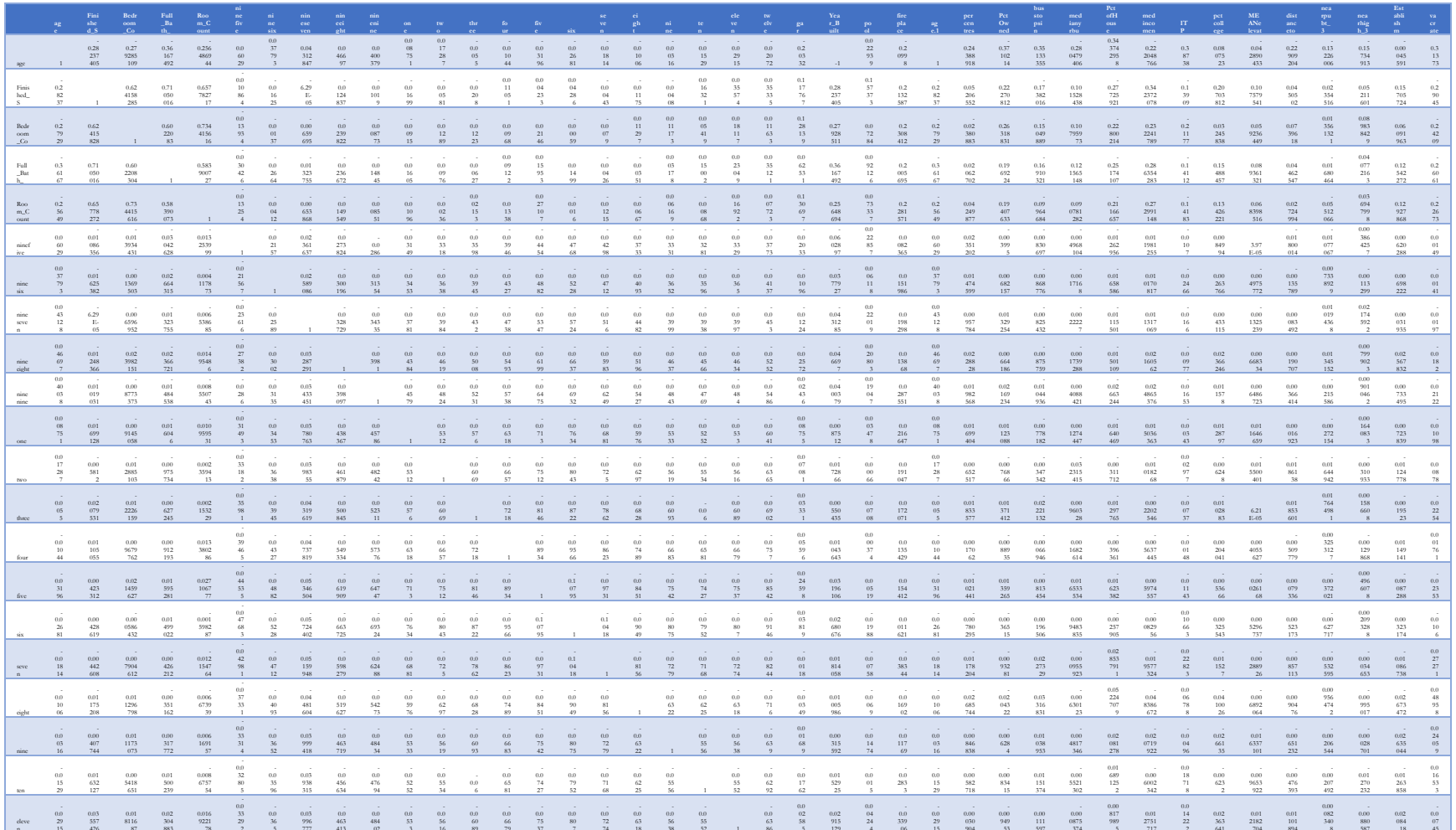
Table 28 Continued

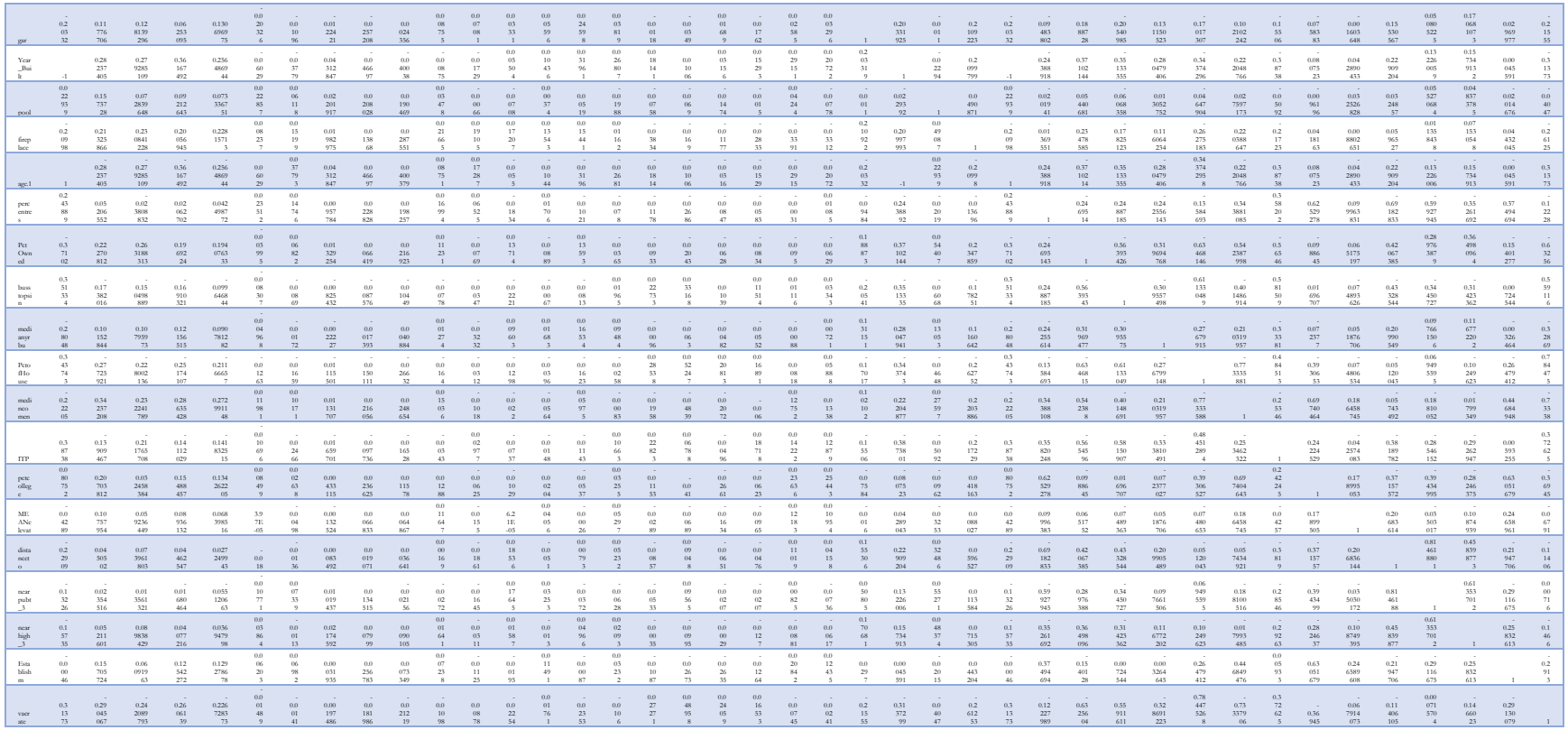
term	Estimate – knn=1	std.error – knn=1	Statistic-knn=1	p.value-knn=1	Estimate – knn=10	std.error – knn=10	Statistic-knn=10	p.value-knn=10
Distance to Nearest Public Transportation Facility	-0.00000119	0.000000413	-2.8887	0.003869	-1.3647E-06	5.6169E-07	-2.4297	0.0151127
Distance to Nearest Highway	0.000000682	0.000000351	1.9416	0.052186	7.0362E-07	4.9562E-07	1.4197	0.1556991
Vacancy Rate of Neighborhood	-0.0182	0.00206	-8.8487	<2.2e-16	-0.016158	0.0027108	-5.9607	2.511E-09
Diagnostic Test	**Value**		**P value**		**Value**		**P value**	
Lambda	0.12521				0.40456			
LR test value	359.02		<2.22e-16		749.46		<2.22e-16	
Asymptotic standard error	0.006302				0.013732			
z value	19.869		<2.22e-16		29.461		<2.22e-16	
Wald statistic	394.77		<2.22e-16		867.98		<2.22e-16	
Log likelihood	-11178.37				-10983.15			
Observations	14980				14980			
Number of parameters estimated	38				38			
AIC	22433				22042			
AIC for OLS	22790				22790			

Table 29: Studentized Breusch-Pagan Test

Studentized Breusch-Pagan test	Knn=1	Knn=10
BP	858.43	824.09
df	35	35
p value	2.20E-16	<2.2e-16

Appendix D: Correlation Matrix





Chapter 8: Understanding the Determinants of House Price Changes during the Housing Boom and Bust: Metropolitan Atlanta: 2000-2013

Abstract

The purpose of this paper was to analyze the extent to which the variation in our urban form and neighborhood characteristics may or may not contribute to changes in the local housing market and changes in neighborhood level housing prices.

In other words, what is the role that neighborhood attributes play in the stability of house prices in the region? Does this impact change when we are experiencing a broader increase in housing prices in the metropolitan area versus a broader decrease in housing prices?

Overall, this report sought to analyze how the varying levels of house prices and the stability of these house prices are related to a variety of neighborhood related characteristics related to land use, accessibility, and demographics.

Findings show that increases in median neighborhood income, population density and a zip code being an ITP zip code are generally associated with greater stability of prices during periods of macro level price declines. Alternatively, we generally find that increases in the vacancy rate of a neighborhood and the median year built for a neighborhood are generally associated with increased price fluctuation during periods of overall price declines.

Introduction/Literature Review

Many factors contributed to the housing boom and bust of the early 21st century in the United States. Perhaps the strongest factors were easy access to credit, a desire to rebuild the economy after the post-9/11 recession, and what some may see as irrational exuberance from real estate investors. These are all macro level factors that contributed to the sharp increases and decreases in house prices.

However, did all neighborhoods experience these increases and decreases in prices at the same rate? Perhaps there are neighborhood factors that contribute to the magnitude of price increases and declines during these periods. In other words, perhaps there are characteristics of the neighborhoods that serve to shield them from the worst price declines during overall periods of macro level price decline.

Therefore, the goal of this research was to investigate the neighborhoods and the attributes of neighborhoods in our study area that appear to possess a stabilizing effect during periods of volatility in house values.

In addition, this chapter seeks to understand if there are differences in the neighborhood attributes that serve as stabilizing effects between the period of housing gains as opposed to the housing bust period in our metropolitan area.

For example, it is possible that neighborhoods with higher incomes experienced a greater magnitude of house price increases during the housing boom, but also suffered a lower magnitude of house price declines during the housing bust. That is, certain neighborhood attributes may have possessed

a stabilizing effect during decreases in house values but not during periods of house price increases and vice versa.

Increased accessibility to services is often touted as a way to spur economic development and as a way to increase surrounding property values. Economic growth caused by increases in accessibility to valued services is routinely stated as a reason for new infrastructure or commercial development projects.

Research from the field of transportation economics has led many policy makers to believe that new development projects and the increased accessibility and amenities that follow will increase land values and housing prices in an area as it becomes more connected to the surrounding region (Kuminoff and Pope 2013).

This is the cornerstone of accessibility/land value theory. This improved accessibility may include becoming more accessible to schools, employment, and shopping as accessibility preferences likely vary across neighborhoods and household composition types.

While previous hedonic models investigated this relationship between neighborhood attributes and prices, this study attempts to investigate how urban development in the form of changes in accessibility measures along with local neighborhood attributes contribute to the economic stability of an area using residential property values as a proxy for economic stability.

Through understanding the role that demographic, economic and accessibility measures play in stabilizing residential property values over time and during macro level price shifts, society can establish more resilient and sustainable neighborhoods.

This research thus seeks to investigate not simply whether changes in accessibility immediately lead to increases in surrounding property values, but rather how neighborhood attributes and accessibility measures contribute to economic stability in the surrounding area and what types of attributes have a stronger impact on values.

Sustainability and the economic sustainability of neighborhoods has been a relatively active area of research in recent years. However, few studies are focusing on the stability of residential property values specifically and even fewer researchers are looking at the spatial heterogeneity of property value stability within metropolitan areas.

Residential property values may give us more information about the economic sustainability of areas as it can be used as a proxy for neighborhood level economic sustainability. Thus, through an analysis of the performance of real estate prices in various neighborhoods and the extent to which neighborhood characteristics contribute to house price changes at the neighborhood level allows for a discussion of sustainable communities.

In this case, the concept of sustainable communities has a focus on financial stability of the households that live there as seen through their house prices (the largest purchase most households make). For example, it may be that centrally-located, walkable neighborhoods with good access to public transportation contribute to more stable house prices than more auto-oriented neighborhoods.

The goal of this research paper was to identify and quantify how the relative variation in house price changes during the most significant housing event in decades is explained by variation in the location and design of different communities.

This project contributes to the existing literature and is timely given that house prices nationwide have recovered and, in many cases, surpassed those from before the Great Recession.

The data analyzed in this report covers the full evolution of the downturn, from its peak to its trough. While the Atlanta MSA did not experience as severe of price changes as some other metro areas, it was still significantly impacted by the housing boom and bust; more so than many of the other metro areas in the region.

There has been a significant amount of research in the past decade concerning the instability of house prices in the United States, though the vast majority of this research has focused on more macroeconomic factors contributing to the housing boom and subsequent burst.

While we agree that these factors are the most important determinants, this study contributes to that knowledge by investigating the micro level price changes and the extent to which some neighborhoods may be more resilient to price changes and promote greater price stability than others, within a metropolitan area.

There are many studies that view this kind of economic sustainability in a decidedly macroeconomic way in that they look at the stability of housing markets across countries (Duca et al. 2010), states and regions (Holly et al. 2010) and related to national macroeconomic conditions (Liu et al. 2011); few studies have looked at this phenomenon from the perspective of urban geography and the role that the urban form as measured through neighborhood attribute may play in this type of local economic temporal sustainability.

Research regarding local level variation in prices has been more common as it relates to foreclosures (Lin 2009) and the time it takes for neighboring houses to recover after a neighboring default (Chan et al. 2013). Research is now beginning to come out regarding which neighborhoods have successfully climbed back from the depths of the recession (Fitzpatrick et al. 2013) and the disparate impacts associated with the current recovery of house prices we have recently experienced (Raymond et al. 2016; Williams et al. 2010).

Opportunities remain within this literature to investigate the role that urban structures and the form of our metropolitan areas may play in the spatial and temporal dynamics of residential property values at the local level within large metropolitan areas. This is an important scale of inquiry and one where we may see significant differences in the stabilizing effects between neighborhoods.

Data and Methodology

For this project, yearly house price indices were obtained from the Federal Housing Finance Agency at the zip code level. We were interested in the years 2000-2013 for this project. In addition, the census data used in this paper is 2000 zip code level publicly available summaries along with user-

created variables. Other neighborhood attributes such as land use information and access to public transportation facilities were calculated using data from the Atlanta Regional Commission.

While there have likely been many periods of rising and falling house prices in the region, data limitations restrict us to focusing on two different time periods: one period for overall rising prices and one period for overall declining prices.

It should be noted that from 2000-2007, all zip codes in our study area experienced an increase in house prices. Likewise, from 2008-2013, all zip codes in our study area experienced a decrease in house prices.

The period of overall rising prices includes that of 2000-2007 while the period of overall price declines includes 2008-2013. The declines and increases are measured by the percent change in the zip code house price index through these time periods.

For price decline, we use the absolute value since all zip codes in the study area experienced declines during this time. This aides in our model interpretation. Figure 38 and Figure 39 highlight percent increases and decreases at the zip code level for our study area, while Figure 40, Figure 41, Figure 42, and Figure 43 highlight the more detailed trend in house price indices for zip codes.

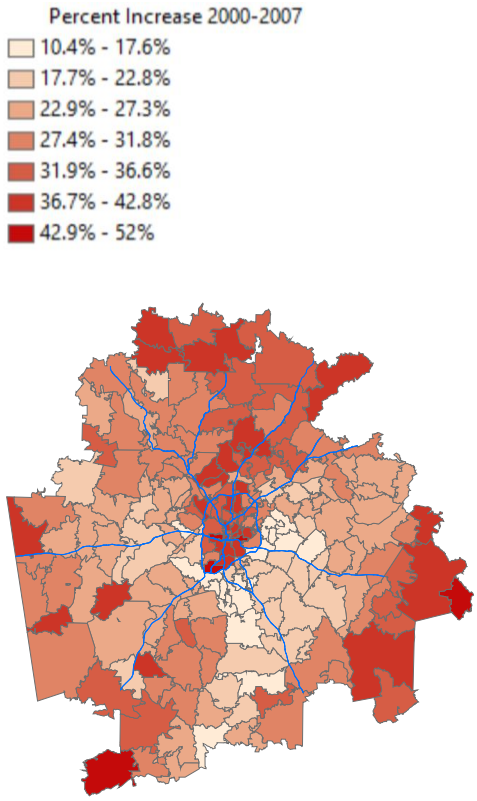


Figure 38: Percent Increase (2000-2007)

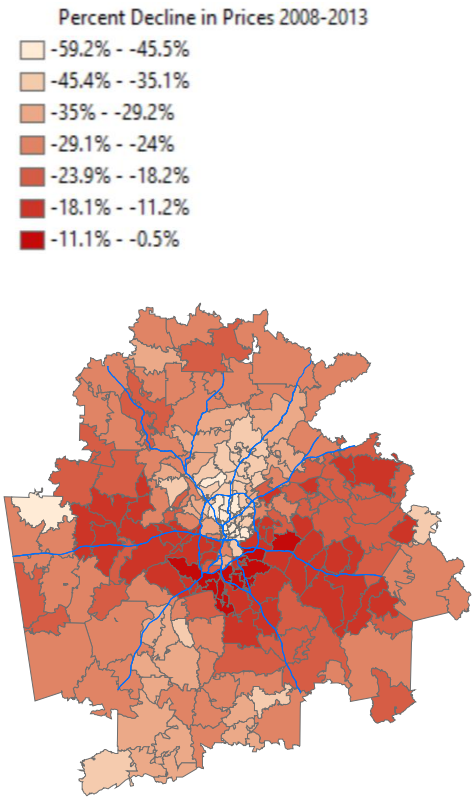


Figure 39: Percent Decrease (2008-2013)



Figure 40: 2000 House Price Indices (Base)

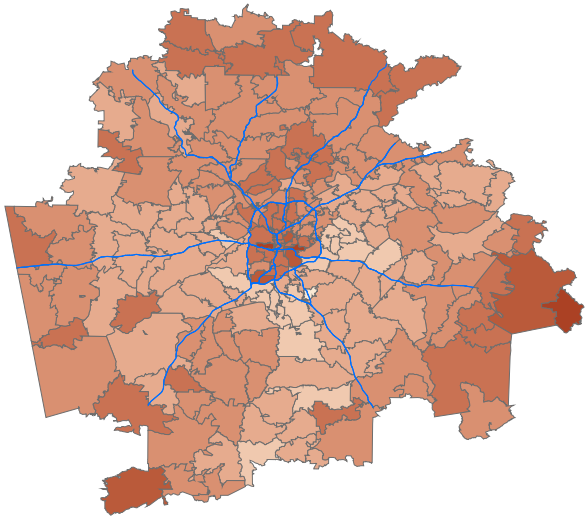


Figure 41: 2007 House Price Indices

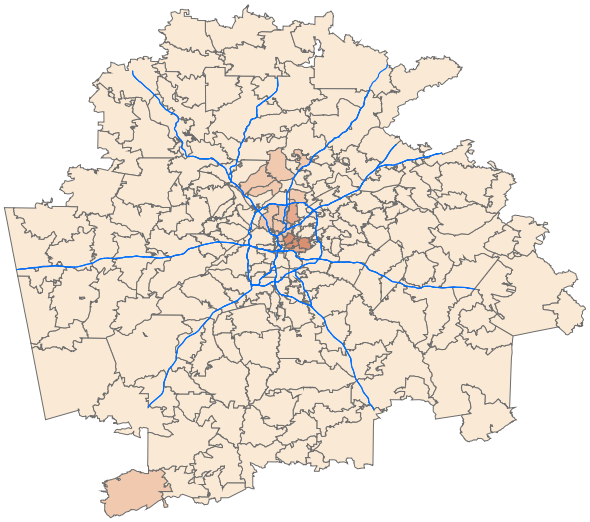


Figure 42: 2012 House Price Indices

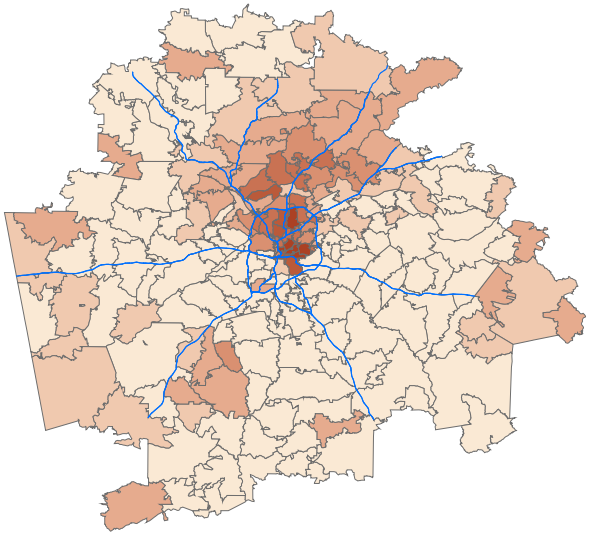


Figure 43: 2015 House Price Indices

Atlanta MSA

HPI - 2000 Base

- 110.0 and under
- 110.1 - 118.0
- 118.1 - 126.0
- 126.1 - 134.0
- 134.1 - 142.0
- 142.1 - 150.0
- 150.1 and over

Initially, it appears that the neighborhoods located north of downtown and some of the northern suburbs experienced the least amount of home price declines in the region along with some of the steepest increases. However, this also appears to have been true for some of the outlying counties in the metropolitan area.

Overall, the patterns we see here are similar to most social/economic patterns in the metropolitan area. That is, areas south of downtown did not enjoy an increase in prices to the same extent as other areas, but it did experience more severe declines. You would likely see a similar spatial pattern for almost all social and economic phenomenon in the area.

We are then able to expand the scope of research to include a variety of attributes that may correlate with the local performance of the housing market. This is done via ordinary least squares regression where the dependent variable represents the total percent change in house prices (decline in one model, increase in the other) at the zip code level.

As we can see from the legend above, these are the home price indices at the zip code level for 2000-2015, with 2000 as the base year. For some zip codes, their lowest home price level was actually in 2012. However, 2013 was chosen for this study to correspond to research that has since been thrown away. Table 30 below highlights the distribution of changes in the house price index from 2000 to 2007. We see that the median increase across 222 zip codes was approximately 29 percent, with the minimum increasing by 10 percent and the maximum increasing by 52 percent.

Table 31 below highlights the distribution of changes in the house price index from 2008 to 2013. We see that the median decline across 222 zip codes was approximately 27 percent, with the minimum barely decreasing and the maximum decrease of 59 percent.

As discussed previously, it may be that the true bottom was in 2012. However, 2013 corresponded to other work that I was doing, and I wanted to be consistent. Regardless, Figure 44 below highlights the trend in house prices going to 2017 where price levels are actually above where they were at the peak of the housing boom.

Table 32 highlights the sources of the variables used in these models. Table 33 highlights the summary statistics for the variables of interest for our models.

Table 30: Percent Change in HPI from 2000 (all Zips with 100 HPI) to 2007

Percent Increase in HPI from 2000 to 2007 by Zip Code	
Minimum	10.39
1st Quantile	24.22
Median	29.01
Mean	29.05
3rd Quantile	34.42
Maximum	51.98

Source: Federal Housing Finance Agency

Table 31: Percent Change in HPI from 2008 to 2013

Percent Decrease in HPI from 2008 to 2013 by Zip Code	
Minimum	-59.2303
1st Quantile	-34.4017
Median	-27.4461
Mean	-27.191
3rd Quantile	-20.5431
Maximum	-0.5368

Source: Federal Housing Finance Agency

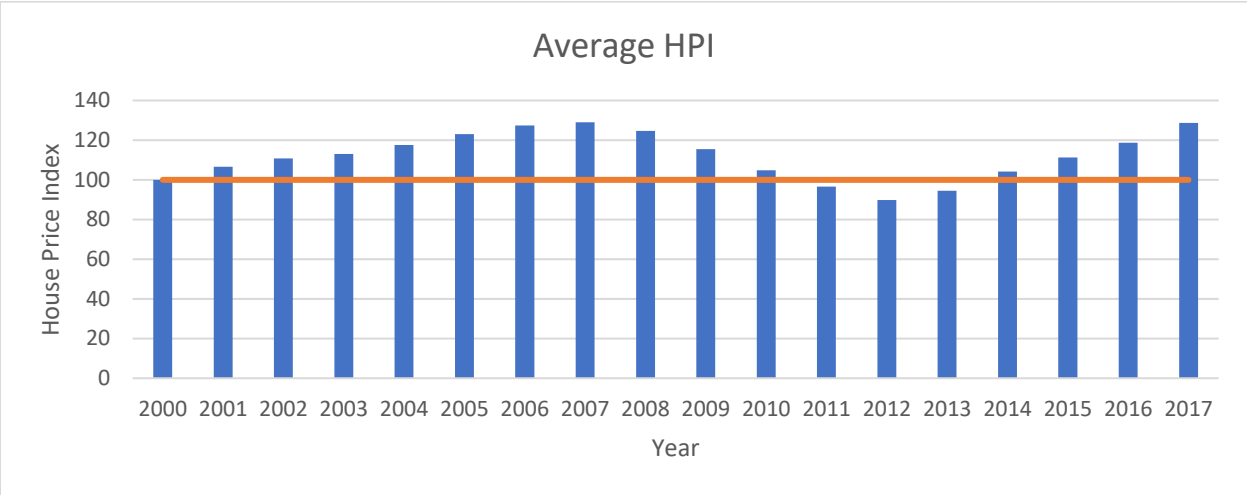


Figure 44: Average HPI Across Metropolitan Atlanta Zip Codes

Source: Federal Housing Finance Agency

Table 32: Description of Variables

Variable	Description	Source
Percent of Neighborhood that is Residential	Percent of Zip Code that is Residential	Atlanta Regional Commission
Percent of Neighborhood that is Owned	Percent of Zip Code that is Owned	Census
Population Density per square mile	Population Density per square mile	Calculated
Population	Population of Zip Code	Census
Sq Mile	Size of Zip Code	Calculated
Distance to CBD (feet)	Distance of Zip Code to CBD	Calculated
ITP	Dummy if Zip Code is ITP	Calculated
Bus Stops	Number of Bus Stops in Zip Code	Atlanta Regional Commission
Rail/Other Public Transportation	Number of Other Public Transportation Facilities in Zip Code	Atlanta Regional Commission
Closest Public Transport Facility	Distance from Zip Code to Nearest Public Transportation Facility	Atlanta Regional Commission
Distance to Highway	Distance from Zip Code to Nearest Highway	Atlanta Regional Commission
Household Income	Median Household Income of Zip Code	Census
Households in Poverty	Percent of Zip Code Households in Poverty	Census
Percent Black	Percent of Zip Code that is Black	Census
Percent Other	Percent of Zip Code that is Race other than white or black	Census
Establishment Density	Establishments per sq. mile	Census
Vacancy Rate	Vacancy Rate of Zip Code	Census
Median Year Built	Median Year Built of Zip Code	Census
Elevation	Mean Elevation of Zip Code	Atlanta Regional Commission

Table 33: Summary of Variables

Variable	N	Mean	SD	Min	Max
Percent of Neighborhood that is Residential	222	31.35097	24.13953	6e-06	87.46314
Percent of Neighborhood that is Owned	222	70.48425	18.81699	2.055623	94.96038
Population of Neighborhood	222	20435.28	15687.48	55	66229
Percent of Neighborhood in Poverty	222	10.34561	7.510848	0.43919	50
Median Income of Neighborhood	222	49117.81	16009.05	13084	114674
ITP	222	0.1367925	0.3444		
Distance to CBD	222	143809.9	86571.35	1780.315	358699.9
Bus Stops in Neighborhood	222	46.99528	100.8094	0	676
Rail/Other Public Transportation Facilities in Neighborhood	222	0.1792453	0.5642958	0	4
Distance to Nearest Public Transportation Facility	222	8.339859	9.854497	0.01037737	38.63477
Distance to Nearest Highway	222	5.731637	5.803104	0.001350816	25.77662
Mean Elevation of Neighborhood	222	282.0593	44.72735	108.7797	474.1594
Population Density of Neighborhood	222	1256.188	1470.325	8.070932	8336.625
Establishment Density of Neighborhood	222	65.71244	191.3808	0.0752284	1726.136
Vacancy Rate of Neighborhood	222	11.4685	4.943743	4.459921	37.03599
Median Year Built of Neighborhood	222	1986.991	10.75403	1948	2005
Percent Black	222	25.24	25.11	0.1	97.4
Percent Other	222	6.0	5.71	0.9	32.1

The methodology employed in this research is simply a series of OLS regression models. Initially, we investigate a full model for both percent increase and percent decrease. The, final model specifications are selected after investigating any issues of multicollinearity.

Finally, we conduct an iterative, stepwise analysis for variable selection. We analyzed possible interaction terms and decided that there were not any that needed to be included. Table 34 highlights the results from the full model with the dependent variable as percent increase in house price index for zip codes.

Table 35 below is the same model as above except the dependent variable has been replaced by the percent decrease in house price indices for zip codes. Please remember that the absolute value of percent decrease was taken to aid in interpretation since all zip codes experienced declines during this time period.

Results

Table 36 highlights our final model specification for percent increase. As we can see, all variables are significant at the 5 percent level except for the mean elevation of the neighborhood which is significant at 10 percent.

The F statistic indicates that this model is preferable to no model and the R squared value indicates that 56 percent of the variation in house price increases between 2000-2007 across our study area are explained by the attributes of the neighborhoods/zip codes.

We see that public transportation facilities are related to higher levels of price increases during this time. As we can see in Figure 45 (Fitted vs. Residuals plot), it does not appear as though we are not violating basic assumptions concerning non-linearity or heteroskedasticity. The residuals also follow a normal distribution.

Table 37 highlights the final model specification for percent decrease. Here we see that all variables are significant at the 10 percent level. The R squared value of 0.64 indicates that approximately 64 percent of the variation in house price declines are explained by these characteristics of zip codes. In this situation, positively signed coefficients are associated with greater house price declines while negative coefficients are associated with relatively smaller house price declines.

Overall, it seems as though the empirical evidence indicates that communities and neighborhoods that are centrally located with good access to public transportation facilities have generally held their value better during the most recent housing downturn. In general, it seems as though house prices declined less in zip codes where incomes and population density were higher.

Table 34: Full Model - Percent Increase

term	estimate	std.error	statistic	p.value
(Intercept)	148.5166	110.3052	1.346415	0.179748
Percent of Neighborhood that is Residential	-0.01892	0.037786	-0.50066	0.61718
Percent of Neighborhood that is Owned	-0.10656	0.044254	-2.40787	0.016987
Population of Neighborhood	-8.33E-05	3.57E-05	-2.33633	0.0205
Percent of Neighborhood in Poverty	0.272001	0.089532	3.038024	0.002711
Median Income of Neighborhood	0.000338	4.89E-05	6.920987	6.45E-11
ITP	6.586598	1.780004	3.700327	0.000281
Distance to CBD	3.41E-05	1.77E-05	1.929211	0.055171
Bus Stops in Neighborhood	0.014477	0.006291	2.301271	0.022444
Rail Stations in Neighborhood	3.268714	0.990717	3.299343	0.001154
Distance to Nearest Public Transportation Facility	0.231042	0.132658	1.74164	0.083165
Distance to Nearest Highway	-0.26648	0.109473	-2.43425	0.015833
Mean Elevation of Neighborhood	0.015277	0.009968	1.532582	0.127016
Population Density of Neighborhood	0.000508	0.000531	0.956689	0.339921
Establishment Density of Neighborhood	-0.00776	0.002907	-2.66903	0.008255
Vacancy Rate of Neighborhood	0.304158	0.122171	2.489611	0.013634
Median Year Built of Structures in Neighborhood	-0.07165	0.055389	-1.29357	0.19736
Percent of Neighborhood Black	-0.7205	0.02692	-2.67629	0.008084
Percent of Neighborhood Other	-0.07247	0.096225	-0.75312	0.452297
Residual standard error	**R-square**	**F statistic**		
5.371	0.56	14.9***		

Table 35: Full Model - Percent Decrease

term	estimate	std.error	statistic	p.value
(Intercept)	-211.849	135.7167	-1.56096	0.120171
Percent of Neighborhood that is Residential	0.009451	0.046491	0.203281	0.83913
Percent of Neighborhood that is Owned	0.290143	0.054449	5.328748	2.74E-07
Population of Neighborhood	0.000157	4.39E-05	3.57741	0.000439
Poverty Rate of Neighborhood	-0.39822	0.110158	-3.61496	0.000383
Median Income of Neighborhood	-0.00043	6.01E-05	-7.14021	1.85E-11
ITP	-6.84686	2.190072	-3.12632	0.002044
Distance to CBD	-4.30E-05	2.18E-05	-1.97542	0.049645
Bus Stops in Neighborhood	-0.01666	0.00774	-2.15276	0.032578
Rail Stations in Neighborhood	-0.84721	1.218953	-0.69503	0.487871
Distance to Nearest Public Transportation Facility	-0.10265	0.163219	-0.62891	0.530155
Distance to Nearest Highway	-0.0424	0.134693	-0.31478	0.753268
Mean Elevation of Neighborhood	-0.01372	0.012265	-1.11894	0.264558
Population Density of Neighborhood	-0.0019	0.000653	-2.9127	0.004006
Establishment Density of Neighborhood	-0.001	0.003576	-0.27952	0.780148
Vacancy Rate of Neighborhood	0.516578	0.150316	3.436618	0.000721
Median Year Built of Structures in Neighborhood	0.122885	0.068149	1.803186	0.072919
Percent of Neighborhood Black	0.166426	0.033122	5.024594	1.15e-06
Percent of Neighborhood Other	0.257494	0.118393	2.17491	0.030853
Residual standard error	**R-squared**	**F statistic**		
6.608	0.64	18.88***		

Table 36: Final Specification - Percent Increase

term	estimate	std.error	statistic	p.value
(Intercept)	5.450361	4.76219	1.144507	0.253802
Percent of Neighborhood that is Owned	-0.10522	0.036754	-2.86282	0.004653
Population of Neighborhood	-8.58E-05	3.38E-05	-2.53951	0.011873
Poverty Rate in Neighborhood	0.265069	0.08798	3.01282	0.002928
Median Income of Neighborhood	0.000327	4.52E-05	7.224574	1.08E-11
ITP	7.568075	1.656897	4.567619	8.68E-06
Distance to CBD	2.91E-05	1.53E-05	1.907148	0.057956
Bus Stops in Neighborhood	0.0151	0.006207	2.432643	0.015882
Rail Stations in Neighborhood	3.585547	0.967434	3.706243	0.000273
Distance to Nearest Public Transportation Facility	0.285564	0.123259	2.316789	0.021543
Distance to Nearest Highway	-0.27415	0.108987	-2.51542	0.012688
Mean Elevation of Neighborhood	0.016935	0.009608	1.762596	0.079519
Establishment Density in Neighborhood	-0.00797	0.0028	-2.84662	0.004887
Vacancy Rate of Neighborhood	0.341366	0.114594	2.978931	0.003256
Percent of Neighborhood Black	-0.06804	0.025864	-2.63088	0.00919
Residual standard error	**R-squared**	**F statistic**		
5.358	0.56	17.86***		

Table 37: Final Specification - Percent Decrease

term	estimate	std.error	statistic	p.value
(Intercept)	-251.5705	111.35656	-2.25914	0.024958
Percent of Neighborhood that is Owned	0.3032074	0.0492609	6.155132	4.06E-09
Population of Neighborhood	0.0001619	4.05E-05	4.00143	8.88E-05
Poverty Rate of Neighborhood	-0.425768	0.1076563	-3.95489	0.000106
Median Income of Neighborhood	-0.000438	5.27E-05	-8.30403	1.53E-14
ITP	-6.875254	2.1527358	-3.19373	0.001633
Distance to CBD	-5.52E-05	1.07E-05	-5.15994	5.96E-07
Rail Stations in Neighborhood	-0.018055	0.0074911	-2.41019	0.016854
Population Density of Neighborhood	-0.001923	0.0005806	-3.31207	0.0011
Vacancy Rate of Neighborhood	0.4557042	0.1392333	3.272954	0.001255
Median Year Built of Neighborhood	0.1413113	0.055871	2.529241	0.012206
Percent of Neighborhood Black	0.1792099	0.0303002	5.914487	1.43E-08
Percent of Neighborhood Other	0.2788641	0.1132614	2.462128	0.014662
Residual standard error	**R-squared**	**F statistic**		
6.55	0.64	28.6***		

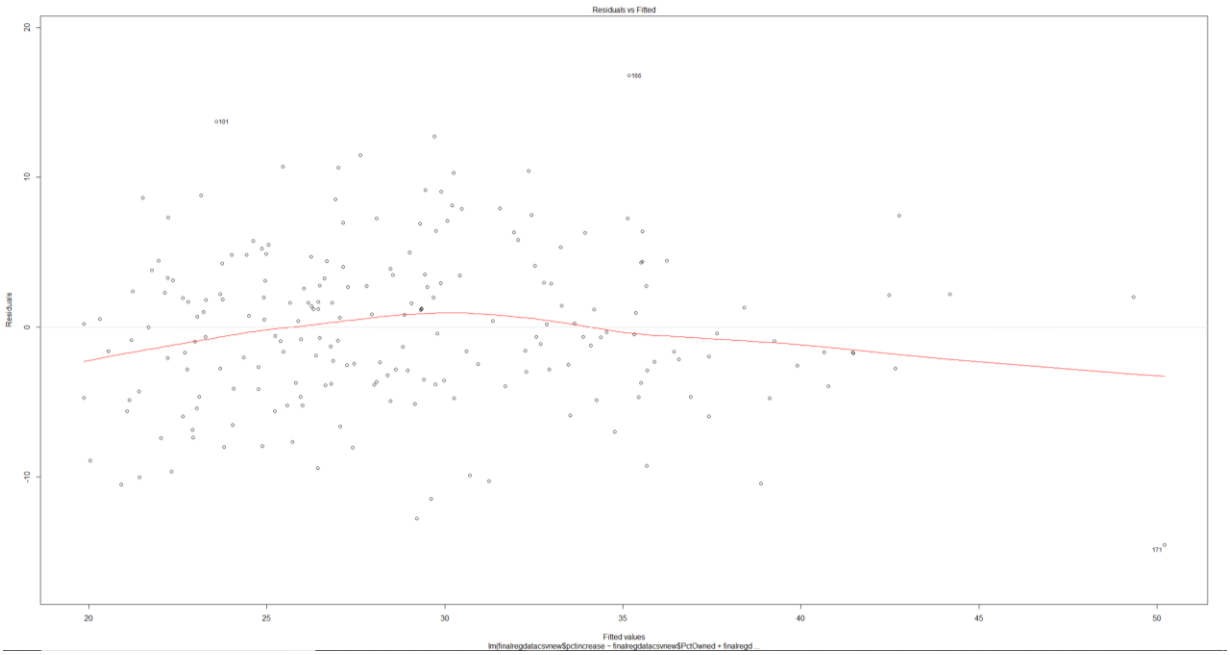


Figure 45: Residuals vs. Fitted Plot

Limits of Study/Future Research

The main limits to this study are that the models likely suffer due to unavailability of data and a lack of variables that we could include in the model. Additional data is needed to improve the specification of these models to obtain a better assessment of the role of neighborhood structure on the magnitude of price gains and declines.

As with the previous chapter, the inclusion of things like crime rates and school quality may improve our understanding of these processes. In addition, this chapter investigates how price changes over a significant period of time. We use neighborhood attributes from 2000 to identify neighborhood attributes that contribute to the magnitude of price changes.

However, given that this chapter investigates prices going to 2013, it would be beneficial to incorporate neighborhood changes into this as well. For example, when looking at the magnitude of price declines from 2008-2013, neighborhood attributes from 2000 may no longer be relevant. We designed the study this way because 2000 was when we felt as though the phenomenon of significant price changes began. However, a different approach may be preferable.

Conclusion

Given out hypothesis and results, it appears as though the relationship between house price changes and the urban form is quite complicated. Through this project, we have gained a greater insight into home prices than simply comparing metropolitan area level prices.

In conclusion, this report provides evidence that not only is the magnitude of the recent housing increase and subsequent downturn unique, but as is its structure. We see that certain elements of our urban environments are related to the magnitude of price changes that we see at the neighborhood level. This report has provided unique evidence that not only is the magnitude of the recent housing increase and subsequent decrease unique, but as is its relationship to the urban form.

Chapter 9: The Dynamic Causal Relationship between Neighborhood House Values, Local Employment Opportunities and Metropolitan Area Level Economic Indicators: Metropolitan Atlanta 1990-2017

Abstract

This paper investigated the temporal relationships between neighborhood (zip code) level house prices and macroeconomic indicators at the county and metropolitan area level. This was done to investigate the neighborhoods within the metropolitan area where house prices are not temporally linked to broader economic conditions and economic shifts.

This allowed for an investigation into whether the rapid changes in house prices during our study time period is justified by fundamental economic factors. This paper looks at this phenomenon at a very local level to identify those neighborhoods that are linked with broader economic conditions and movements along with identifying neighborhoods that are not linked to these processes.

In general, results seem to show that there are not strong spatial patterns in terms of neighborhoods that are significantly cointegrated with macroeconomic factors versus those that are not.

Introduction/Literature Review

This chapter incorporated cointegration techniques and methods to investigate the dynamic causal relationship between neighborhood house values, local employment opportunities and a variety of metropolitan area level economic indicators.

These methods are used to investigate the relationship between neighborhood house prices and local employment. In addition, we also investigate the potential cointegrating relationship between local house prices and macroeconomic indicators at the metropolitan area level.

For the purpose of this study, macroeconomic variables refer to those variables at the county or metropolitan area level. While these may not be considered variables are a macroeconomic level in other studies, this project has largely investigated prices at a more neighborhood level, so we refer to these variables as 'macroeconomic' in relation to our neighborhood house price indices.

In general, macroeconomic variables are related to those that focus on the overall economy. While this is often researched at the national level, one could certainly argue that national measures do not include the overall economic picture. Again, in this study, we use the term 'macroeconomic factors' and 'macroeconomic variables' to refer to those economic measures for the broader, metropolitan area economy as opposed to more local neighborhood economies. In reality, we could simply say that these are broader economic measures compared to our more 'local' house price measures.

Thus, results from this chapter produce maps of test statistics that assist us in understanding the level of cointegration between local house prices at the zip code level and these various factors. This allows us to visualize the neighborhoods of the metropolitan area where house prices move along with these economic indicators through time and those areas where this is not the case.

We use zip code level house price indices provided to us by the Federal Housing Finance Agency. This allowed us to have additional years of house price indices, allowing us to perform a better cointegration analysis.

House price indices for each zip code are then joined with county level employment corresponding to the county that the zip code is in. For the other measures, such as the Case-Shiller home price index, all zip codes are joined to the same values since it is a metropolitan area level measure.

We conduct cointegration analysis on these variable pairs to understand whether they are significantly cointegrated through time. For example, do all zip codes in our study area contain house price indices that are temporally cointegrated with the metropolitan area level Case-Shiller home price index? What are the attributes of the zip codes that are not significantly cointegrated to these macroeconomic conditions?

Statistical cointegration is the concept that two or more time series variables move together through time. In other words, the ratio between to time series remains stable so that as one time series increases, another will increase at the same rate (Enders 2010). This may involve any relationship that is said to exist in equilibrium among a set of nonstationary variables (Beenstock and Felsenstein 2010).

While there are existing studies regarding this process related to house values (Ball and Kirwan 1977; Osland and Thorsen 2005; Gallin 2006; Mikhed and Zemcik 2009; Yasumoto 2013), these studies often look at this relationship at a macro level and often test for cointegration for variables at the same scale. Few studies have investigated the extent to which neighborhood prices are linked with broader economic conditions with the goal of identifying intra-metropolitan area spatial patterns.

In order to conduct cointegration analysis, it is necessary to begin by testing if a time series is stationary or non-stationary. A common approach is to use the Augmented Dickey-Fuller test (Enders 2010), which we use in this analysis. In economic related data, most time series are nonstationary in nature and become stationary when taking the first difference of the series (Enders 2010).

Enders (2010) gives an example of cointegration theory suggesting that in the short run, prices of similar products in various markets differ. Using the example of arbitrage, he suggests that various prices will not move too far apart if the prices are nonstationary. In other words, various prices will not move too far apart if the products are deemed substitutable.

For example, the prices of PC and Apple computers have exhibited sustained declines in prices while economic theory suggests that simultaneous price declines are related to each other since a price discrepancy between these similar products should not continually grow. Of course, one can perhaps debate whether they are similar products, but one can also see how these methods can be utilized in regards to the substitutability between multiple housing markets.

Studies in empirical macroeconomic almost always involve non-stationary and trending variables. Examples of this include income, consumption, money demand, the price level, trade flows, and exchange rates. If the two variables of interest are an integrated series, then the series would be drifting together at roughly the same rate (Greene 2012).

Beenstock and Felsenstein (2010) integrated spatial econometrics with panel cointegration tests to design a methodology that studies spatial data that are temporally nonstationary. Mikhed and Zemcik (2009) investigated the relationship between house prices in the United States and a variety of economic fundamentals using standard unit root and cointegration tests. Lauridsen (1999)

introduced a procedure for a spatial variant of the time series based cointegration approach providing understanding of stationarity applied to spatial series, spatial unit roots, and spatial integration.

In terms of the variables being used in this study, it is typically thought that there is a cointegrating relationship between house prices and real per capita incomes, which often exhibit non-stationarity (Holly et al. 2010). However, Gallin (2006) has concluded that there is no cointegration between home values and income changes.

Considering significant disparities in the socio-economic conditions across neighborhoods, the aim of this paper is to investigate the causal relationship between housing prices and various economic factors. We wish to examine the extent to which neighborhood house prices are driven by fundamentals. The existence of a cointegrating relationship between house prices and macroeconomic factors can highlight neighborhoods that are linked to broader economic conditions in a metropolitan area and those neighborhoods that are not.

Data/Methodology

There are two main datasets that are used in this study. The first is zip code level house price indices obtained from the Federal Housing Finance Agency for 1990-2017. This provides us with a measure of local neighborhood house prices for each year. As discussed previously, we also join several additional datasets to these zip codes to determine whether zip code indices are tied in the long term with macroeconomic indicators.

The following represents the second required dataset for this project:

- County Employment
- Metropolitan Employment
- Unemployment Rate/Employment Rate
- Metropolitan Case-Shiller home price index
- Metropolitan Housing Starts
- Metropolitan GDP
- Metropolitan Income
- Metropolitan Size of the Civilian Labor Force
- Metropolitan per capita GDP
- Metropolitan Population

This information is obtained from a variety of sources including the Bureau of Economic Analysis, the U.S. Census Bureau, the Bureau of Labor Statistics and others. All of these indices were available yearly for the Atlanta Metropolitan Statistical Area. However, there is some discrepancy regarding the years available for some of this data. Figure 46, Figure 47, Figure 48, Figure 49, Figure 50, Figure 51, and Figure 52 highlight this discrepancy in data availability along with the trends of our macroeconomic variables compared to an example zip code's house price index.

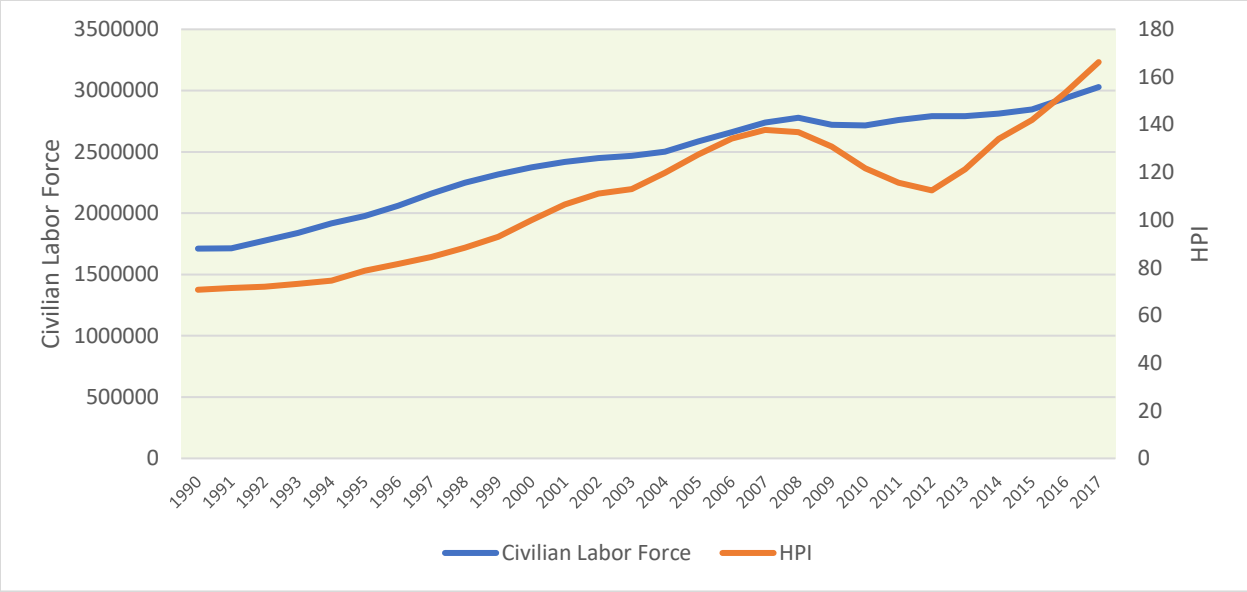


Figure 46: Civilian Labor Force versus 30075 HPI

Source: United States Bureau of Labor Statistics

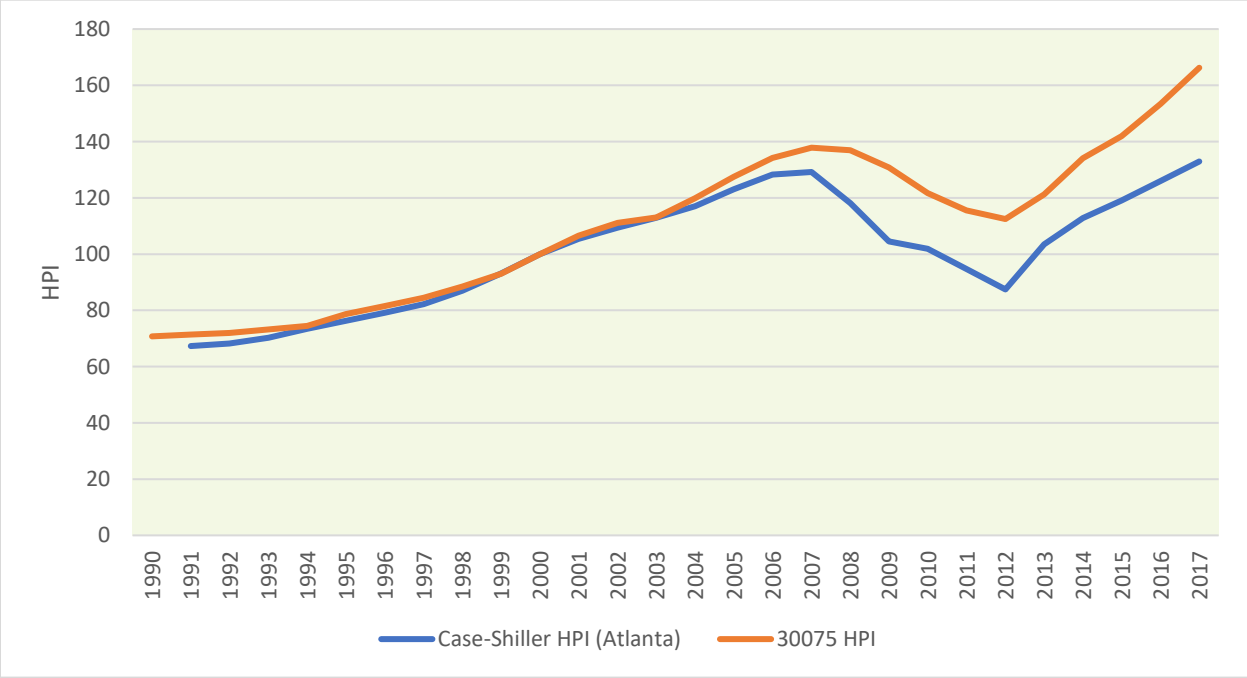


Figure 47: Case-Shiller HPI versus 30075 HPI

Source: S&P Dow Jones Indices LLC

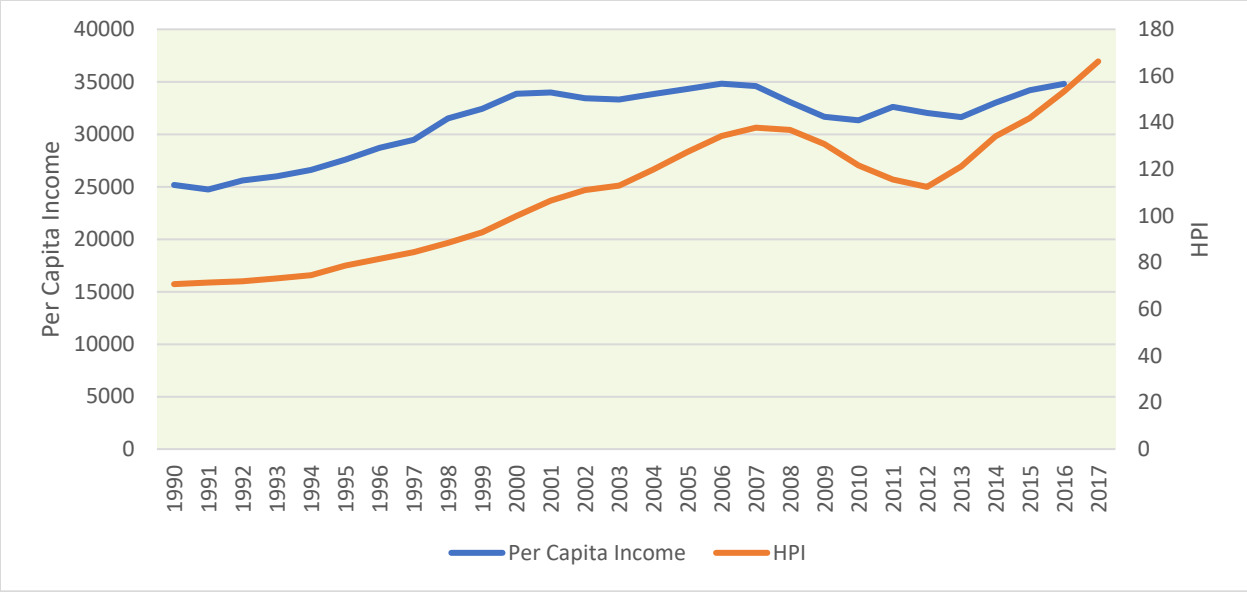


Figure 48: Per Capita Income versus 30075 HPI

Source: United States Bureau of Economic Analysis

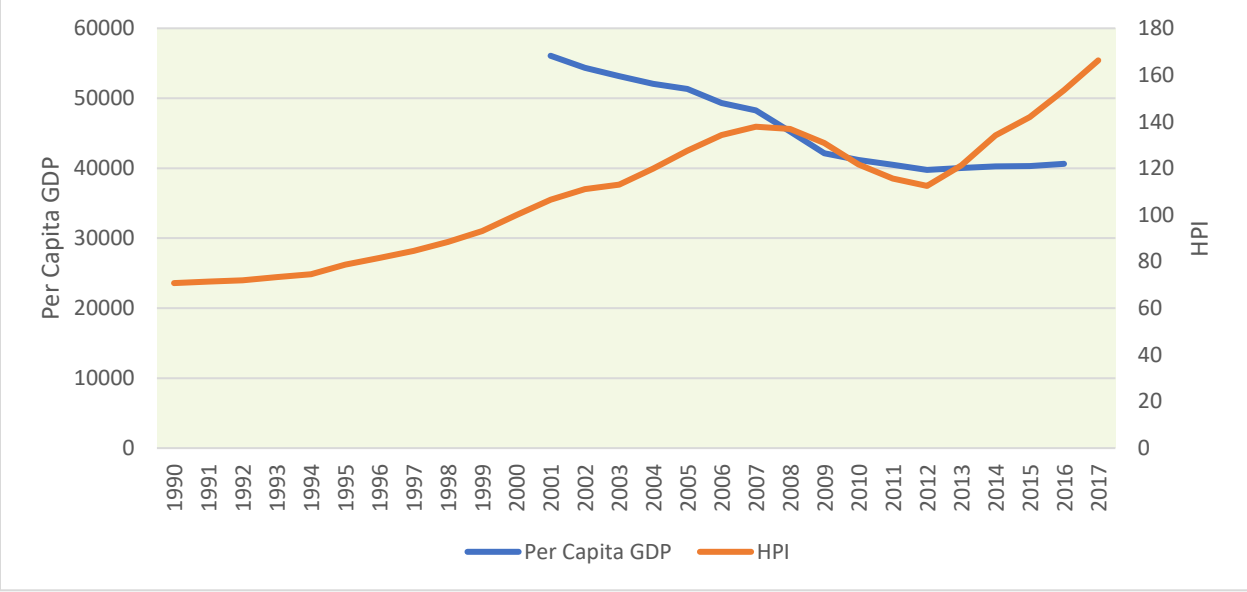


Figure 49: Per Capita GDP versus 30075 HPI

Source: United States Bureau of Economic Analysis

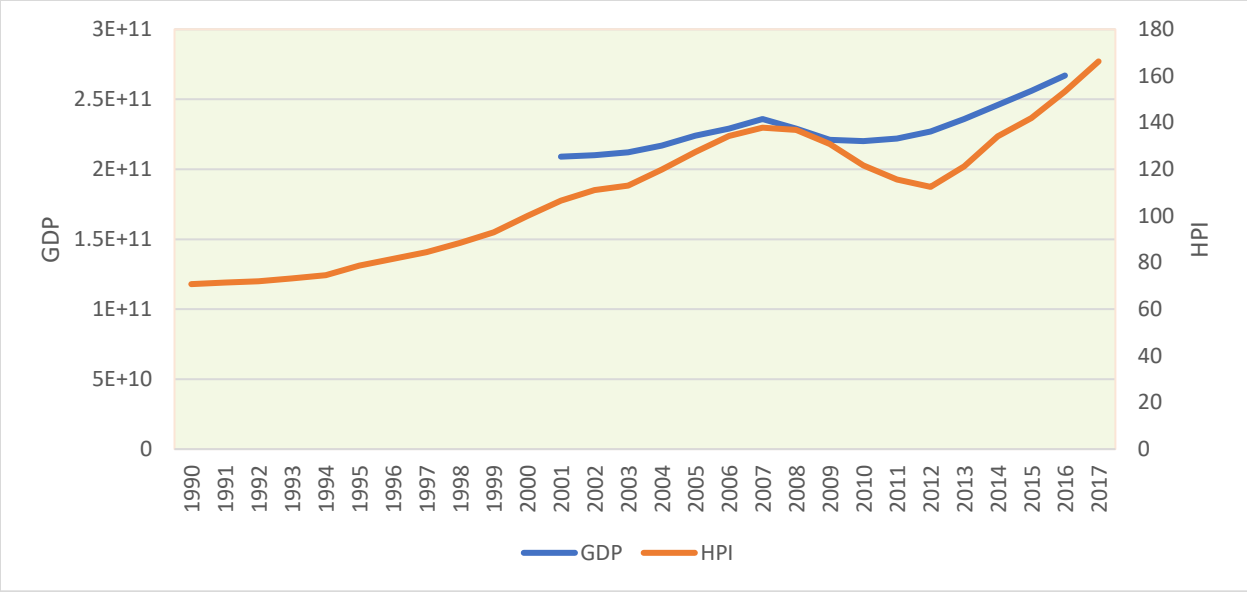


Figure 50: GDP versus 30075 HPI

Source: United States Bureau of Economic Analysis

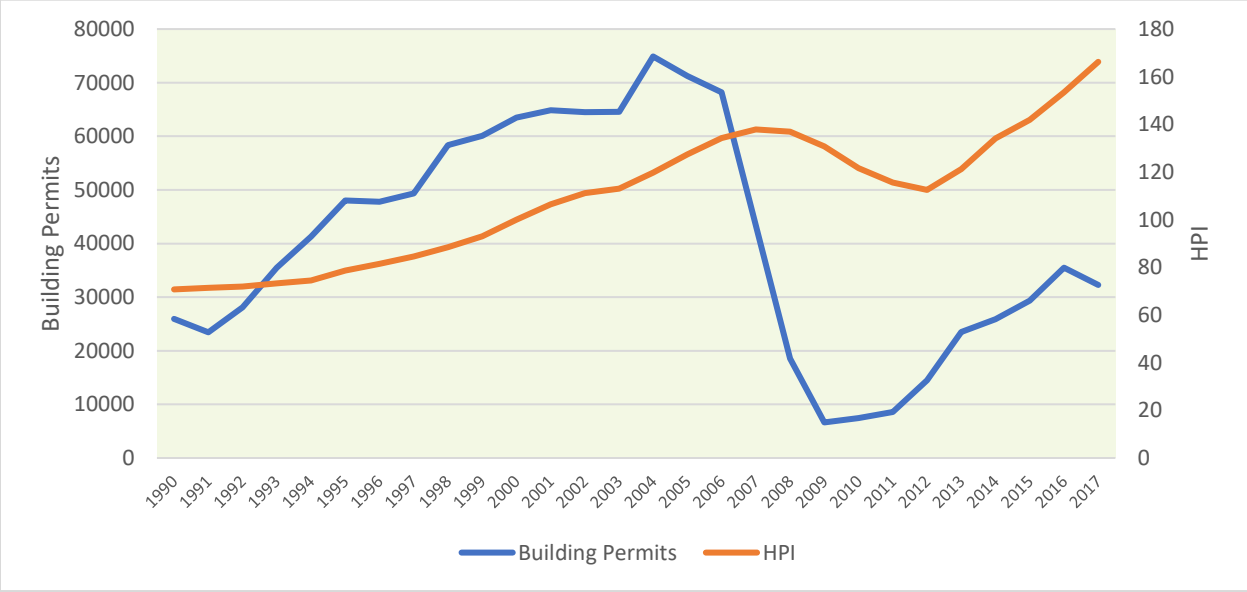


Figure 51: Building Permits versus 30075 HPI

Source: United States Bureau of the Census

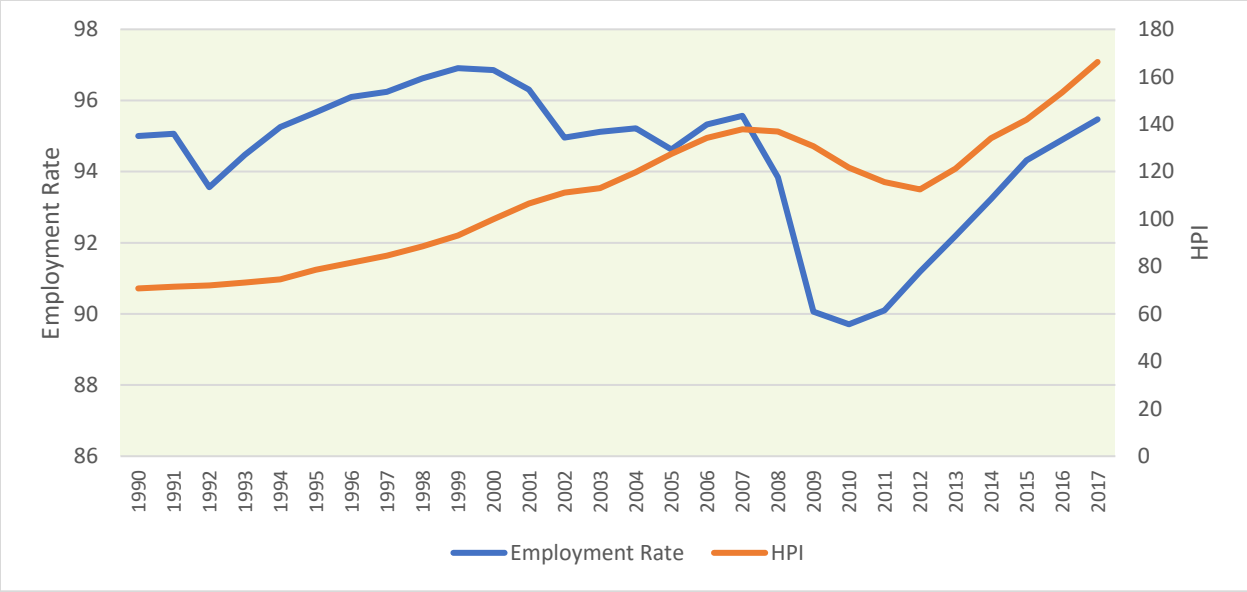


Figure 52: Employment Rate versus 30075 HPI

Source: United States Bureau of Labor Statistics

These simple charts also provide some insight into the relationship between time series. For example, from looking at Figure 47, it appears that the house price index for zip code 30075 tends to move along in time with the Case-Shiller metropolitan level home price index.

This chapter advances previous research by using cointegration as a technique to visualize and compare neighborhoods in terms of their integration into the economy of the metropolitan area as a whole. This is important as it advances research by incorporating local level cointegration analysis and the study of outlying relationships.

The dynamic causal relationship between local house prices and macroeconomic indicators has not been studied before and the detailed investigation of the spatial pattern of neighborhoods that do not experience cointegration with these variables has also been neglected. This is important because there are likely many significant disparities in the socio-economic conditions across regions making some neighborhoods less susceptible to macroeconomic shifts.

The first step that must be taken is to test all of the time series being used in this study to determine if the series are stationary or non-stationary. In order to move forward with our tests of cointegration, time series must be nonstationary. We accomplish this by implementing an Augmented Dickey-Fuller test for unit root. Lag lengths are chosen using AIC criteria with a max length of 3 given that we have yearly time series (Enders 2010). For this test, the alternative hypothesis is stationarity. As we can see from Table 38, we can conclude that our time series possess non-stationarity and thus we are able to proceed with our cointegration tests.

We then wish to understand the relationship between two time series. If there is truly a relationship between two time series that is constant through time, then the distance between the two series will be constant. Hence, the difference between these two time series becomes a stationary process.

Table 38: Testing for Non-Stationarity of Time Series Variables

Time Series	ADF	p value
Case-Shiller HPI	-2.1578	0.5122
Civilian Labor Force	-1.8251	0.6395
Per Capita Income - 2000 dollars	-1.3068	0.8365
Per Capita GDP - 2000 Dollars	-0.4258	0.7911
GDP - 2000 dollars	-2.6165	0.3375
Building Permits/Housing Starts	-2.1509	0.5148
Employment Rate	-2.0614	0.549
Total Employment	-2.3414	0.4419
Example - Fulton County Employment	-2.5002	0.3818
Example - 30075 HPI	-2.4293	0.4083

Once this occurs, we can say that the two series are cointegrated. We can then posit that there is some type of true relationship between the two time series that holds through time.

This is accomplished by incorporating Johansen tests for cointegration between time series. All Johansen cointegration tests that were part of the study were tested at levels. The resulting levels of cointegration are then visualized and assessed for their spatial distributions. Unfortunately, for this study, we did not see strong spatial dynamics in this relationship. Perhaps if we were able to use house price indices at the block group or tract level, we would have experienced stronger spatial patterns.

Results

Below, we have some resulting test statistics from the Johansen cointegration tests between our example zip code and our economic fundamentals time series (Table 39 and Table 40). We conduct this analysis for each zip code in our study area to determine the level of cointegration. As discussed previously, it appears as though this zip code's house prices are significantly cointegrated with metropolitan level house prices as seen through the Case-Shiller house price index. Overall, after going through all the results for all 222 zip codes in our study area, we do not find clear trends in neighborhoods that are cointegrated with our macroeconomic fundamentals. Exploring these results with different lag specifications may yield different results.

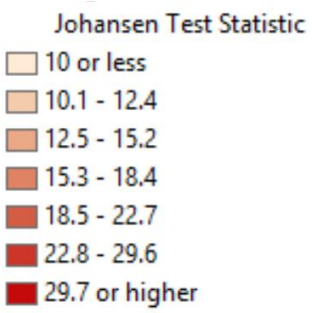
We then visualize these test statistics to investigate if there are spatial patterns of cointegration across our metropolitan area for different economic fundamentals. Unfortunately, as we can see from Figure 53 to Figure 61 below, there is not a clear spatial pattern in regards to the significance of cointegration between neighborhood level house prices and these macroeconomic fundamentals.

Table 39: Johansen Cointegration Test Statistics

Example - Cointegration with 30075 HPI	Test Statistic - 30075 example
Case-Shiller HPI (k=2)	18.27
Civilian Labor Force (k=2)	18.7
Per Capita Income - 2000 dollars (k=3)	38.06
Per Capita GDP - 2000 dollars (k=2)	17.13
GDP - 2000 dollars (k=3)	18.02
Building Permits/Housing Starts (k=2)	9.25
Employment Rate (k=2)	13.71
Total Employment (k=3)	12.88
County Employment - Fulton County in this Example (k=3)	22.06

Table 40: Critical Values

Critical Values	10 percent	5 percent	1 percent
r=0	13.75	15.67	20.20



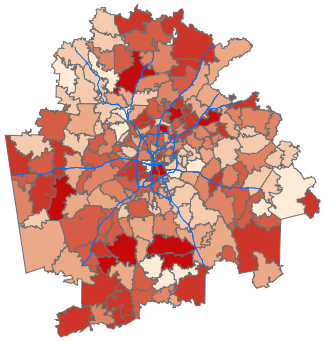


Figure 53: County Employment

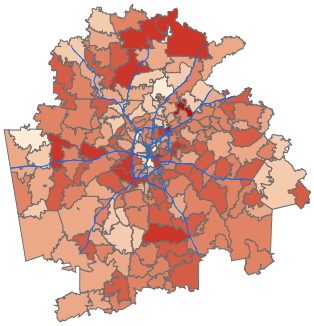


Figure 54: Total Employment

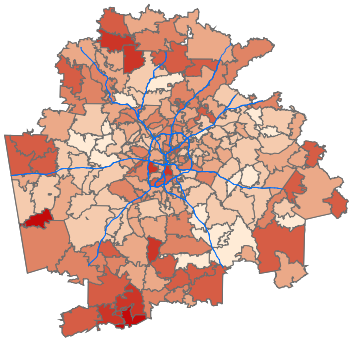


Figure 55: Employment Rate

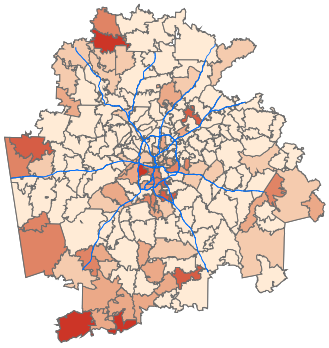


Figure 56: Building Permits/Housing Starts

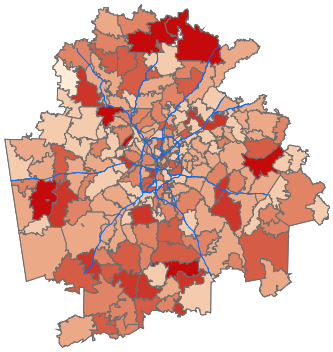


Figure 57: GDP

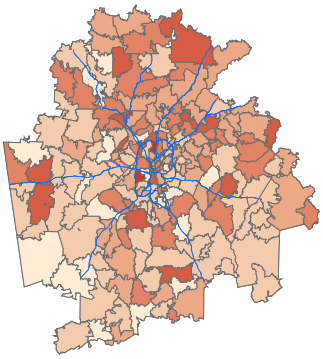


Figure 58: GDP Per Capita

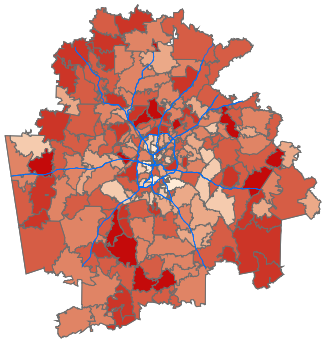


Figure 59: Per Capita Income

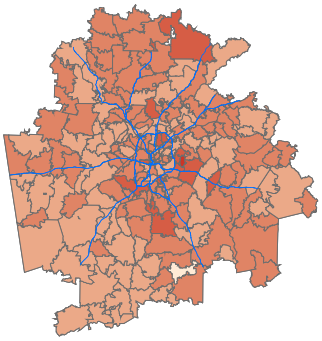


Figure 60: Civilian Labor Force

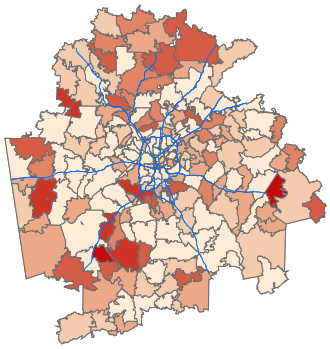


Figure 61: Case-Shiller HPI

While we did not discover strong spatial patterns across zip codes in relation to their level of cointegration, we investigate further by testing the differences in means between various attributes of these zip codes. We wished to discover the attributes of neighborhoods that were significantly cointegrated with macroeconomic fundamentals at the 10 percent level versus those neighborhoods that were not. The results of this investigation can be found in Appendix E.

Limits to Study/Future Research

The limits to this study largely fall within the methodology and data selection process. While we believe that this chapter had a good motivation, it is clear that results are not as expected. As discussed in previous sections, much of what we do in this chapter is reliant on the chosen lag length and we may find significantly different results under different scenarios. Additionally, more data is needed in these models to better understand how local house prices move in time with macroeconomic conditions. The choice of variables may not have been ideal and additional exploration into our model specifications and variable choices is needed to improve our understanding. In addition, it is likely important to try to include interest rates in future model specifications.

Conclusion

This chapter incorporated cointegration techniques to investigate the dynamic causal relationship between neighborhood house values, local employment opportunities and a variety of metropolitan area level economic indicators.

These methods were used to investigate the relationship between neighborhood house prices and local employment along with the potential cointegrating relationship between local house prices and macroeconomic indicators at the metropolitan area level.
It is important to investigate these processes because the geographical distribution of house prices will likely contain different economic conditions across regions which may not be aligned with metropolitan area macroeconomic conditions and indicators.

This would have allowed for an understanding of if there are certain kinds of neighborhoods in certain parts of the metropolitan area where house values do not move with metropolitan area level economic indicators. Unfortunately, results do not show a clear picture regarding cointegration in our study area.

Appendix E: Difference in Means

Table 41: Case-Shiller HPI

Variable	Mean of Zip Codes not Significantly Cointegrated	Mean of Zip Codes Significantly Cointegrated	T Statistic	P Value
Population Density per Square Mile	1621.402	885.9448	2.4936	0.01345
Establishments	617.6024	429.4545	2.2369	0.02734
Percent Residential	32.90977	26.64621	1.7165	0.08928
Percent Owned	67.0102	78.15431	-4.8428	2.888e-06
Population	19900.3	18817.44	0.40247	0.6884
Households	10278.45	9229.673	0.84604	0.3999
Vacant Households	1109.482	910.8545	1.4038	0.1638
Vacancy Rate	12.0457	10.7	1.8568	0.06542
Median Year Built	1986	1990	-2.5244	0.01262
Percent of Households in Poverty	10.35379	9.11	1.1586	0.2489
Median Income	47441.83	49270.35	-0.71527	0.476
Distance to CBD	131357.3	178099.8	-3.8707	0.0001862
Bus Stops	55.7656	13.4	4.0236	8.037e-05
Rail Stations	0.2289157	0	4.6883	5.742e-06
Distance to Nearest Public Transportation Facility	39453.86	57222.11	-2.2695	0.0255
Distance to Nearest Highway	28912.21	34156.69	1.0075	0.315
Observations	166	55		

Table 42: Civilian Labor Force

Variable	Mean of Zip Codes not Significantly Cointegrated	Mean of Zip Codes Significantly Cointegrated	T Statistic	P Value
Population Density per Square Mile	265.1054	1482.436	-4.4472	0.0001591
Establishments	128.75	587.3803	-7.3062	3.6e-07
Percent Residential	12.90915	32.04362	-7.126	1.135e-06
Percent Owned	75.37813	69.5735	1.0708	0.3155
Population	7259.125	20095.47	-6.2551	2.439e-05
Households	3499.75	10262.24	-7.8762	4.681e-07
Vacant Households	479.625	1081.85	-3.8471	0.00327
Vacancy Rate	12.0978	11.69213	0.27876	0.7874
Median Year Built	1986	1987	-0.25871	0.8026
Percent of Households in Poverty	11.81672	9.989	0.81725	0.4379
Median Income	39636.25	48207.15	-2.5351	0.03145
Distance to CBD	195318.5	141024.7	1.856	0.1024
Bus Stops	22.375	46.07981	-1.1374	0.2854
Rail Stations	0	0.1784	-4.6239	6.543e-06
Distance to Nearest Public Transportation Facility	81220.91	42473.19	2.1226	0.06861
Distance to Nearest Highway	50726.96	29447.09	2.8711	0.02328
Observations	8	213		

Table 43: Per Capita Income - 2000 Dollars

Variable	Mean of Zip Codes not Significantly Cointegrated	Mean of Zip Codes Significantly Cointegrated	T Statistic	P Value
Population Density per Square Mile	3163.126	1124.778	1.9999	0.05364
Establishments	470.8235	588.9519	-1.2803	0.2058
Percent Residential	41.17697	29.56442	2.4544	0.01818
Percent Owned	62.18934	71.1644	-2.1532	0.03712
Population	19481.06	19658.03	-0.076351	0.9394
Households	10379.47	9951.62	0.37781	0.707
Vacant Households	1302	1016.059	1.6471	0.1065
Vacancy Rate	13.42544	11.40049	1.5144	0.1382
Median Year Built	1981	1988	-2.3016	0.02734
Percent of Households in Poverty	11.09624	9.866802	0.80865	0.4231
Median Income	46915.26	48075.37	-0.32412	0.7474
Distance to CBD	84930.47	153546.3	-5.2813	2.239e-06
Bus Stops	85.73529	37.85561	2.1152	0.04075
Rail Stations	0.4411765	0.1229947	2.0282	0.04996
Distance to Nearest Public Transportation Facility	17898.76	48598.93	-5.0396	2.46e-06
Distance to Nearest Highway	15327.24	32924.7	-2.8847	0.005735
Observations	34	187		

Table 44: Per Capita GDP

Variable	Mean of Zip Codes not Significantly Cointegrated	Mean of Zip Codes Significantly Cointegrated	T Statistic	P Value
Population Density per Square Mile	1141.749	1824.595	-1.6949	0.0927
Establishments	429.2	755.125	-4.0104	9.242e-05
Percent Residential	28.07939	35.61083	-2.2918	0.02299
Percent Owned	71.86233	67.07697	1.7083	0.08942
Population	17382.14	22558.76	-2.4135	0.01671
Households	8806.872	11593.71	-2.7747	0.006043
Vacant Households	1012.592	1121.844	-0.90097	0.3686
Vacancy Rate	12.21	11.03033	1.5383	0.1255
Median Year Built	1986	1988	-1.4004	0.163
Percent of Households in Poverty	11.11965	8.67	2.4321	0.01584
Median Income	44683.18	52081.41	-3.0484	0.002681
Distance to CBD	153289.1	129579.8	2.055	0.04111
Bus Stops	45.192	45.26042	-0.0050716	0.996
Rail Stations	0.144	0.2083333	-0.84003	0.402
Distance to Nearest Public Transportation Facility	52247.21	32975.59	2.8814	0.004354
Distance to Nearest Highway	33812.84	25535.85	4.7415	4.222e-06
Observations	125	96		

Table 45: GDP

Variable	Mean of Zip Codes not Significantly Cointegrated	Mean of Zip Codes Significantly Cointegrated	T Statistic	P Value
Population Density per Square Mile	1770.95	1201.181	1.3663	0.1746
Establishments	598.8913	550.7287	0.58519	0.5591
Percent Residential	34.43991	29.148	1.6161	0.1077
Percent Owned	69.86246	69.72739	0.050297	0.9599
Population	20951.11	18689.19	1.0288	0.3049
Households	10430.52	9722.845	0.68482	0.4943
Vacant Households	1049.239	1067.76	-0.1519	0.8794
Vacancy Rate	11.12519	12.12392	-1.3425	0.1808
Median Year Built	1987	1986	0.56793	0.5707
Percent of Households in Poverty	9.2027	10.66446	-1.4456	0.1498
Median Income	50149.49	46290.39	1.6383	0.1029
Distance to CBD	138079.3	146492.3	-0.71332	0.4765
Bus Stops	45.03261	45.35659	-0.024879	0.9802
Rail Stations	0.08695652	0.2325581	-2.1834	0.03028
Distance to Nearest Public Transportation Facility	41793.27	45361.06	-0.49698	0.6198
Distance to Nearest Highway	27675.96	32029.9	1.5432	0.1252
Observations	92	129		

Table 46: Building Permits/Housing Starts

Variable	Mean of Zip Codes not Significantly Cointegrated	Mean of Zip Codes Significantly Cointegrated	T Statistic	P Value
Population Density per Square Mile	1469.071	1263.467	0.63689	0.5258
Establishments	623.2819	271.6667	5.0242	2.745e-06
Percent Residential	31.49589	30.52533	0.21108	0.8338
Percent Owned	69.92166	68.99718	0.27393	0.7853
Population	20223.1	16256.55	1.3943	0.17
Households	10503.77	7246.848	2.583	0.01286
Vacant Households	1060.601	1056.909	0.018432	0.9854
Vacancy Rate	11.35348	13.688	-2.5532	0.01369
Median Year Built	1988	1980	3.8401	0.0003984
Percent of Households in Poverty	9.4504	13.50564	-2.8428	0.006778
Median Income	49339.24	39679.85	3.6514	0.0005863
Distance to CBD	140718	155933.7	-0.72981	0.47
Bus Stops	37.82447	87.36364	-1.6951	0.099
Rail Stations	0.1542553	0.2727273	-0.90584	0.3707
Distance to Nearest Public Transportation Facility	40316.36	64153.97	-1.9051	0.06447
Distance to Nearest Highway	28591.15	39482.09	0.10597	0.916
Observations	188	33		

Table 47: Employment Rate

Variable	Mean of Zip Codes not Significantly Cointegrated	Mean of Zip Codes Significantly Cointegrated	T Statistic	P Value
Population Density per Square Mile	1417.727	1456.389	-0.10995	0.9126
Establishments	593.4563	550.9831	0.53608	0.5925
Percent Residential	34.08794	28.96191	1.5857	0.1143
Percent Owned	72.7125	67.22705	2.0896	0.03782
Population	23021.91	16670.77	3.0172	0.002863
Households	11855.05	8413.432	3.4795	0.0006097
Vacant Households	1182.544	953.1271	1.8928	0.0597
Vacancy Rate	11.01744	12.32	-1.6938	0.09184
Median Year Built	1988	1986	1.6448	0.1015
Percent of Households in Poverty	8.99098	10.98553	-1.9867	0.04821
Median Income	49435.05	46554.26	1.2328	0.219
Distance to CBD	132603	152056.7	-1.7181	0.08729
Bus Stops	32.75728	56.10169	-1.8071	0.07225
Rail Stations	0.1359223	0.2033898	-0.91286	0.3623
Distance to Nearest Public Transportation Facility	32187.34	54078.48	-3.3115	0.001103
Distance to Nearest Highway	25527.45	34311.17	-0.43061	0.6672
Observations	103	118		

Table 48: Total Employment

Variable	Mean of Zip Codes not Significantly Cointegrated	Mean of Zip Codes Significantly Cointegrated	T Statistic	P Value
Population Density per Square Mile	1868.444	1243.139	1.1692	0.246
Establishments	597.6667	558.5724	0.42681	0.6703
Percent Residential	31.74239	31.17328	0.16467	0.8694
Percent Owned	69.60746	69.86358	-0.086671	0.9311
Population	19447.51	19714.01	-0.11388	0.9095
Households	9612.13	10201.43	-0.53438	0.594
Vacant Households	1002.188	1086.316	-0.60313	0.5476
Vacancy Rate	11.84366	11.64507	0.2222	0.8246
Median Year Built	1986	1987	-0.73707	0.4624
Percent of Households in Poverty	9.914254	10.12027	-0.18074	0.8569
Median Income	48464.64	47639.16	0.30981	0.7573
Distance to CBD	155216.3	137440	1.3473	0.1805
Bus Stops	49.73913	43.17105	0.41744	0.6772
Rail Stations	0.1594203	0.1776316	-0.21955	0.8266
Distance to Nearest Public Transportation Facility	51974.35	40199.52	1.475	0.143
Distance to Nearest Highway	30476.65	30099.72	2.9594	0.00398
Observations	69	152		

Table 49: County Employment

Variable	Mean of Zip Codes not Significantly Cointegrated	Mean of Zip Codes Significantly Cointegrated	T Statistic	P Value
Population Density per Square Mile	963.1205	1636.39	-2.2884	0.02307
Establishments	403.7692	640.3654	-3.1978	0.001646
Percent Residential	28.05692	32.72348	-1.3401	0.1826
Percent Owned	75.9593	67.21042	3.5799	0.0004422
Population	19679.65	19610.46	0.028959	0.9769
Households	9942.615	10048.62	-0.094519	0.9249
Vacant Households	1068.862	1056.378	0.089586	0.9288
Vacancy Rate	10.90431	12.04804	-1.4921	0.1378
Median Year Built	1989	1986	1.6425	0.1027
Percent of Households in Poverty	9.4613	10.3037	-0.81581	0.4159
Median Income	47545.08	48043.48	-0.23309	0.8159
Distance to CBD	160851.1	135547.9	2.0356	0.04389
Bus Stops	38.55385	48	-0.66285	0.5086
Rail Stations	0.15384	0.1794872	-0.3094	0.764
Distance to Nearest Public Transportation Facility	53894.73	39701.28	1.9027	0.05939
Distance to Nearest Highway	33609.41	28804.07	3.7586	0.0003121
Observations	65	156		

Chapter 10: Conclusion

The significance of this study is that it focuses on the extent to which the urban form may contribute to overall economic stability as seen through the stability of residential property values. This research builds on past research by 1) incorporating more detailed and accurate neighborhood measures, 2) contributing to the cointegration and time series literature by conducting cointegration at a very local level and 3) assessing the impact that neighborhood, demographic and economic attributes at the local level may have on the long-term stability of property values in our urban areas.

The framework created in this study is thus able to be incorporated by cities and other municipalities using their own data and assumptions to assess the impact that these neighborhood attributes have on their property values. This allows policy makers to gain an understanding regarding how to potentially create and maintain urban designs and neighborhood attributes that promote the long-term stability of residential property values and thus more economically sustainable communities.

By understanding price changes, valuations across household types and other important aspects of the local house price dynamics, steps can be taken to improve community creation. The contributions from the project include a greater understanding of the role that neighborhood attributes and other factors have on property values. This is valuable given that a home is the biggest investment most people will make in their lives.

Several chapters in this research also expand on the economic research of the last few years by looking at local, within city fluctuations in residential property values and the extent to which the way we structure our urban areas may leave some neighborhoods more economically vulnerable while other neighborhoods more resilient when it comes to dealing with macroeconomic shifts in home prices.

The results from this project would be of interest to researchers in a wide range of fields including geography, civil engineering, real estate, urban planning, finance and economics.

This research project also fills in gaps in the housing and urban planning literature where local dynamics and the heterogeneity in the temporal stability of residential property values has not been adequately addressed.

The results of this study are also likely to be of interest for many policy makers as well as decision makers outside of the academic world such as city planners and those involved in housing policy decisions.

Previous research has been limited regarding our understanding of these processes by typically only looking at these house price dynamics at the national or metropolitan area level. Thus, local level home price dynamics have not been fully explored. This presents an opportunity for us to incorporate methods that allow for a more in depth understanding of the local spatial and temporal dynamics of residential property values.

Many local government jurisdictions are currently dealing with uncertain budgets and neglected neighborhoods because of the housing crash that occurred in the early part of the 21st century. It is hoped that this research framework and results will serve to inform the decisions of city governments as to the localized spatial and temporal house price dynamics along with these dynamics across different neighborhood and household composition types.

This project will ideally lead to better designs and a more complete understanding of how local communities can help mitigate some of the sources of residential property value fluctuations in the future. Several of the chapters in this research also expand on the economic research of the last few years by looking at local, within city fluctuations in residential property values and the extent to which the way that we structure our urban areas may leave some neighborhoods more vulnerable while other neighborhoods more resilient when it comes to adjusting to macroeconomic shifts in home prices.

The issue of residential property values is an important one as we are still dealing with the effects of the recent housing bubble and burst. Cities are not collecting as much tax revenue as predicted because of depressed housing prices and the global economy has remained sluggish at least in part because of it. This development has also disrupted entire economies of cities and disrupted generational wealth transfer.

Economists and others have studied the causes of the instability in property values in recent years from many angles. Once again, that type of research is perhaps more influential in explaining what happened in the housing market during the earliest part of the century. Yet, what is missing is a detailed level analysis of how our spatial structure of cities may contribute to this instability or stability in residential property values and a better understanding of their local dynamics. While economists are correct, there is still room for research on the role that local factors may have played or will play in the determination of residential property values. Even within metropolitan areas, there may have been a difference in magnitude of property value fluctuation.

While not all of the research revealed interesting results, findings from this research highlight the temporal trends in house prices in this region. We see clear trends in house prices through the period of the housing boom and housing bust periods.

In addition, we also confirm some expected results concerning neighborhood factors that lessen the magnitude of price declines in the region. For example, neighborhoods with higher incomes that are more centrally located generally did not experience as severe of price declines during the housing bust as other neighborhood types in our study area. Expanding on these results will allow us to better understand how neighborhood attributes may serve as stabilizing forces during periods of significant price changes. While more research is needed, overall it appears as though neighborhoods that are more centrally located, with better access to transportation and other urban amenities were somewhat shielded from the most severe impacts of the housing bust in the Atlanta area.

Chapter 11: Limits to Study/Potential for Future Research

It is clear that the research presented here can be extended in many ways and there are many potential paths for future research that continues with similar themes. For example, we could incorporate data from the American Community Survey for the years 2005-2013 and additional data from the Atlanta Regional Commission to investigate how household valuations for structure and neighborhood amenities vary depending on attributes of the household. In other words, we could explore how different household types possess different willingness to pay for certain amenities. For example, households with children may place a premium on certain structure and neighborhood attributes (such as percent of neighborhood households with children) that may be different from households without children.

This would allow for a very detailed investigation concerning household composition types and their valuation of amenities. Very little research has been conducted at this level of detail due to severe data limitations, particularly regarding the ability to know where the household lives at a very detailed level.

However, it is important to understand that valuations are likely heterogeneous across households. Understanding this in more detail could potentially provide important insights to city planners and other policy makers. For example, if the valuation and willingness to pay for proximity to public transportation facilities is different for households with certain vehicle ownership to worker ratios compared to others, this could have important implications for planning projects.

In addition, future work should also include an investigation into whether these willingness to pay values are temporally stable during periods of macroeconomic shock to the housing market. This could provide detailed insight into whether willingness to pay for structure and neighborhood amenities are stable over time. The temporal stability of valuations may be an important element to understand for long-term planning.

In addition, another potential research avenue was experimented with to understand relationships between prices and travel patterns with the goal of using household travel patterns as an additional component in identifying housing submarkets. The Secure Transportation Data Center at the National Renewable Energy Laboratory was kind enough to provide access to detailed travel survey data for the Atlanta region. Given that we also obtained detailed property transaction data for the region, it was attempted to match this information to explore general relationships between house prices, household attributes, household travel patterns and potential housing submarkets.

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Vita

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