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Spacial analysis of foreclosure and neighborhood characteristics in Miami metropolitan area, Florida

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SPATIAL ANALYSIS OF FORECLOSURE AND NEIGHBORHOOD CHARACTERISTICS IN MIAMI METROPOLITAN AREA, FLORIDA

An Abstract of a Thesis

Submitted

in Partial Fulfillment

of the Requirements for the Degree

Master of Arts

Adejoh Emmanuel Ogbe

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ABSTRACT

In 2013, the State of Florida had 13 of the top 20 metropolitan statistical areas (MSA) with the highest foreclosure rate in the country. Despite the high ranking, extensive research on foreclosure has yet to be carried out within the Miami-Fort Lauderdale-Pompano Beach MSA. This research is a foray into an uncharted territory to understand the relationship between foreclosure and neighborhood characteristics in the Miami metropolitan area (MMA) within Miami-Dade County. The study was conducted in two phases: The first phase was to identify the foreclosure pattern in the MMA from 2010-2013 by implementing the use of spatial analysis such as nearest neighbor analysis, spatial autocorrelation, and cluster and outlier analysis. The statistical analysis used also included correlation analysis, principal component analysis, and regression analysis. The dataset used contained foreclosure count from 2010-2013 and the 2010 census tract level data on neighborhood characteristics such as ethnicity and racial compositions, socioeconomic, demographic, and housing. The spatial and statistical analysis carried out was used to identify the relationship between foreclosure and the neighborhood characteristics. The second phase studied the effect of foreclosure on crime in the city of Miami. Crime data from 2011-2012 was used to study the relationship between crime, foreclosure, and the above mentioned neighborhood characteristics. The statistical analysis carried out in this phase included correlation analysis and regression analysis. Results of the study showed that in MMA, the relationship between foreclosure and other neighborhood characteristics was insignificant. However, the result for the spatial pattern of foreclosure in MMA showed that houses of similar market values were clustered in the

northeastern, southeastern and central areas. Additionally, areas dominated by the African American population showed low economic activity and high foreclosure concentration compared to other areas, which could be an influence of subprime lending. Finally, foreclosure alone had no impact on crime whatsoever, but vacancy rate was statistically significant to property crime in the city of Miami. These findings are important in understanding foreclosure distribution and clustering patterns in MMA

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I dedicate this thesis to my mother.
Whatever I have achieved today is because
of her unwavering faith in me. She always
provides the best of everything I ask for.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Foreclosure is taking possession of a property as a result of default in payment. Foreclosure occurs when a borrower or a mortgage holder fails to meet the deadline for the payment of a property that was acquired on a loan from a mortgage lender. This chapter covers background information on housing foreclosure, the knowledge gap of foreclosure studies in the United States and in Florida, the study goal and objectives, and importance of this study.

1.2 Research Background

The majority of homeowners are not a stranger to the term “foreclosure,” considering it has been a huge problem for decades across a large number of communities, cities, and counties in the United States. Studies from different disciplines have been carried out on housing foreclosure and how its social implications have affected the integral system of our daily lives (Arnio & Baumer, 2012; Baxter & Lauria, 2001; Cui, 2010; Delgadillo & Erickson, 2006; Demyanyk & Hemert, 2009; Immergluck & Smith, 2005; Immergluck & Smith, 2006; Katz, Wallace, & Hedberg, 2011; Mummolo & Brubaker, 2008). The housing market timeline for the past decade shows the transition from the housing boom to the bubble burst, which in turn led to foreclosure increase in the United States. Years 2001-2005 recorded the period of the United States housing bubble, which affected the housing market in over half of the American states in subsequent years (Byun, 2010). It was the period when the market value of houses rose to a substantial level, employment in the construction sector grew notably, and also there was an increased interest for investments in the real estate market (Byun, 2010). In 2004-2005, Arizona, California, Florida, and Nevada recorded increased house prices in excess of 25% (Olesiuk & Kalser, 2009; Xu & Zhang, 2012). These states are commonly referred to as the "Sand States." They were known for having the highest market price increase during the housing boom in the last decade (Olesiuk & Kalser, 2009; Sailer, 2009). 2006 records the peak of the housing bubble, but from 2006-2007 the value of houses began to depreciate. This was known as the bubble burst.

The bursting of the real estate bubble, according to general consensus, triggered the financial crisis of 2007 (Baker, 2008; Davies, 2014; Wallison, 2009). There was a direct impact not only on home valuations, but also on the nation's mortgage markets, home builders, real estate, and home supply retail outlets. For example, roughly a quarter of the jobs created since the 2001 boom were in construction, real estate, and mortgage finance (Byun, 2010; Laperrierre, 2006). Sand States, which benefitted from the price increase in the wake of the housing boom, were hit the hardest after the market crashed (Immergluck, Alexander, Balthrop, Schaeffing, & Clark, 2011; Olesiuk & Kalser, 2009; Sailer, 2009). Job loss was apparent in the United States after the housing bubble burst not only in states that enjoyed the housing boom but all over the country, which subsequently resulted in increased foreclosures (Laperrierre, 2007). RealtyTrac, the leading online marketplace for foreclosure properties in the United States, recorded increased foreclosure rates from 2006-2008 among U.S. homeowners. Foreclosure total at the year-end of 2005 was 855,000 houses (RealtyTrac, 2007). In the fourth quarter of 2006, home sales fell drastically and foreclosure filing rose to 1,259,118 with a foreclosure rate of one foreclosure filing for every 92 U.S. households (RealtyTrac, 2007).

The year 2007 marked the beginning of the U.S. subprime mortgage crisis. Subprime loans are given to borrowers who have a weakened credit history. The subprime industry collapsed with more than 25 subprime lenders declaring bankruptcy, announcing significant losses, or putting themselves up for sale. By year-end of 2007, there were 1,285,873 foreclosures filed (RealtyTrac, 2008).

The highest numbers of foreclosure occurred in 2009, and Florida registered the nation's third highest foreclosure rate with 5.93% of its housing units receiving at least one foreclosure filing during the year (Blomquist, 2010). In the same year, the Troubled Asset Relief Program (TARP) bailout bill was passed, allowing the write off of 7-9 million mortgages to help prevent foreclosure (Amadeo, 2010; United States Department of Treasury, 2011). After TARP was implemented, a decrease of 29% of the total foreclosed houses was reported in December 2010 from the previous year total. Foreclosure activities in Florida dropped by 22% from its previous year (RealtyTrac, 2011). RealtyTrac recorded their biggest annual drop in foreclosure activity in the United States since it began publishing foreclosure reports in January 2005 (RealtyTrac, 2011). Foreclosure activity in 2012 was 33% below the 2011 total and 51% below the 2010 total. A total of 1,836,634 properties received foreclosure notices during the year (RealtyTrac, 2013). This decrease in foreclosure was not celebrated across the United States, especially in major metropolitan areas in Florida, Nevada, California, New Jersey, etc. that were initially heavily affected. In 2012, Florida posted the nation's highest foreclosure rate for the first time since the housing crisis began with 3.11% of housing units (1 in 32) receiving a foreclosure filing (RealtyTrac, 2013).

According to a 2013 analysis of metropolitan serious delinquency data (Center for Housing Policy, 2014), extremely high foreclosure rates still persist in Florida and many Northeastern metro areas with rates well above normal nationwide rates. The State of Florida alone contained 13 of the top 20 metropolitan statistical areas (MSA) with the highest foreclosure rate in the country (Center for Housing Policy, 2014). Figure 1 shows the distribution of the top ranking foreclosure rates across United States metropolitan areas. With the background information provided in this section, it is inescapable to notice the need for understanding the foreclosure crisis and the impact it could possibly have on large and small scale communities. Florida, compared to other states in the United States, serves as a pacesetter for serious foreclosure cases; this provides the optimal destination for studying foreclosure.

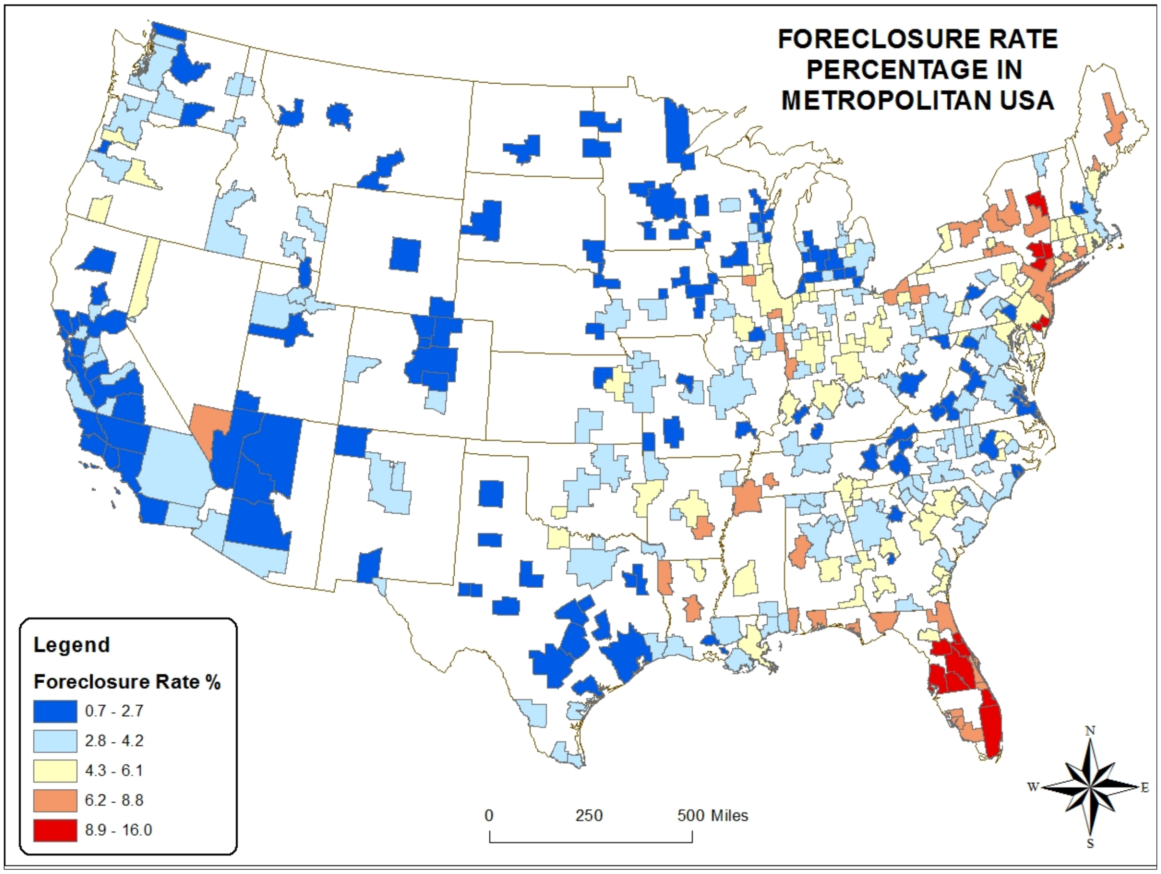

Figure 1. Foreclosure rate in metropolitan USA

1.3 Knowledge Gap

Majority of the studies in foreclosure have included the causal factors that are responsible for the housing crisis and the foreclosure increase in the United States (Brevoort & Cooper, 2010; O'Toole, 2008). While tremendous knowledge has been devoted to exploring the trigger events responsible for the housing crisis, little has been done in studying the spatial distribution of foreclosure and its relationship to other neighborhood characteristics. In 2008, among the 50 states in the United States, California, Florida, Nevada, and Arizona had 62% of the country's foreclosure (Lucy, 2010). In Florida, the metropolitan areas of Miami, Orlando, and Tampa-St. Petersburg contained 62% of all foreclosures (Lucy, 2010). Bearing in mind the severe delinquency rate of foreclosure in Florida since the housing crisis, one has to wonder why no extensive research has studied its spatial distribution in the MMA region; one of the state's most populous metropolitan areas. This research is aimed at exploring the existing gap by studying the spatial pattern of foreclosure as well as its relationship to other neighborhood characteristics in the MMA.

Also, very few studies bridge the gap between academic disciplines. This study has implemented the use of theories and concepts that are popular among sociologists and criminologist to assist in tackling geographical problems. The spatial analysis, statistical analysis, and theories such as the social disorganization theory and the concentrated disadvantage theory were combined in this study for the sole purpose of identifying the housing foreclosure's relationship to neighborhood characteristics; neighborhood characteristics such a crime, population, education attainment,, housing, poverty level in the neighborhood, family income, and racial composition.

To achieve this task, the following hypotheses will be addressed:

Hypothesis 1:

There is a higher concentration of foreclosure among the African American neighborhoods and low income neighborhoods. Research indicates that block groups or tracts with the highest proportion of foreclosure are commonly present among clusters of

African American population and low income neighborhoods (Baxter & Lauria, 1998; Chan, Gedal, Been & Haughwout, 2013; U.S. Department of Housing and Urban Development, 2000). The lack of certain socioeconomic stimulus, for example, education attainment, is a common trait among those block groups or tracts that may exhibit a higher proportion of foreclosure increase. Given the spatial segregation pattern by race or ethnicity of most U.S. Cities, the first hypothesis (H1) will be tested on the major racial composition in the MMA to see if any race in particular exhibits evidence of a higher count of foreclosure clustering than the rest.

Hypothesis 2:

Increase in foreclosure-led vacant houses leads to increase in crime. The second hypothesis (H2) will be tested on the relationship between foreclosure-led vacant houses and crime to determine if the increase in vacant properties leads to an increase in crime. Online statistics of the index crimes in the city of Miami (http://www.neighborhoodscout.com/fl/miami/crime/, 2014) shows that the crime rate in the city of Miami (violent and property combined) is higher than the national average (Table 1). Violent offenses tracked according to uniform crime report (UCR) standard are: murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault. According to the most recent neighborhoodscout's report, the chance of becoming a victim of one of these crimes in Miami is 1 in 85. Property crimes tracked are burglary, larceny, motor vehicle theft, and arson. In Miami, the chance of becoming a victim of a property crime is 1 in 19, which is a rate of 54 per one thousand populations (http://www.neighborhoodscout.com/fl/miami/crime/, 2014). This poses the question of whether the high crime rate in the city of Miami can be attributed to foreclosed, unmonitored buildings. To answer the question, a multivariate analysis in the following sections will help test whether we should accept the hypothesis that a relationship exists between foreclosure-led vacant houses, and crime.

Table 1. *2014 statistics on index crime in Miami.*

		United States	US rate per 1,000	Miami	Miami rate per 1,000
Violent Crime	Murder	14,827	0.05	69	0.17
	Rape	84,376	0.27	65	0.16
	Robbery	354,522	1.13	2,096	5.06
	Assault	760,739	2.42	2,626	6.34
Property Crime	Burglary	2,103,787	6.7	4,255	10.27
	Larceny	6,150,198	19.59	15,305	36.94
	Motor Vehicle theft	721,053	2.3	2,711	6.54

Among criminologists and sociologists exists theories dating back to the 90s which depict the influence of neighborhood characteristics on crime distribution. Shaw and McKay's theory of community social disorganization discusses how the physical deterioration of a neighborhood could lead to increase in crime (Shaw, Zorbaugh, McKay, & Cottrell, 1929; Shaw & McKay, 1942). The theory pointed out that delinquency was not caused at the individual level, but was considered to be the normal response of normal individuals to abnormal social conditions (Wong, 2011). According to Shaw and McKay (1942), social disorganization circles around three sets of variables: (1) physical status, (2) economic status, and (3) population composition. The physical status was measured using population change, vacant and abandoned housings, and proximity to industry. Their study showed that areas with high delinquency rates tended to be physically deteriorated, geographically close to areas of heavy industry, and populated with highly transient residents. The economic status was measured by the number of families receiving social assistance, the median rental price of the area, and the number of homes owned rather than rented. Their conclusion on the economic status variable indicated an increase in delinquency in areas with low economic status when compared to those areas with high economic status. They found that delinquency rates dropped as the median rental price of the area rose (Miller, 2009). In the analysis between the population composition and the delinquency rate, Shaw and McKay (1942) found that areas with the highest delinquency rates contained higher numbers of foreign-born and black heads of household. Delinquency rates in areas containing foreign-born and minority heads of households remained constant despite the total population shift to another group (Miller, 2009). The social disorganization theory has been one of the most revered theories in criminology, and was the foundation on which several other theories were birthed. The concept for some more recent criminology theories such as the broken window theory by Wilson and Kelling (1982), and the theory of concentrated disadvantage by Sampson and Wilson (1995) were adapted from the social disorganization theory. A similar conclusion identified in most theories post the social disorganization theory is that delinquency emanates from a series of events which begins from disorder in a neighborhood. This disorder can be linked to certain ethnic groups or minority population residing in a neighborhood with low economic conditions.

Introducing the social disorganization theory sheds light on the importance of both hypotheses considering how they pertain to the negative impact of housing foreclosure and crime to the minority population. Abandoned buildings are considered among one of the contributors to physical deterioration. The foreclosure crisis created an environment where the number of vacant and deteriorating houses as a result of foreclosure was on the rise, which could in turn lead to an increase in crime.

1.4 Purpose and Objective of the Study

In proceeding with this study, 3 questions come to mind (1) if clustering exists, what is the clustering pattern of foreclosure in MMA? (2) What is the relationship between foreclosure and other neighborhood characteristics at the census tract level? (3) Does increase in foreclosure lead to increase in crime in the City of Miami? The purpose of this study is to examine the spatial distribution of foreclosure by using neighborhood characteristics such as crime, housing, demographics, racial composition and other socio economic factors at the census tract level to achieve the following objectives:

1. Use nearest neighbor analysis, spatial autocorrelation, and cluster and outlier analysis on the MMA to show foreclosure distribution pattern in the study area

2. Use correlation analysis, principal component analysis (PCA), and regression analysis to check the relationships between housing foreclosures alongside the selected neighborhood attributes to determine if any relationship exists in the MMA.
3. Run a regression analysis with the selected neighborhood attributes and also with the vacancy period of the foreclosure process to study the relationship between foreclosure, vacancy, and crime in the city of Miami, Florida.

To this end, data of foreclosed houses in Miami-Dade County was collected between 2010-2013, along with 2011-2012 crime data, and a census tract level database for the year 2010 containing information on neighborhood characteristics.

1.5 Significance of Study

This research on foreclosure is significant in the following ways: (1) it explores the use of spatial analysis to geographically study the foreclosure distribution pattern in MMA. Also, it examines the relationship between foreclosure and crime in the city of Miami, both of which are above the national rate in the country. The outcome of this study can help the government and agencies responsible for alleviating the impact of foreclosure to focus on specific areas within Miami-Dade County where aid is crucial. Selected platforms such as the Miami-Dade County Regulatory Economic and Resources, the Miami-Dade County Assistance Program, and the U.S. HUD might find the information in this study useful for future foreclosure assistance in the county. (2) It contributes to the knowledge of foreclosure and its relationship with other neighborhood characteristics. Drawing the attention of the city planners to those neighborhood characteristics that might influence foreclosure decrease will help improve policy making decisions and fund allocations, which will in turn assist in reducing foreclosure. City planners have a better chance of tackling the rise of foreclosure when they know the deficient socioeconomic status or the particular development project to give special attention to.

1.6 Structure of the Thesis

This thesis is comprised of six chapters. Chapter 1 offers an introduction of the research background, knowledge gap, study objectives, and significance of study. Chapter 2 reviews previous works on causal factors responsible for foreclosure; especially subprime mortgage, methodology approaches to foreclosure studies from past literatures, and the use of GIS in foreclosure studies. Chapter 3 describes the two study areas as well as the methodology including data sources, software, and spatial and statistical analysis conducted in this research. Chapter 4 presents the results on the spatial, and statistical analysis carried out on MMA, and the city of Miami. Chapter 5 discusses the findings of this study. Finally, Chapter 6 concludes this study, addresses the limitations encountered, and suggests a future direction for further study.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter reviews studies that are relevant to the relationship between foreclosure and several selected neighborhood characteristics. This review addresses the following: (1) Causal factors that have been attributed to foreclosure increase in the United States. (2) The relationship between foreclosure and various attributes like crime, and also neighborhood characteristics like population, demographic, housing and racial composition.

2.2 Foreclosure Causal Factors in the United States.

Several factors such as job loss, unreasonable interest rate from subprime mortgage, death or severe health issues, etc. have been considered to be the leading causes of foreclosure on the national level (Brevoort & Cooper, 2010; Immergluck & Smith, 2006; O'Toole, 2008). According to Brevoort and Cooper (2010), the rise of foreclosures can be seen as a consequence of unforeseen borrower stress such as job loss, divorce, death, or an adverse health event, that renders borrowers insolvent. O'Toole (2008) discussed a base rate of foreclosure that happens during even the best economic times and housing markets. This base rate can largely be explained by the Five D's of Foreclosure: Death, Disease, Drugs, Divorce, and Denial.

Foreclosure increase has been attributed to different causal events and numerous contributing factors, but the most unswerving cause of foreclosure discussed is a result of the subprime mortgage crisis (Immergluck & Smith, 2004; Immergluck & Smith, 2006; Kaplan & Sommers, 2009; U.S. Department of Housing and Urban Development, 2000). In the past decade, many cities have experienced substantial growth in foreclosures, with particularly large increases occurring during the recent economic downturns (Immergluck & Smith 2006). However, the downward economic condition does not provide a sufficient explanation as to why some regions and cities have experienced particularly severe foreclosure increase. Most of the initial increase in foreclosures was driven by subprime loans due to the fact that these inherently risky loans had become a last resort for mortgage holders with low credit scores seeking to own a house. From 1994-2005, the subprime home loan market in the United States grew from $35 billion to $665 billion (Schloemer, Li, Ernst & Keest, 2006). Mortgage loans are broken into the following general categories: prime loans, alternate-A loans, and subprime loans. A prime loan is a low-risk loan, an alternate-A loan is a mid-risk loan, and a subprime loan is a high-risk loan. Serving those with weak payment capacity and low credit who would not qualify for a mortgage in the prime market, subprime mortgages have grown to be a major component of home financing.

Subprime mortgages have traditionally extended credit to borrowers who could not qualify for prime mortgages, and so by their very nature tend to have higher default risk than the prime mortgages (Chan et al., 2013). Immergluck and Smith (2005) discussed the effect of subprime mortgage in Chicago and how high-risk subprime lending resulted in substantially higher levels of foreclosures. Their study indicated the effect of subprime lending on foreclosures could be 20-30 times more than the effect of prime lending. Goldstein, McCullough, Parker, and Urevick-Ackelsberg, (2005) estimated that in Philadelphia, almost 40% of subprime loans that originated in 1998 were in foreclosure between 2000 and 2003 compared to prime loans which only had a 2.8% rate within the same time span. The 2013 data on metropolitan delinquency and foreclosure rate showed that the subprime foreclosure rate is over 4 times higher than the prime foreclosure rate among some of the top ranking metropolitan areas with the highest foreclosure filing (Center for Housing Policy, 2014). Table 2 shows 2013 data on a comparison between prime mortgage and subprime mortgage of the top ten metropolitan areas in the United States.

Table 2. *Top 10 metropolitan areas' foreclosure rankings in the United States in 2013*

Metropolitan Statistical Area Name	**Rank in Foreclosure Rate**	**Foreclosure Rate**	**Prime Foreclosure Rate**	**Subprime Foreclosure Rate**
Vineland-Millville-Bridgeton, NJ	1	16.0%	10.4%	42.7%
Atlantic City-Hammonton, NJ	2	12.0%	8.6%	40.3%
Kingston, NY	3	11.8%	7.9%	34.5%
Miami-Fort Lauderdale-Pompano Beach, FL	4	11.6%	8.4%	27.2%
Tampa-St. Petersburg-Clearwater, FL	5	10.9%	7.6%	29.3%
Poughkeepsie-Newburgh-Middletown, NY	6	10.7%	7.4%	34.4%
Deltona-Daytona Beach-Ormond Beach, FL	7	10.4%	7.3%	26.2%
Orlando-Kissimmee, FL	8	10.0%	7.2%	26.4%
Lakeland-Winter Haven, FL	9	9.7%	6.6%	23.7%
Port St. Lucie, FL	10	9.7%	7.0%	26.0%

Financial distress, housing foreclosure, and high unemployment rate were, in many cases, initiated by rampant predatory lending through subprime mortgage loans sold to borrowers in the early 2000s (Nembhard, 2010). Although there is no legal definitions in the United States for the term predatory lending, the Federal Deposit Insurance Corporation (FDIC) defines predatory lending as imposing unfair and abusive loan terms on borrowers (FDIC, 2006). These loans, attached with unrealistic repayment terms and an excessive interest rate, are in some cases, targeted to African American neighborhoods and low income families (U.S. Department of Housing and Urban Development, 2000). The U.S. HUD (2000) made evident the rapid growth of subprime lending in the 1990s in relation to income and racial characteristics of neighborhoods nationwide. The HUD Study on over one million mortgages in 1998 showed that some lenders engaged in predatory lending by making homeownership more costly for African Americans and low income earners than for Whites and middle-class families. The U.S. HUD study also demonstrated that with a ten-fold increase from 1993-1998, subprime loans are three times more likely in low income neighborhoods than in high-income neighborhoods (U.S. Department of Housing and Urban Development, 2000). Further results showed that African American neighborhoods were five times more likely to receive these loans than in White neighborhoods, and that homeowners in high-income African American neighborhoods are twice as likely as homeowners in low-income White areas to have subprime loans. The U.S. HUD study found a similar pattern among five metropolitan areas in Baltimore, Atlanta, Philadelphia, New York, and Chicago. These areas exhibited a trend where the African American neighborhood accounts for the majority of subprime mortgage loans (U.S. Department of Housing and Urban Development, 2000).

2.3 Methodological Approaches to Foreclosure Studies

Some of the recent foreclosure-related studies include Immergluck and Smith's (2006) study that examined the impact of foreclosure and the effect it has on property values of houses in Chicago, Illinois. Delgadillo and Erickson (2006) examined the application of GIS technology to study the spatial relationship between foreclosure rates and neighborhood characteristics in a metropolitan county in Utah. A more recent study carried out by Cui (2010), and Katz et al., (2011) examined the impact of foreclosure on neighborhood levels of crime in Pittsburg, Pennsylvania and Glendale, Arizona respectively. Several authors have studied foreclosure and neighborhood characteristics (Arnio & Baumer, 2012; Cui, 2010; Ellen, Lacoe, & Sharygin, 2011; Immergluck & Smith 2006; Katz et al., 2011; Mummolo & Brubakar, 2008; Wilson & Paulsen, 2008; Wolff, Cochran, & Baumer, 2014). An examination on the most recent studies in foreclosure across the United States showed several methods that were adopted in these studies.

In recent times, vacant and abandoned houses have drawn the attention of government officials who believe that the increasing number of vacant properties spawning from the foreclosure crisis now serves as a safe haven for criminals. Law enforcement officers are targeting vacant houses on regular patrols, using maps of foreclosed properties as guides because they believe one of the impacts of foreclosure is crime (Mummolo & Brubakar, 2008). These aforementioned studies from both academic literature and popular press cut across a variety of subject areas and methods that address issues on foreclosure in relation to several neighborhood characteristics which include but are not limited to crime, population, demographics, housing, racial composition, etc. As far as most of these studies go, the study area and the variables may be different, but the methods applied are somewhat similar. For example, statistical analysis appears to be the primary tool used for studies relating foreclosure and crime. Different variables and approaches were examined in several foreclosure and crime studies. Cui (2010) studied the impact of residential foreclosures and vacant houses on violent and property crime in Pittsburgh, Pennsylvania. The regression analysis implemented in Cui's (2010) study used the number of violent crime in a census block group as the dependent variable and a series of neighborhood characteristics which also includes foreclosure rate and foreclosure-led vacancy rate as the independent variable. The result showed that foreclosure rate is found to have a positive and statistically significant impact on violent crime. However, the concern is further strengthened by the fact that results on vacancy rate are sensitive to demographic controls. Seamon (2013) used regression analysis to identify relationships with urban foreclosure risk as the dependent variable, and the mean household income, mean canopy coverage, and number of people who speak French Creole in Boston area as the independent variable. A scatterplot of the three independent variables over the dependent variable was used to perform regression analysis. The resulting visual output map exhibited a clustering effect of all three independent variables with respect to the foreclosure risk score. Katz et al. (2011) examined the longitudinal impact of foreclosure on neighborhood crime in Glendale, Arizona. Their study showed four separate regression analyses where the following variables: total crime, property crime, drug crime, and violent crime served as the dependent variables for each. The results indicated foreclosure has a short term impact, typically no more than 3 months, on total crime, property crime, and violent crime and no more than 4 months on drug crime. Despite the increase in foreclosure, there was a steady decline on the call for service for crime activities over the study period.

2.4 Using GIS to Study Foreclosure Pattern

Modern studies in foreclosure from a geographer's point of view have implemented the use of Geographic Information System (GIS) to examine the spatial relationship of foreclosure in a study area. GIS is a computer system designed to integrate hardware, software, and data for capturing, managing, analyzing, and displaying all types of geographical data (ESRI, 2014). GIS has been an important tool in modern geography foreclosure studies for bolstering statistical analysis with spatial patterns. Herrmann (2009) used GIS to explore changes in clustering of foreclosures during two separate time frames (1990s and 2000s) in Boston. Studies carried out by Forsyth County, North Carolina also used GIS to locate areas affected by foreclosure in Forsyth County from 2007-2010 and to follow subsequent sales of those properties to determine what (if any) effect foreclosure has on the market area. And there is the occasional mash-up between GIS and statistical analysis (Arnio & Baumer, 2012). Arnio and Baumer (2012) studied the possibility of spatial heterogeneity and its effect on neighborhood crime rates within the city of Chicago by examining the housing transitions that leads to foreclosure. Indicators such as demographic, racial composition, socioeconomic disadvantage, residential instability, and immigrant concentration were examined. Their study used geographically weighted regression (GWR) to test for spatial heterogeneity among the aforementioned attributes and to also highlight the pattern of demographic context observed from the GWR model result. The results indicated significant variation across Chicago census tracts in the estimates of logged percent black, immigrant concentration, and foreclosure for both robbery and burglary rates.

2.5 Conclusion

This chapter provided an insight into the works of other authors' contributions to the widespread foreclosure crisis study in the United States. It listed several factors conceived by different authors as to what might be responsible for the increase in foreclosure. It also examined different studies where several neighborhood characteristics like demographics, housing cycles, crime, and so on, were discussed in relation to housing foreclosure and also how researchers from different disciplines investigated the problem using both qualitative and quantitative methods.

CHAPTER 3

STUDY AREA AND METHODOLOGY

3.1 Introduction

This chapter provides a description of the study area and the methodology including data sources, software, spatial analysis, statistical analysis, and the data preparation methods applied towards the study of foreclosure in two study areas.

3.2 Study Area

The United States Office of Management and Budget (OMB) classifies Miami-Fort Lauderdale-West Palm Beach as one of the metropolitan statistical areas (MSA) in Florida (OMB, 2013). The Metropolitan Divisions that make up this MSA falls within Miami-Dade, Broward, and Palm Beach Counties – Florida's three most populous Counties. The study area is located within Miami-Dade County.

Miami-Dade County is located on the southeastern part of Florida with a total land area of 2,431 square miles, of which 1,898 square miles is land and 533 square miles (21.9 %) is water, making it Florida's third largest county in terms of land area (U.S. Census Bureau, 2013). The 2010 census on Miami-Dade County shows a population of 2,496,435 people and 990,558 housing units (US Census Bureau, 2013) out of which the major percentage of the population consists of Whites, African American, and Asians with 77.8%, 19.0%, and 1.7% respectively. It is the most populous county in Florida, containing approximately half of the MSA population, and the seventh most populous county in the United States. The majority of the urbanized land use in Miami-Dade is situated at the eastern part of the county. Florida's 22 largest counties accounted for 85.4% of total employment within the state, and among those counties, employment was highest in Miami-Dade (1,016,700 people) in September 2013 (U.S. Department of Labor, 2014, April 23). Industry employment in the MMA such as trade, transportation, and the utilities super sector experienced the largest employment increase in June 2014, up 15,200 or 2.8% from the previous year. Professional and business services had the second largest over-the-year increase in jobs locally in June 2014, growing by 14,400 or 3.9% (U.S. Department of Labor, 2014, July 31). Like most counties in Florida, Miami-Dade has a high presence of water bodies. The county is surrounded by the Biscayne Bay, which is located on the Atlantic coast of South Florida. The areas located at the southern and western part of the county comprises mostly of agricultural land use and national parks, while the communities are all concentrated on the eastern part. There are 34 incorporated municipalities in Miami-Dade County, which is comprised of 19 cities, 6 towns, and 9 villages (Figure 2). The county seat is located in the city of Miami, which is also the largest of the incorporated city and the main economic hub of the county.

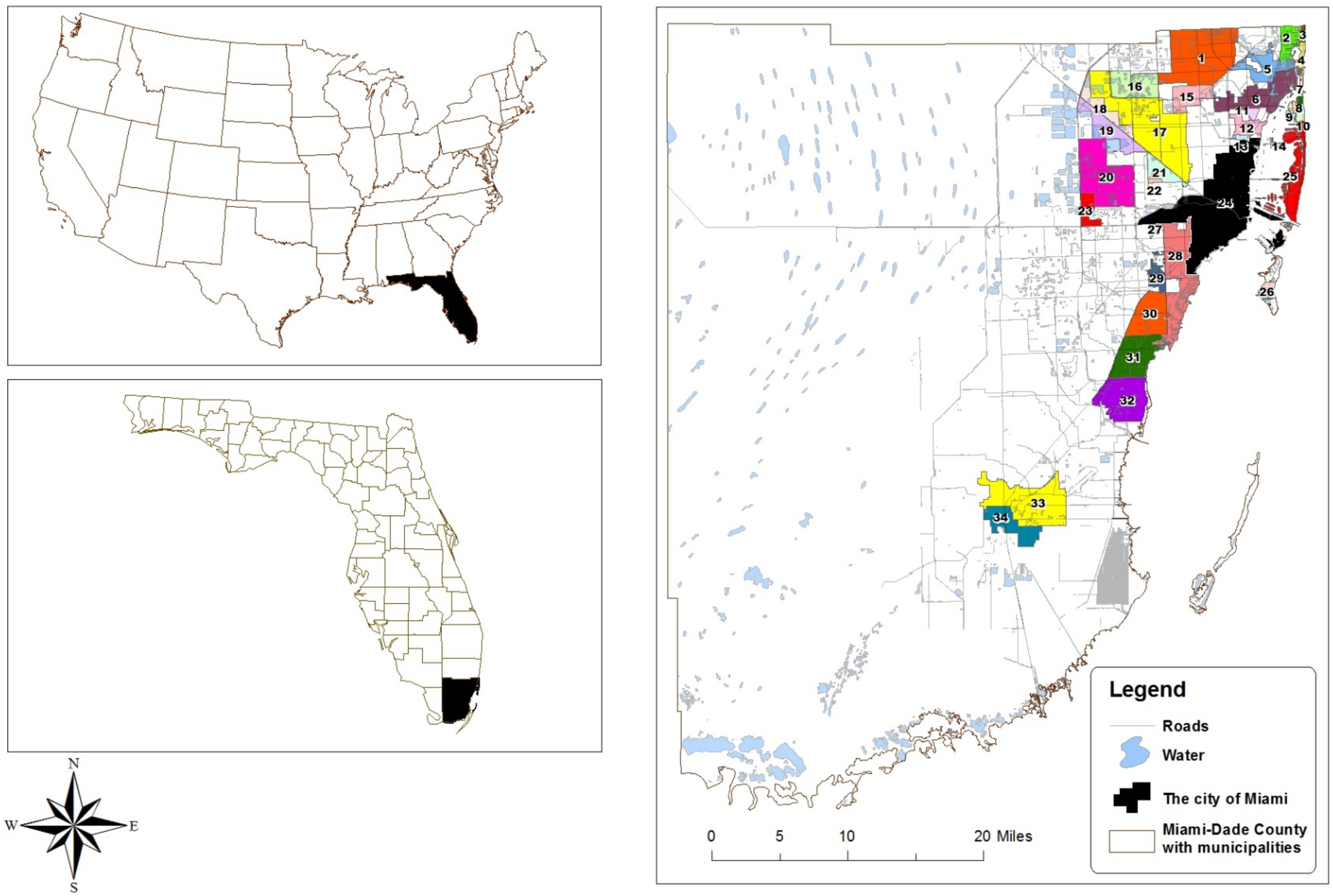

Figure 2. Study area showing the incorporated Communities in Miami-Dade County. The number ranking represents the location of each incorporated community (See Appendix B for table)

The city of Miami is the seat of Miami-Dade County, and it is located at the eastern part of Miami-Dade metropolitan division along with the majority of the urbanized areas in the county (Figure 2). It has a total land area 35.87 square miles with 11,135.9 persons per square mile. The 2010 census on the city of Miami shows a total population of 399,457 people (US Census Bureau, 2013) out of which the major percentage of the population goes to Whites and African American with 72.6% and 19.2% respectively. The Hispanic or Latino ethnicity in the city of Miami makes up of about 70% of the total population (US Census Bureau, 2013). Miami, been dubbed as “the capital city of Latin America” comprises of a high percentage of Hispanic and Latino population. The city of Miami and its suburbs are located on a broad plain between the Everglades to the west and Biscayne Bay to the east. A total number of 117 census tract are located in the city of Miami

3.3 Methodology

3.3.1 Data Sets

The data used for this study included the foreclosure counts, and 2010 Census data for socioeconomic, population, racial composition, housing, and education attainment variables for Miami-Dade County, and the city of Miami. Data collected specifically for the city of Miami included the index crime data, and data on the vacant houses. All the data used in this study were collected at the census tract level. The combinations of these datasets were used on both Miami-Dade County, and the city of Miami to study foreclosure relationships with the above mentioned variables.

1. Foreclosure data. Excel table format on a total of 18,155 foreclosure data containing the addresses, market values, and date of foreclosure filing from 2010-2013 for the housing units under foreclosure was purchased from a Miami-Dade foreclosure online source (miamidadeforeclosures.com, 2013). Miamidadeforeclosure.com is the leading online marketplace for foreclosure properties in Miami-Dade County. The data comprised of information on the upcoming foreclosure, the cancelled foreclosure, and those foreclosed houses that have been resold. It also showed the types of property, the year the houses were built, and the bidding information for the auctioned sold houses.

2. Crime data. Crime data in excel table format from 2011-2012 was purchased from the Miami-Dade Police Department showing the description of crimes committed, the addresses, the time, and the dates of each reported crime incident. A total of 733, 994 crime cases were collected. The types of crime described in the data included embezzlement, murder, forgery, false pretenses, driving under the influence of alcohol (DUI), aggravated assault, receipt of stolen goods, rape, arson, burglary, etc. These data which were purchased for the 117 census tract in the city of Miami was used to run correlation and regression statistical analysis on the study area.

3. Socioeconomic and housing data. 2010 data was collected for the 519 census tracts in Miami-Dade, and the 117 census tracts in city of Miami. A total number of 26 variables on various categories of the total population counts, socioeconomic, racial composition, housing characteristics, and education attainment were collected from American FactFinder (factfinder2.census.gov, 2013).

4. USPS vacant houses data. Embracing the social disorganization theory where vacant and abandoned houses could be considered among the contributing factors which leads to increase in crime, data on vacant houses was used in the foreclosure and crime study. A compilation of the 2013 vacant houses data was collected from the U.S. Department of Housing and Urban Development online portal (U.S. Department of Housing and Urban Development, 2013). This data was collected at the census tract level, and was used solely for studying the relationship between foreclosure, crime, and vacant houses in the city of Miami. The data contained descriptions on a total of 316,075 housing addresses, out of which 13,577 were the total vacant addresses for the residential and commercial properties in the city of Miami.

3.3.2 Software

Two types of software were used for this research. (1) ESRI ArcMap was used for data processing and spatial analysis and (2) Statistical Package for the Social Sciences (SPSS) was used for the statistical analysis.

3.3.3 Data Preparation

The foreclosure data downloaded were first classified under three foreclosure status (1) upcoming, (2) cancelled, and (3) sold. The sold data category was used for studying the spatial pattern of foreclosure in MMA. This is because only the sold houses listings had data on the property's appraisal, and contained the winning bid information for the auctioned houses. The remaining two categories of foreclosed houses did not have their market values attached to them, and this was an important criterion for identifying the existence of a spatial pattern by using the housing market value. The first step in the data preprocessing procedure required the conversion of the excel foreclosure and crime data into geographic location on a map for spatial analysis. This is known as geocoding (Figure 3, and Figure 4). A total number of 18,155 foreclosure addresses were downloaded, 9,087 of which belonged to those foreclosed houses that have been sold to a new homeowner or are considered a real estate owned property (REO). REO properties are those foreclosed houses that are usually repossessed by a bank or a government loan insurer after an unsuccessful sale at a foreclosure auction. This is common because most of the bank-financed houses that make it to auction are worth less than the amount owed to the bank. When this occurs the property becomes listed as a REO property and categorized as an asset until the bank re-sells the property, usually through a real estate agent. The sold houses listings might either be re-occupied or is a REO property waiting to be sold or rented out.

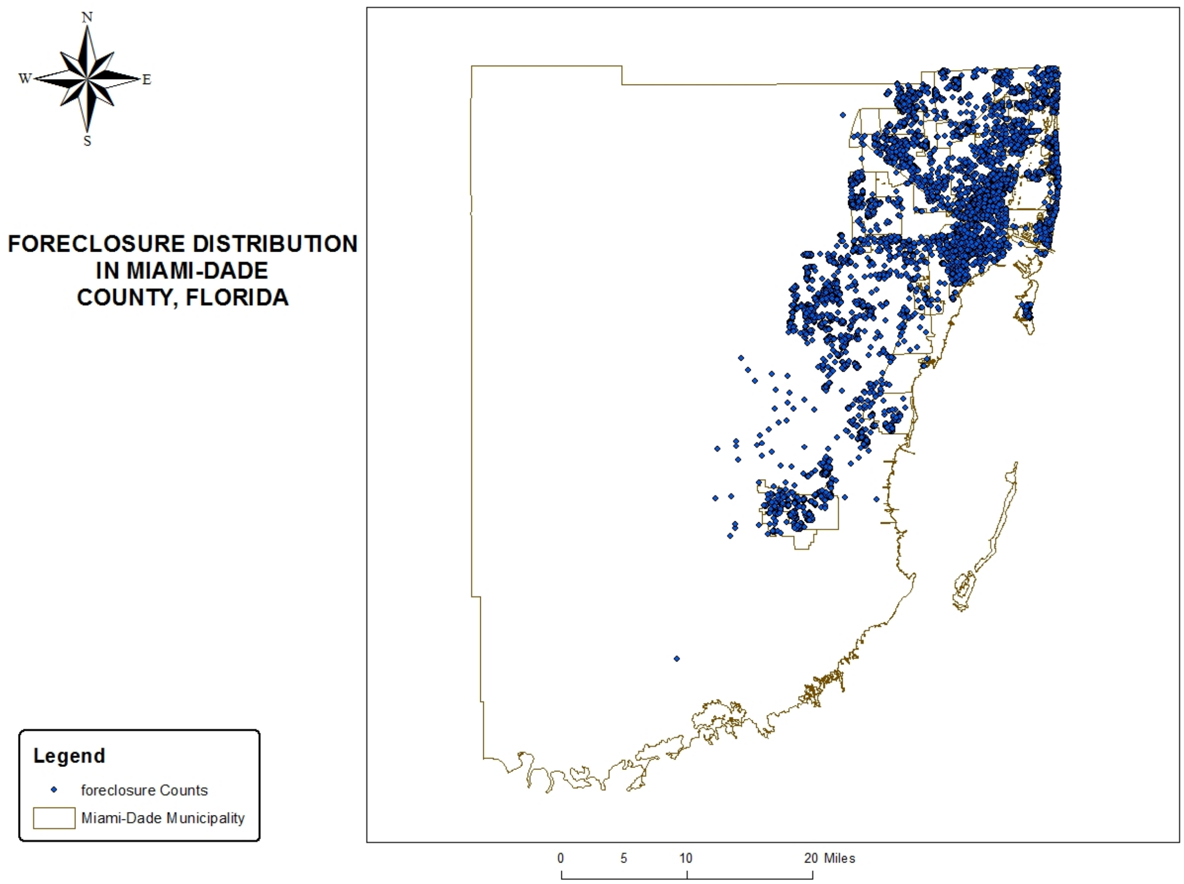

Figure 3. Spatial representation of foreclosure distribution in Miami-Dade County

To address the issue of foreclosure and crime in the city of Miami, the second step is selecting the index crime cases (both violent, and property crime indexes) according to the Uniform Crime Report (UCR) classification. Florida, among the majority of the states in the United States follows the guidelines set by the UCR handbook (U.S. Department of Justice, 2004). The Federal Bureau of Investigation (FBI) set up the UCR program in the 1930s to collect a uniform crime statistics for the nation. Violent and property crimes were the selected dataset used in this study. Other classification of crimes such as embezzlement, forgery, false pretenses, driving under the influence of alcohol (DUI), and receipt of stolen goods are not regarded as index crimes and are therefore not relevant for this study. A total of 75,159 index crimes from 2011-2012 were downloaded and geocoded; 6,727 were violent crimes while 68,432 were property crimes. Cui (2010) weighed in in his study that foreclosure alone has no effect on crime, but the vacant houses which serve as a disturb-free zone for criminal may be a contributing factor for crime. In that spirit, the vacancy period of the REO properties were added into the study of crime in the city of Miami to also examine how foreclosure and/or vacant houses relates to crime. Attention should be drawn to the fact that the research on foreclosure, vacancy and crime in this paper focuses on the city of Miami alone and not on Miami-Dade County. The city of Miami was selected for the second phase because of it had the highest population, highest foreclosure count, and highest crime total in the county; an ideal location for the study.

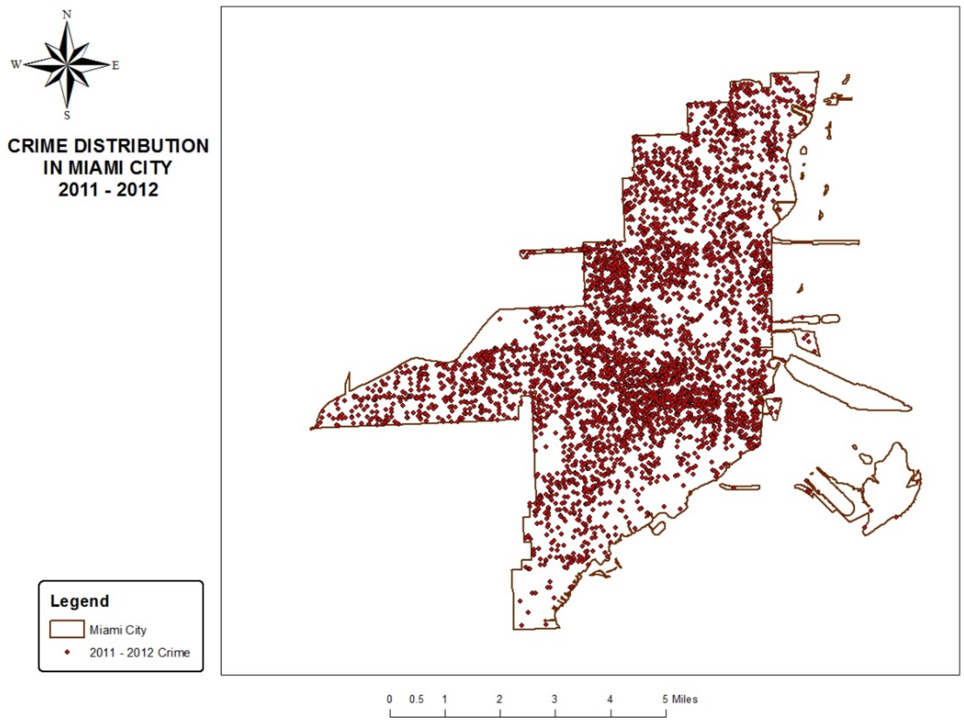

Figure 4. Spatial representation of crime distribution in the city of Miami

The foreclosure process in Florida takes about 600 days to run its course from the first notice until the date of sale. During this process lies the vacancy period where some houses sold at auctions might not yet be re-occupied, or were classified as REO properties and put back in the market (Figure 5). HUD has entered into an agreement with the United States Postal Service (USPS) to receive quarterly aggregate data on addresses identified by the USPS as having been "vacant" or "no-stat" in the previous quarter. HUD makes these data available for researchers and practitioners to explore their potential utility for tracking neighborhood change on a quarterly basis. The vacancy data are produced only in census tract level, which was convenient since this study used census tracts as a proxy for neighborhoods. HUD vacancy data collected for 2013 were grouped into 4 quarterly data records. For this study, the data were aggregated from January to December in order to get the median number of the total housing addresses, and total vacant addresses. From the median vacant addresses, the residential vacant buildings, commercial vacant buildings, and vacancy rate were acquired.

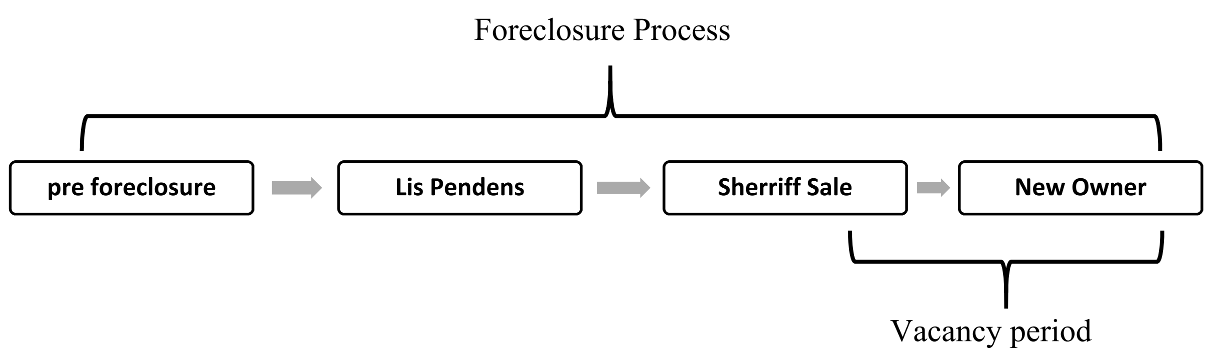

Figure 5. Foreclosure process

<u>3.3.4 Spatial Analysis of Foreclosure and the Neighborhood Characteristics in MMA</u>

The techniques applied in this study were for the purpose of identifying the spatial pattern of foreclosure distribution across the MMA in Miami-Dade County. A similar method was adopted by Seamon (2013) in Boston, and Schintler, Istrate, Pelletiere, and Kulkarni (2010) in New England study area. The nearest neighbor analysis and spatial autocorrelation were used to test for the presence of clustering of foreclosed houses in MMA.

1. Nearest neighbor analysis (NNA). NNA examines the distances between each point on the map and the closest point to it from a complete random sample of point pattern (Chen & Getis, 1998). This was carried out on the geocoded point data for sold foreclosure houses to see the pattern of foreclosure in MMA. To determine the distribution pattern, if the Nearest Neighbor index is less than 1, the pattern exhibits clustering but if the index is greater than 1, the trend is toward dispersion. For the NNA, the z- score and p-value results are measures of statistical significance, which tells whether or not to reject the null hypothesis that features are randomly distributed. The p-value is the probability that the observed spatial pattern was created by some random process. When the p-value is very small (between -1.96 and +1.96,) it means it is very unlikely that the observed spatial pattern is the result of random processes. This means that the null hypothesis can be rejected. The z-score are simply standard deviations associated with the normal distribution.

2. Spatial autocorrelation. Spatial autocorrelation identifies the pattern of the sold foreclosure market value to determine if the data is thought to be clustered, dispersed or if it occurs randomly. This was done to observe the possibility of an existing pattern among areas of high and low market values of the foreclosed houses. Just like the NNA, the z-score and p-value results are also measures of statistical significance, which tells whether or not to reject the null hypothesis that features are randomly distributed. The p-value result in the spatial autocorrelation is also the probability that the observed spatial pattern was created by some random process. When the p-value is very small, it means it is very

unlikely that the observed spatial pattern is the result of random processes. This means that the null hypothesis can be rejected.

3. Cluster and outlier analysis. The Moran's I test indicates spatial autocorrelation in ArcMap. This was used to identify statistically significant hot spots, cold spots, and spatial outliers using the Anselin Local Moran's I statistic. This tool identifies statistically significant spatial clusters of high market values of foreclosed houses and low market values of foreclosed houses. The purpose of this analysis is to identify the clustering relationship and spatial distribution of foreclosure in MMA.

3.3.5 Statistical Analysis of Foreclosure and the Neighborhood Characteristics in MMA, and Foreclosure and Crime in the City of Miami

1. Correlation analysis. Pearson's correlation coefficient was first computed on a total number of 26 variables. These variables acquired at the census tract level comprised of the income, housing, population, racial composition, foreclosure, and education attainment in Miami-Dade County, and the city of Miami. The purpose of correlating these variables was to measure the strength of the association that existed among all the 26 variables.

2. Principal component analysis (PCA). PCA extracts a set of latent components that explain as much of the covariance as possible from the aforementioned neighborhood characteristics. PCA was carried out to identify groups of inter-correlated variables. These variables accounted for the relationship between foreclosure, and the selected components which were comprised of neighborhood characteristics in the study area.

3. Regression analysis. Several regression analyses depicting the relationship between foreclosure and the neighborhood characteristics in MMA, and foreclosure and crime in the City of Miami were used in the study. An exploratory analysis using the Enter Linear Regression method on SPSS was carried out for the MMA. For the MMA, the foreclosure rate was used as the dependent variables, and the components derived from the PCA that accounts for most of the variance in the neighborhood characteristics as the independent variables.

The second phase of the regression analysis was used to test H2 on the relationship between foreclosure and crime. Based on recent literature on foreclosure and crime (Immergluck & Smith, 2006; Cui, 2010), the following variables were constructed on neighborhood characteristics that might be expected to affect crime:

Total population in Miami-Dade County for 2010
Percentage of all people below poverty level
Median family income in 2010
Vacancy rate
Foreclosure rate
Vacant residential addresses
Vacant business addresses
Percentage of income less than $10,000
Percentage of income $200,000 or more
Percentage of male population from 15 – 24
Percentage of Hispanic or Latino population
Percentage of Black or African American population

With crime as the dependent variable and the above indicators as the independent variables, the relationship between crime (violent and property), vacancy, and foreclosure were observed by using this equation.

$$C_i = a + b_1P_i + b_2V_i + b_3Z_i + b_4F_i + \varepsilon_i$$

Where:

C_i is the dependent variable representing the number of index crimes, with a combination of both violent and property crime incidents in census tract i, and i will be the unit of observation in a census tract. P_i is the population of the census tract, and V_i is the vacant foreclosed houses in a census tract. Z_i is a vector of characteristics that might be expected to affect neighborhood crime; characteristics such as the male population from 15-24 years, percentage of all people below poverty level, etc. F_i are census tract level housing foreclosure rate. Foreclosure rate and vacancy rate were measured by dividing each of them by the number of owner occupied housing units in the same census tract (Immergluck, & Smith, 2006; Cui, 2010).

CHAPTER 4

RESULTS

4.1 Introduction

This chapter presents the foreclosure results from the MMA, and the foreclosure and crime results from the city of Miami. An output of the visual representation acquired from the spatial analysis and the result of the statistical analysis carried out in both study areas was also portrayed in this chapter.

4.2 Nearest Neighbor Analysis Result for Foreclosure in MMA

The result shows a nearest neighbor index of 0.134. This result means there is evidence of clustering among housing foreclosure. The z-score of -222.370 is outside the critical value range between -1.96 and +1.96, indicating that there is a less than 1% chance that the pattern is as a result of a random distribution. Thus, the pattern exhibited is not the result of a random distribution but an unusual distribution; in this case, clustering.

4.3 Spatial Autocorrelation Result for Foreclosure in MMA

The spatial autocorrelation result showed the clustering of similar market value foreclosed houses to determine if a pattern exists among the clustered foreclosure houses in MMA. The purpose of this result is to identify clustering patterns using the attribute values as well as locations of the foreclosed houses. The z-score of 53.161 falls outside the critical value range between -1.96 and +1.96. This shows that the pattern exhibited among the foreclosed houses is the result of a clustered distribution.

4.4 Cluster and Outlier Analysis Results for Foreclosure in MMA

The z-score of the spatial autocorrelation analysis demonstrates the presence of clustering in MMA. Spatial representation (Figure 6) displays the result of the Anselin Local Moran's I statistic by showing areas of random distribution and those areas where clustered values are surrounded by similar values. Clustering of foreclosed houses where high market values are surrounded by similar high valued houses is represented with red dots. The orange and light blue dots are those outliers where high market value houses are surrounded with low market value houses and vice versa. The dark blue dots represent the areas where houses of low market values are surrounded by similar values. Finally, the black dots are areas where the distributions of houses market values are random. Observations from the figure show a large amount of high market value clustering in the city of Miami region in the central part of Miami-Dade County. The north and southeastern parts show clustering of houses with low market values. The black dots show a dense random distribution of foreclosed houses in the north-central section of MMA.

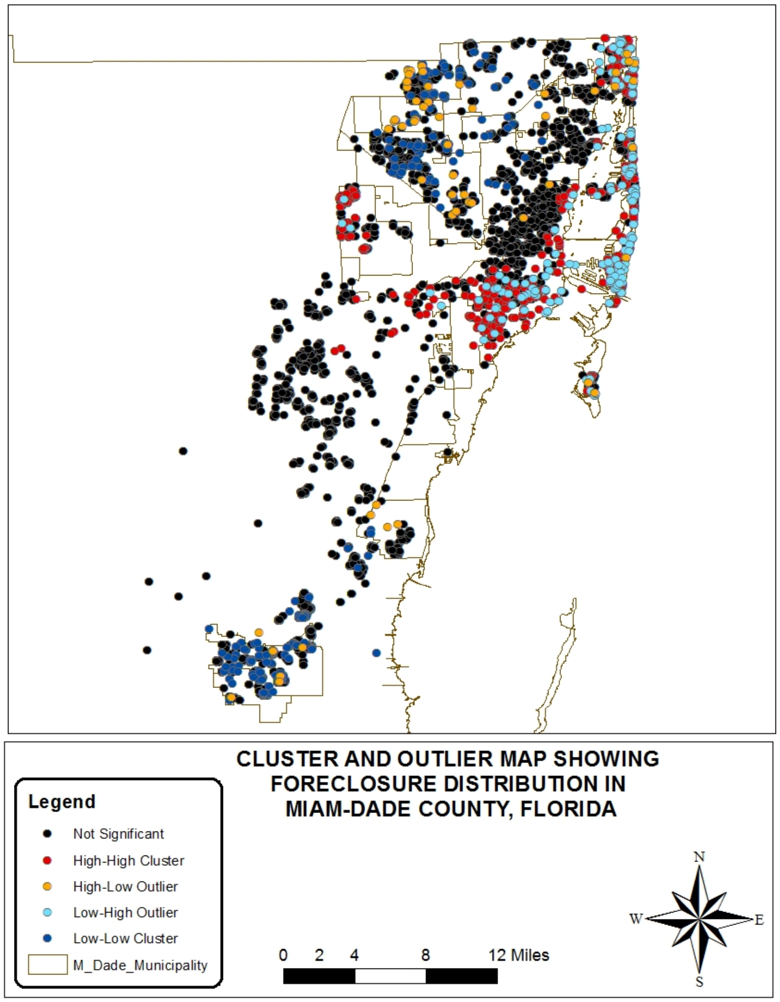

Figure 6. Spatial distribution of foreclosure market value in MMA

To test for H1 which is aimed at observing areas with increased foreclosure across the major racial composition in MMA, Figure 7, Figure 8, and Figure 9 showed an overlay of foreclosure counts over three racial groups. These three races which comprises of the White, African American, and Asian population have been the focus of this study because they make up 99.3% of the total population with 77.8%, 19.0%, and 1.7%

respectively (U.S. Census Bureau, 2013). The black dots in all three figures represent the foreclosure count distribution across the county. In MMA, most of the foreclosed houses are located on the eastern part of the county. This was expected considering the fact that the western areas have lesser cities and populations in general. In the eastern part of the county, the segregation pattern of the major racial compositions showed a high foreclosure concentration among the African American population (Figure 8). In Figure 8, the visual representation of the map indicated that the cluster of foreclosed houses especially at the northern part of the county was mostly occupied by the African American population when compared to the rest of the other two races. With the exception of the city of Miami, and Miami Beach region, the majority of the neighborhood with a dominant White population in MMA showed a low concentration of foreclosure (Figure 7). In Figure 9, the map indicated a low percentage of Asian population in MMA, and among the Asian neighborhood, the presence of foreclosed houses appeared to be low compared to that of the African American, and White population. All three maps represented the foreclosure concentration among the dominant racial groups in MMA.

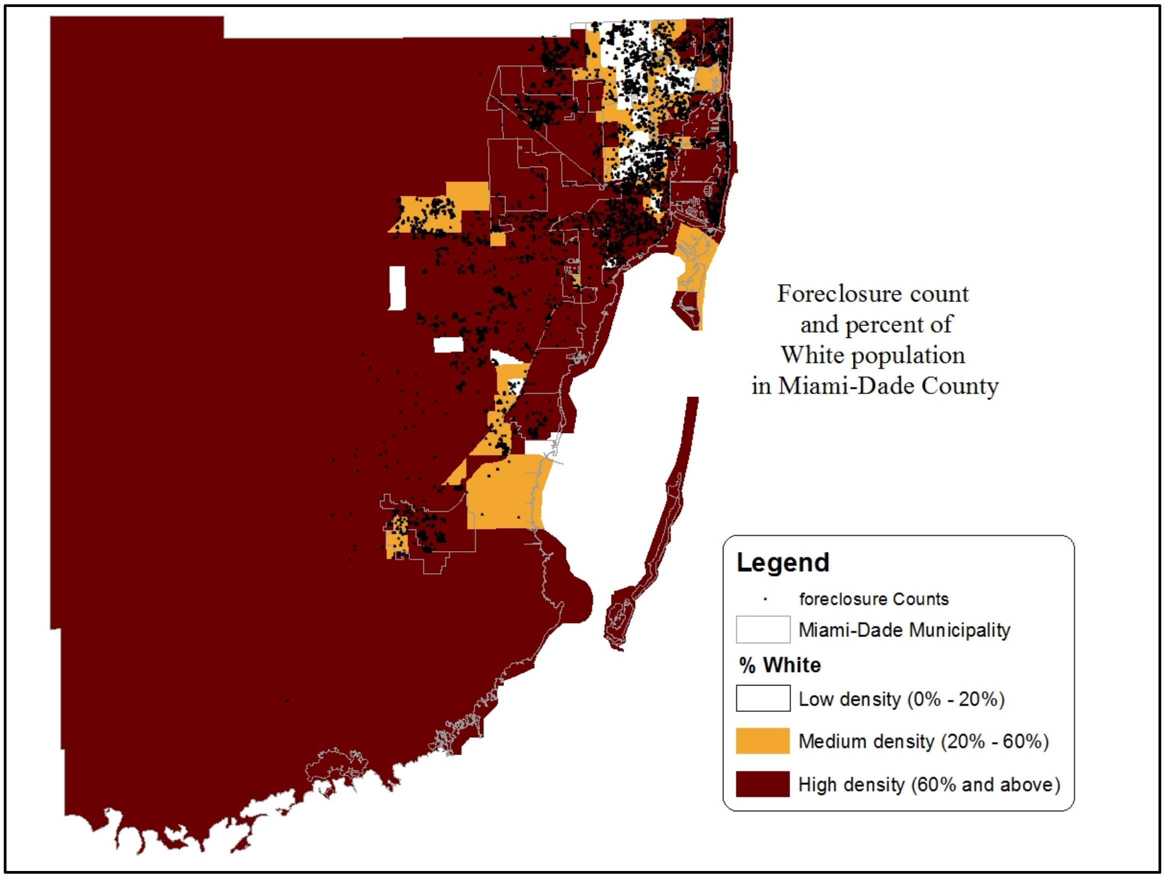

Figure 7. Foreclosure count and the percent of White population in Miami-Dade County

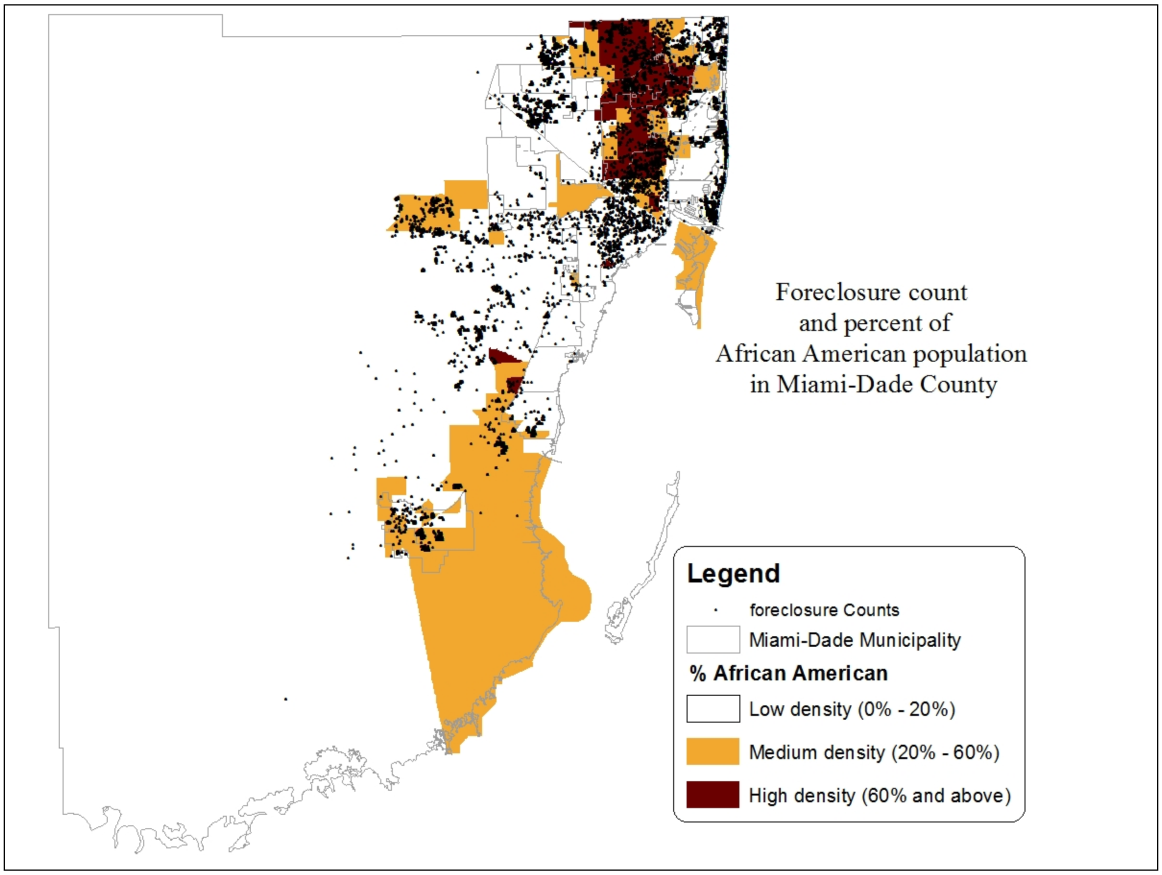

Figure 8. Foreclosure count and the percent of African American population in Miami-Dade County

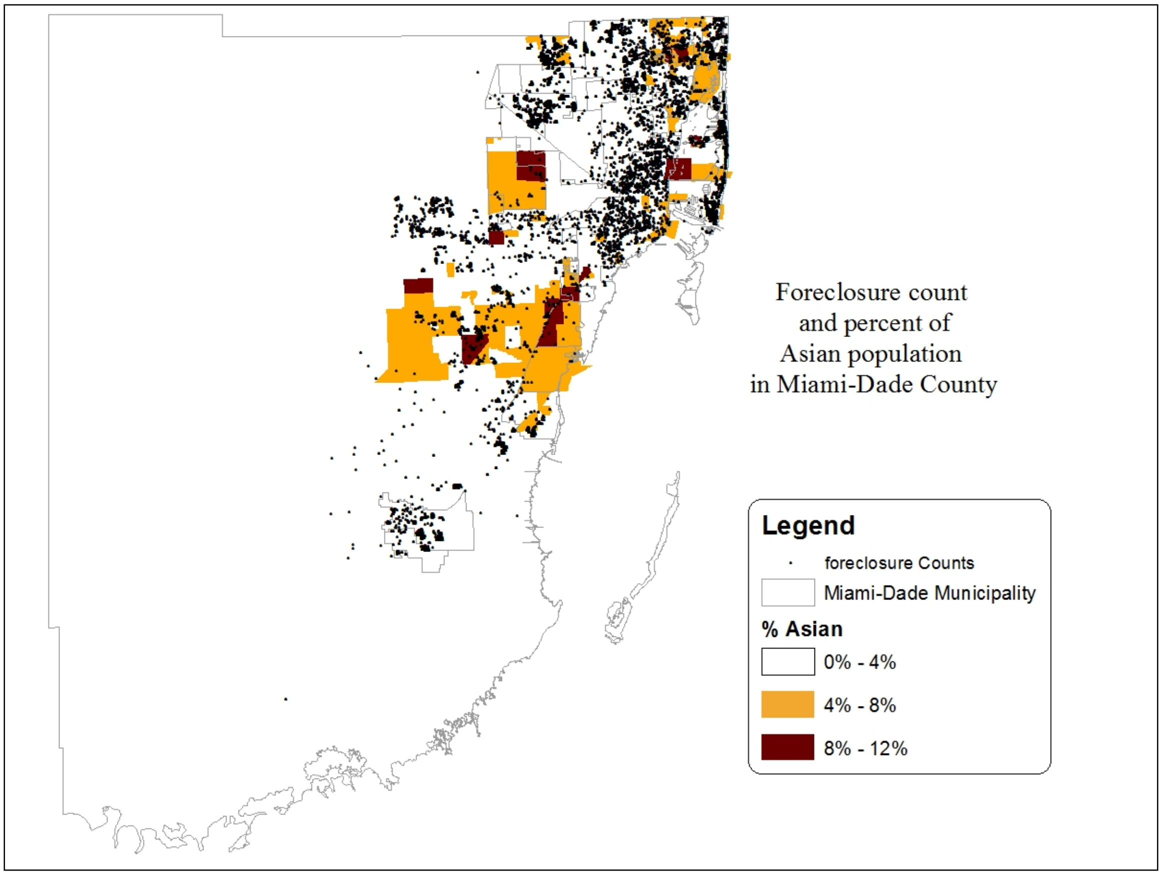

Figure 9. Foreclosure count and the percent of Asian population in Miami-Dade County

4.5 Correlation Analysis Results.

The Pearson correlation can take a range of values from +1 to -1. A value of 0 indicates that there is no association between the two variables. A value greater than 0 indicates a positive association, that is, as the value of one variable increases, so does the value of the other variable. A value less than 0 indicates a negative association, that is, as the value of one variable increases, the value of the other variable decreases. For this study, there were 26 total number of variables selected to run the Pearson's correlation analysis. These 26 variables were comprised of the foreclosure rate, the total population of people in MMA, the sex and age group of the population, median income and education attainment for different education levels, housing data, employment status, poverty level, population density, family household income, racial compositions, etc. Among all the variables used for correlation, the foreclosure data, being the main focus of this study showed the lowest correlation with other variables (Table 3). The highest correlation with foreclosure rate from all 26 variables was with the population of people in owner-occupied housing units (-.200). This means that an increase in foreclosure rate indicates a decrease in the population of people in owner occupied housing unit.

Table 3. *Foreclosure rate correlation with the selected 26 variables.*

Variable	Description	Foreclosure rate
MEDFINC	Median family income (dollars)	-.066
MEDHINC	Median household income (dollars)	-.078
MEDINC25>	Total median earnings in the past 12 months - population 25 years and over with earnings	.002
%BADEG>	% - Bachelor's degree and higher	-.059
%PINCPOV	% of all people whose income in the past 12 months is below the poverty level	.119**
%FINCPOV	Percentage of families whose income in the past 12 months is below the poverty level	.088
TOTMED	Total median earnings - bachelor's degree and above	.012
%INC200,000>	% Income - $200,000 or more	-.030
%INC<10,000	% Income - Less than $10,000	.069
POVRATE25>	Total poverty rate for the population 25 years and over - bachelor's degree or higher	.049
LABFORCE	Employment status - In labor force	-.104*
TOTPOP	Overall total population	-.094*
TOTHH	Income and benefits - Total households	-.041
POHU	Population in owner-occupied housing units	-.200**
%TPH	% of Total population in households	.029
OHU	Owner occupied housing units	-.175**
FAMEMP	Employment status - All parents in family in labor force	-.040
%FAMEMP	Employment status - Percent of All parents in family in labor force	.002
UNEMP	Employment status - In civilian labor force - Unemployed	-.071
%HISP	% Hispanic	-.140**
%WHITE	% White	-.027
%AFA	% African American	.008
TOTHU	Total housing units	.093*
%ASIAN	% Asian	.015
%TP62>	% of Total population - 62 years and over	-.099*
POPDEN	Population density	.162**

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Table 4 shows the result of the correlation between socioeconomic variables and the dominant racial and ethnic group in the study area. These racial and ethnic groups include the White, African American, Asian, and the Hispanic population in MMA. There is a positive correlation between Whites (%WHITE) and Asians (%ASIAN), and people who attained a bachelor degree and higher (%BADEG>). %WHITE and %BADEG> showed a high positive correlation result of .279, the same goes for %ASIAN and %BADEG> with a positive correlation result of .262. This means that an increase in both the White and the Asian population indicates an increase in people with a bachelor degree or higher. The reverse was the case for the African American (%AFA) and Hispanic population's (%HISP) correlation with %BADEG>. %AFA and %HISP both showed negative correlation results of -.273, and -.048 respectively. This means than an increase in both the African American and the Hispanic population indicates a decrease in people with bachelor degree or higher. The %AFA also showed high positive correlation (.416) with people living below the poverty level (%PINCPOV). This means that the increase in the African American population indicates an increase in people living below the poverty level. Some of the highest coefficient results were between the variables containing the dominant racial compositions like the %AFA, %WHITE, and %ASIAN, and the %PINCPOV. The % WHITE and % ASIAN both point to a negative correlation of -.428, and -.415 respectively with %PINCPOV. This means that an increase in either the White or the Asian population indicates a decrease in people living below the poverty level.

Table 4. *Correlation matrix between socioeconomic variables and ethnicity*

		1	2	3	4	5	6	7	8	9	10
1	%BADEG>	1									
2	POVRATE25>	-.140 **	1								
3	%WHITE	.279 **	-.081	1							
4	%HISP	-.048	.066	.786 **	1						
5	%AFA	-.273 **	.061	-.993 **	-.774 **	1					
6	%ASIAN	.262 **	-.251 **	.151 **	-.163 **	-.209 **	1				
7	%INC<10,000	-.164 **	.519 **	-.261 **	-.096 *	.259 **	-.351 **	1			
8	%INC200,000>	.422 **	-.239 **	.302 **	-.141 **	-.281 **	.282 **	-.265 **	1		
9	MEDHINC	.355 **	-.415 **	.343 **	-.042	-.326 **	.421 **	-.565 **	.824 **	1	
10	%PINCPOV	-.300 **	.542 **	-.428 **	-.182 **	.416 **	-.415 **	.782 **	-.381 **	-.661 **	1

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

4.6 Principal Component Analysis Result

Preliminary mandatory tests carried out as part of the PCA were the Kaiser-Meyer-Olkin (KMO) and Bartlett's test value (Liang & Weng, 2011). These two tests measure the sampling adequacy of the variables used in PCA. PCA requires that the KMO Measure of sampling adequacy be greater than 0.50 for the set of variables. Also an acceptable data for PCA should have a significance level of the Bartlett's test that is less than .10 (Liang & Weng, 2011). The results of these two tests from the 26 variables used showed a KMO value of .815 and a Bartlett's test result of 0.000 which both implies the suitability of the input variables for PCA. In order to further validate their capabilities, all the 26 variables were checked for their communalities (Table 5). Communalities indicate the amount of variance in each variable that is accounted for. Variables with small communalities (less than 0.50) do not fit well with the PCA (Liang & Weng, 2011). Total populations in household, all families in labor force, and population density failed to meet the 0.50 cut off marker; these three variables were exempted from the subsequent analysis. The remaining 23 variables left were used to run PCA.

The PCA result generated 6 components with the first 3 components together making up to 71% of the total variance from all input variables (Table 6). Component 1 accounted for 34.2% of the total variance while components 2 and 3 accounted for 24.0% and 12.7% respectively. These components were categorized as: Economic Indicator (EI) for component 1, Crowdedness Indicator (CI) for component 2, and Racial Diversity Indicator (RI) for component 3. The grouping of these variables into components was done based on the high component scores of .70 and above amongst the variables used. The variables that made up EI comprised of social and economic variables such as MEDFINC, MEDHINC, MEDINC>25, %BADEG>, %PINCOV, % FINCOV, %TOTMED, %INC200, 000>. The CI comprised of population and housing variables with high component scores. These variables include LABFORCE, TOTPOP, TOTHH, POHU, OHU, and FAMEMP. The variables that made up RI comprised of % HISP,

%WHITE and, %AFA. These three variables are the racial and ethnic composition in MMA with a high component score.

Table 5. *Communalities result from 26 variables*

Communalities	
	Extraction
POVRATE25>	.545
TOTPOP	.933
% WHITE	.938
% HISP	.899
% AFA	.928
% ASIAN	.589
%TPH	**.427**
FAMEMP	.708
%FAMEMP	**.470**
%INC200,000>	.767
%INC200,000>	.847
MEDHINC	.890
%FINCPOV	.845
%PINCPOV	.890
POPDEN	**.436**
MEDINC25>	.914
TOTMED	.748
%TP62>	.695
OHU	.909
LABFORCE	.931
UNEMP	.706
TOTHH	.937
%BADEG>	.885
MEDFINC	.904
TOTHU	.866
POHU	.925

Bold = <0.50

Table 6. *PCA result showing 3 components*

Component Matrix	Component 1	2	3
MEDFINC	.913	-.087	-.162
MEDHINC	.912	-.007	-.186
MEDINC25>	.887	-.156	-.183
%BADEG>	.844	-.212	-.034
%PINCPOV	-.835	-.146	-.042
%FINCPOV	-.823	-.082	-.060
TOTMED	.782	-.096	-.254
%INC200,000>	.772	-.215	-.127
%INC<10,000	-.688	-.281	.083
POVRATE25>	-.518	-.141	.295
LABFORCE	.009	.956	.096
TOTPOP	-.082	.955	.047
TOTHH	-.070	.824	.210
POHU	.334	.822	-.062
OHU	.465	.796	-.004
FAMEMP	-.073	.780	-.296
UNEMP	-.411	.657	-.212
%HISP	.093	.137	.883
%WHITE	.533	-.034	.816
%AFA	-.520	.038	-.807
TOTHU	.085	.609	.126
%ASIAN	.540	-.032	-.227
%TP62>	.071	-.150	.546
Initial Eigenvalue	7.86	5.53	2.92
% of Variance	34.21	24.05	12.73
Cumulative %	34.21	58.26	70.99

4.6.1 Economic Indicator

The results for Figure 10 and Figure 11 show a comparison between the EI and the White and African American population in the study area respectively. As earlier stated, the majority of the populations in MMA are between the White, African American and Asian populations. For this section a comparison between the Whites and African American population with the EI was observed (these two races alone make up 96.8% of the total population collectively; U.S. Census Bureau, 2013). Variables based on the PCA analysis that had a higher score in the EI are MEDFINC, MEDHINC, MEDINC25>, %BADEG>, %PINCPOV, %FINCPOV, TOTMED, and %INC200, 000>. All the listed variables represent the economic condition of MMA (See Table 6). The darker portion of the map portrays the areas with worse economic condition. The northern and southern part of MMA show deficit in the EI while some areas at the middle of the metropolitan division displays a much better EI condition in MMA. It can be observed from comparing the result of the EI and the White population in Figure 10 that cities in MMA such as Coral Gables, West Miami, South Miami, etc. that generally portrayed adequate economic stimulus such as MEDINC25> and %BADEG> are located where a high portion of the White population are found.

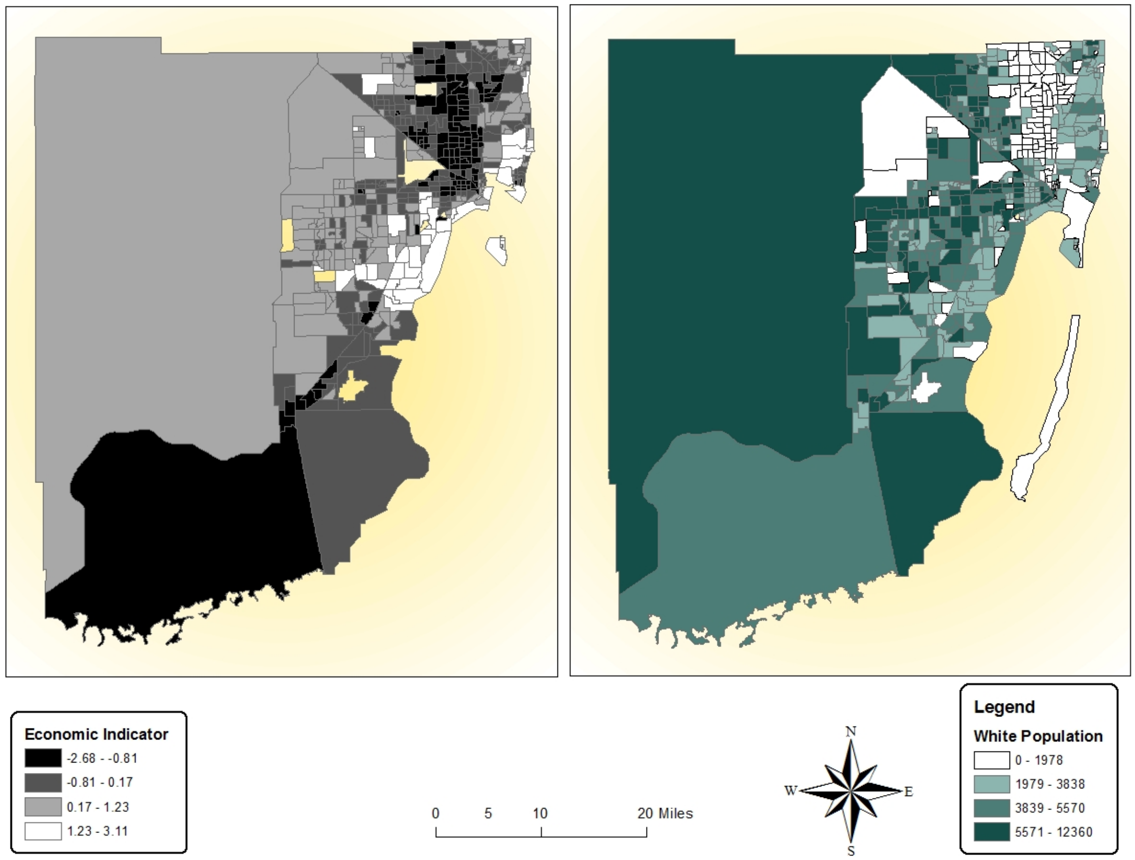

Figure 10. White population and EI locations in MMA

The segregation between the White, and the African American populations in Figure 10 and that of Figure 11 is noticeable. The African American population is more heavily dominant at the municipalities in the northern part of the county such as Biscayne Park, North Miami Beach, Miami Shores, North Miami etc.; the same areas with the lowest values in EI. The isolated areas of the county identifying lower EI such as %PINCPOV and %FINCPOV can be found in the northern and southern part of the study area. These two results demonstrate an irrefutable difference of the economic situation in areas where Whites and areas where African Americans are dominant.

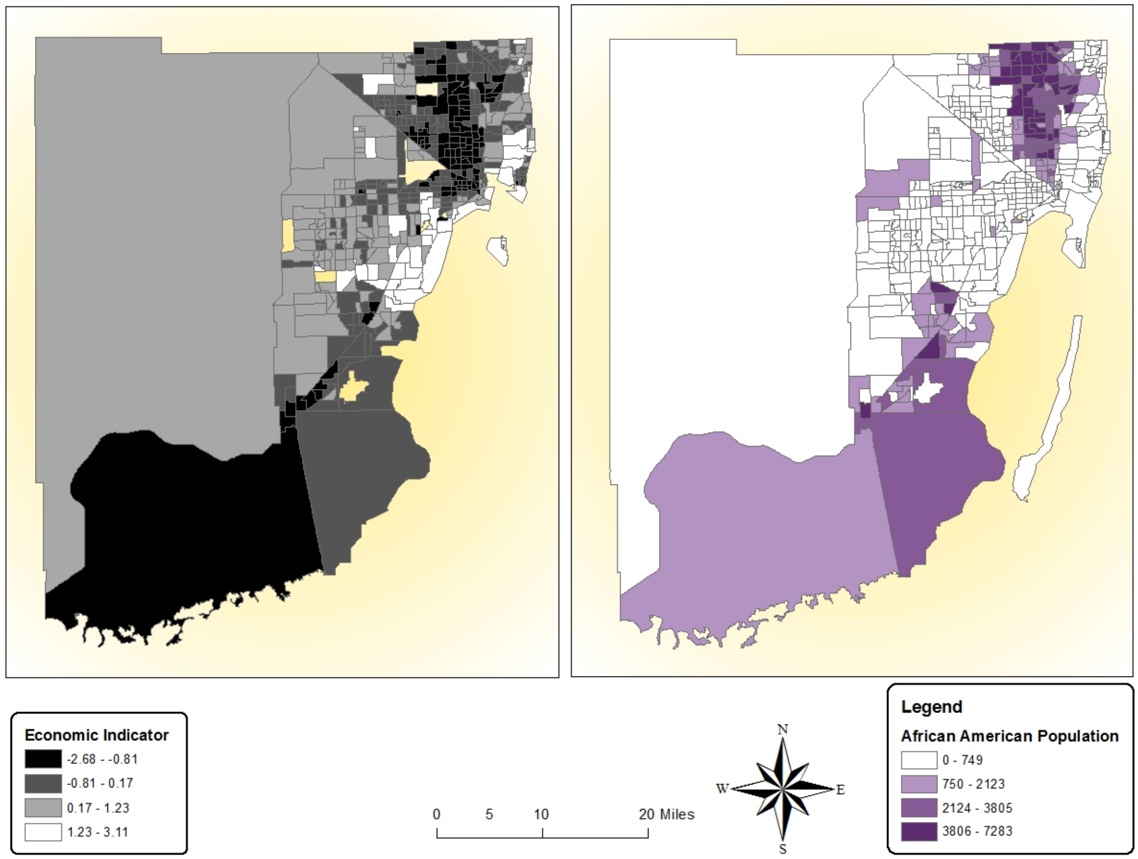

Figure 11. African American population and EI locations in MMA

4.6.2 Crowdedness Indicator

The result for the CI as seen in Figure 12 is a random pattern of distribution across Miami-Dade County. The area around the city of Miami appears to be showing the lowest values in CI. This could be explained by the absence of land in most of the areas in the tract due to the surrounding water bodies around the city of Miami, Miami Beach, etc. This displays an incongruous result by portraying the presence of low CI in areas where it does not exist.

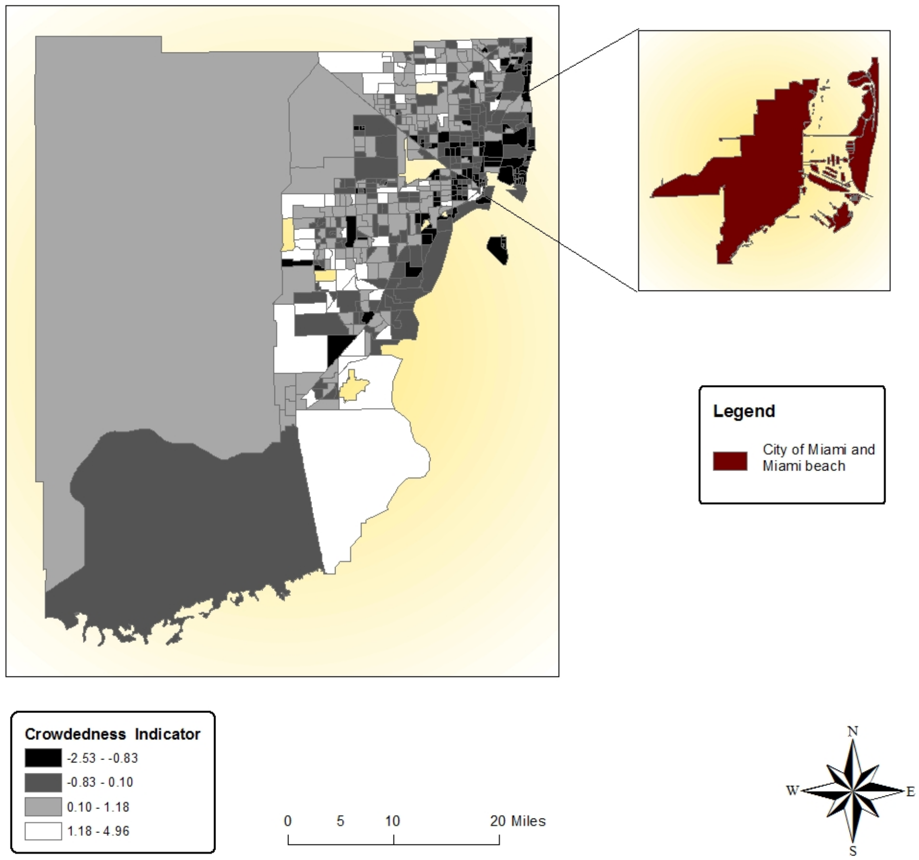

Figure 12. CI showing random distribution in the study area

<u>4.6.3 Racial Diversity Indicator</u>

The variables based on the PCA analysis that have a higher score in the RI are %HISP, %WHITE, and %AFA. All the listed variables represent dominant races and the Hispanic ethnic population of MMA (See Table 6). The spatial representation for RI (Figure 13) shows a high value of %AFA in the north and also a high value of %WHITE and %HISP at the center where Hialeah and Miami municipal areas in Miami-Dade County are located. The spatial representations showing the African American population has been consistently placed in the same northern location throughout this study (See

Figure 8, 11, and 13). Figure 13 showing the RI and the spatial distribution of foreclosed houses were carried out in order to identify the placement of the foreclosure market values when compared with the RI. The resulting outcome of this map identified the city of Miami, Hialeah, Hialeah Gardens, etc. as areas where both houses of high market values and also high dominant White and Hispanic population are concentrated. The northern part also showed a concentration of African American population as well as a concentration of random distribution of foreclosed houses in Miami-Dade County.

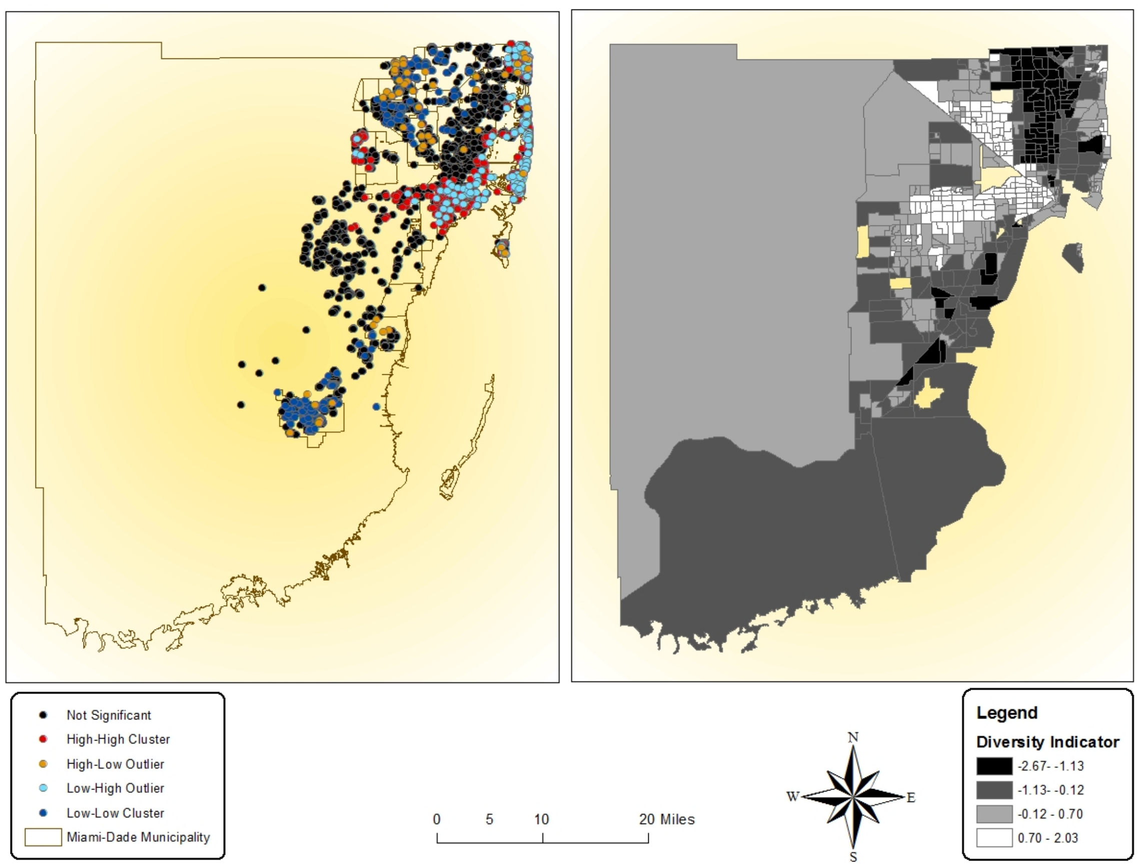

Figure 13. Foreclosure distribution pattern and RI locations in MMA

4.7 Results on the Regression Analysis for Foreclosure Rate in MMA

An exploratory regression analysis was carried out where foreclosure rate was used as the dependent variable, and the three component results (EI, CI, and RI) of the PCA as the independent variables. The independent variables contained a smaller number of artificial variables that accounted for most of the variance from all 23 variables representing the neighborhood characteristics in this study.

This model was used for the regression analysis:

$$F_i = a + b_1EI_i + b_2CI_i + b_3RI_i + \varepsilon_i$$

Where F_i stands for foreclosure rate measured by the number of foreclosures divided by the number of owner occupied housing unit in tract (Immergluck, & Smith, 2006; Cui, 2010). EI, represent Economic Indicator, CI represent Crowdedness Indicator and RI represent Racial Diversity Indicator.

The foreclosure rate regression showed an insignificant result on two out of the three independent variables. The regression model for foreclosure rate ($r^2 = .022$,) showed how much of the variability in the outcome is accounted for by the predictor. This means that only 2.2% of the variance in foreclosure rate is explained. The result showed that for every unit increase in CI there would be a .009 unit decrease in foreclosure rate. The result on CI being the only significant output for the regression on foreclosure rate as the dependent variable, has a significant level of .006; EI and RI had a significant level of .179 and .224 respectively (Table 7). In an attempt to improve the regression output shown for foreclosure rate, the squared version of the foreclosure rate index was employed, but the unsquared version still yielded a better result. A less suitable result was acquired from this approach where the $r^2 = .009$ which indicates that 0.9% of the variance in the squared foreclosure rate is explained by all three independent variables. In the second attempt, all three independent variables were insignificant contributors to foreclosure in MMA. EI, CI, and RI all had a significant level of .982, .122, and .202 respectively (Table 7).

Table 7. *Regression result on foreclosure rate and foreclosure rate squared*

	Foreclosure Rate				**Foreclosure Rate Squared**			
	Coeff.	Std. Error	Stdzd Coeff.	Sig.	Coeff.	Std. Error	Stdzd Coeff.	Sig.
(Constant)	.050	.003		.000	.007	.001		.000
EI	-.004	.003	.000	.179	-2.010E-05	.001	.001	.982
CI	<u>**-.009**</u>	<u>**.003**</u>	<u>**.179**</u>	<u>**.006**</u>	-.001	.001	-.072	.122
RI	-.004	.003	.006	.224	-.001	.001	-.059	.202
N		470				470		
R^2		.022				.009		

Bold and underlined = Sig at $P < 0.01$; Bold = Sig at $P \geq 0.01$ but $p < 0.05$; Underlined = Sig at $P \geq 0.05$ but < 0.1

4.8 Sample Study on the Northern African American Population in MMA.

A second set of analyses was conducted on the northern part of MMA; the same area with census tracts which contains 60 % and above of the African American population, and also a high clustering of foreclosure (see Figure 8). The purpose of running a separate analysis is to observe the possible result that could be acquired from using a sample group in this study. By eliminating the outliers from the barren census tract in the western part of MMA and focusing on a specific area with high foreclosure clustering, the northern part of MMA was selected to study the relationship of foreclosure with the selected variables in MMA. Out of the 519 census tract in MMA, 68 were selected for the high risk sample study. The initial 26 selected variables were retained to run correlation analysis, PCA, and regression analysis with the hope of achieving a more promising result than that which was gotten from all 519 census tracts in MMA.

The overall correlation result between the foreclosure rate and the selected 26 variables improved greatly in the high risk sample group than when compared to that of the initial analysis (Table 8). The highest correlation with foreclosure rate from all 26 variables was with the population of people in owner-occupied housing units (-.359). This means that an increase in foreclosure rate indicates a decrease in the population of people in owner occupied housing units. Other variables with high correlation includes MEDFINC (-.287), MEDHINC (-.291), MEDINC25> (-.293), %BADEG> (-.262), %PINCOV (.351), %FINCOV (.302), TOTMED (-.212), %INC<10,000 (.235), LABFORCE (-.311), TOTPOP (-.288), OHU (-.355), UNEMP (-.229), %ASIAN (-.207), and POPDEN (.302). Among the above 15 listed variables with high correlation with foreclosure rate, 5 variables were significant at .01 level while 6 variables were significant at .05 level. With the exception of %TP62>, the result acquired from the high risk sample study's 68 census tracts showed great improvement with the correlation and the significant level than that of the initial 519 census tracts used.

From the high risk sample PCA, The results of the preliminary KMO, and Bartlett tests for the 26 variables showed a value of .752 and 0.000 respectively which both implies the suitability of the input variables for PCA. Unlike the initial PCA where 3 of the variables were exempted for failure to meet the 0.5 communality marker, the PCA for the high risk sample study showed that all 26 variables were above the 0.50 cut off marker (Table 9). The PCA result generated 6 components with the first 3 components together making up to 63% of the total variance from all input variables (Table 10); a decrease from the initial PCA analysis which had 71% of the total variance for the first 3 components.

Table 8. MMA and AFA *Foreclosure rate correlation with the selected 26 variables.*

Variable	**Foreclosure rate of MMA**	**Foreclosure rate of AFA sample study**
MEDFINC	-.066	-.287*
MEDHINC	-.078	-.291*
MEDINC25>	.002	-.293*
%BADEG>	-.059	-.262*
%PINCPOV	.119**	.351**
%FINCPOV	.088	.302*
TOTMED	.012	-.212
%INC200,000>	-.030	-.096
%INC<10,000	.069	.235
POVRATE25>	.049	.115
LABFORCE	-.104*	-.311**
TOTPOP	-.094*	-.288*
TOTHH	-.041	-.166
POHU	-.200**	-.359**
%TPH	.029	.183
OHU	-.175**	-.355**
FAMEMP	-.040	-.191
%FAMEMP	.002	-.105
UNEMP	-.071	-.229
%HISP	-.140**	.004
%WHITE	-.027	-.108
%AFA	.008	.121
TOTHU	.093*	-.147
%ASIAN	.015	-.207
%TP62>	-.099*	-.034
POPDEN	.162**	.302**

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

From the high risk sample study, Component 1 accounted for 34.3% of the total variance while components 2 and 3 accounted for 16.5% and 12.3% respectively. Variables with high component scores (.70 and above) manifested more in the initial PCA result than the high risk sample PCA result. Similar to that of the initial PCA result, the components from the high risk sample were categorized as: Economic Indicator (EI) for component 1, Crowdedness Indicator (CI) for component 2, and Racial Diversity Indicator (RI) as component 3. These groupings are identical with that of the initial PCA because of the similarity of the variables from both component results. RI remained exactly the same in both results whereas changes were made to EI and CI. Variables such as TOTMED, and %INC200, 000> that were present in the initial PCA were exempted from the EI component of the high risk sample. Variables such as OHU, POHU, %INC<10, 000, and LABFORCE that were exempted from the initial PCA were present for the EI component of the high risk sample study. The remaining socioeconomic variables such as %PINCOV, %FINCOV, TOTMED, %BADEG>, MEDINC25>, MEDHINC, and MEDFINC were present in both EI component results. For the CI, variables such as OHU, POHU, FAMEMP, and LABFORCE that were present in the initial PCA were exempted from the CI component of the high risk sample. TOTHU variable which was not included in the initial PCA was present among the CI component of the high risk sample study. The remaining housing and population variables such as TOTPOP and TOTHH were present in both CI component results. The 3 PCA component results based on the high risk sample study were used as independent variables in Enter Linear Regression analysis, where foreclosure rate was the dependent variable.

Table 9. *Communalities result from MMA and AFA 26 variables*

	Communalities of MMA	**Communalities of AFA sample study**
	Extraction	Extraction
POVRATE25>	.545	.649
TOTPOP	.933	.968
% WHITE	.938	.968
% HISP	.899	.887
% AFA	.928	.970
% ASIAN	.589	.617
%TPH	**.427**	.746
FAMEMP	.708	.820
%FAMEMP	**.470**	.706
%INC200,000>	.767	.585
%INC<10,000	.847	.842
MEDHINC	.890	.937
%FINCPOV	.845	.881
%PINCPOV	.890	.867
POPDEN	**.436**	.545
MEDINC25>	.914	.825
TOTMED	.748	.644
%TP62>	.695	.723
OHU	.909	.869
LABFORCE	.931	.906
UNEMP	.706	.626
TOTHH	.937	.891
%BADEG>	.885	.730
MEDFINC	.904	.921
TOTHU	.866	.844
POHU	.925	.838

Bold = <0.50

Table 10. *PCA result from AFA sample study showing 3 components*

Component Matrix	**Component 1**	**2**	**3**
OHU	.897	.194	.058
POHU	.889	.160	-.014
MEDHINC	.857	-.440	.018
MEDFINC	.852	-.430	.058
%PINCPOV	-.831	.396	.075
%FINCPOV	-.813	.444	.077
LABFORCE	.803	.497	.100
%INC<10,000	-.759	.331	.187
MEDINC25>	.756	-.396	.231
%BADEG>	.735	-.224	.126
TOTMED	.523	-.195	.051
%ASIAN	.496	-.225	-.447
TOTHH	.465	.786	.214
TOTHU	.405	.777	.226
TOTPOP	.668	.715	.089
UNEMP	.397	.604	.245
POVRATE25>	-.108	.513	-.229
%AFA	-.287	-.194	.907
%WHITE	.270	.191	-.906
%HISP	.127	.263	-.881
%FAMEMP	.237	-.092	.184
%TP62>	.015	-.160	.070
FAMEMP	.446	.486	.254
%TPH	.095	-.100	.043
POPDEN	-.309	-.138	.104
%INC200,000>	.372	-.171	.333
Initial Eigenvalue	8.92	4.28	3.20
% of Variance	34.32	16.47	12.30
Cumulative %	34.32	50.79	63.09

The foreclosure rate regression showed an improvement from $r^2 = .022$ in the initial regression analysis to $r^2 = .168$ in the high risk sample regression analysis. The CI was the only notable significant output among the three variables results retrieved from the initial regression analysis, whereas in the high risk sample study, only the EI had a notable significant level of .001. The regression result for EI indicates that for every increase in EI there would be a .017 unit decrease in foreclosure rate. CI and RI had a significant level of .827 and .925 respectively (Table 11).

Table 11. *Regression result on MMA and AFA sample study foreclosure rate*

	Foreclosure Rate on MMA				**Foreclosure Rate on AFA sample study**			
	Coeff.	Std. Error	Stdzd Coeff.	Sig.	Coeff.	Std. Error	Stdzd Coeff.	Sig.
(Constant)	.050	.003		.000	.038	.005		.000
EI	-.004	.003	.000	.179	**-.017**	**.005**	**-.409**	**.001**
CI	**-.009**	**.003**	**.179**	**.006**	-.001	.005	-.025	.827
RI	-.004	.003	.006	.224	.000	.005	.011	.925
N		470				66		
R^2		.022				.168		

Bold and underlined = Sig at $P < 0.01$; Bold = Sig at $P \geq 0.01$ but $p < 0.05$; Underlined = Sig at $P \geq 0.05$ but < 0.1

4.9 Results on the Correlation and Regression Analysis for the City of Miami

The cluster and outlier analysis and the results from the PCA both point towards the city of Miami as an area of interest with high value of the EI, and also a higher evidence of clustering of high market value foreclosed houses than the rest of the county. This is no surprise considering the city of Miami is a major hub in Miami-Dade County. To further examine the city of Miami, an intricate study relating foreclosure and crime was carried out.

Results from Pearson's correlation shows that 9 of the neighborhood characteristics have a positive correlation with violent crime: Percentage of African American population (%AFA), percentage of people below poverty level (%PINCPOV), vacant residential addresses (VACRES), and percentage of income less than $10,000 (%INC<10,000) have the highest positive correlation with violent crime which are significant at the .01 level (r = .548, r = 512, r = 411 and r = 379 respectively)(Table 12). For the property crime, vacancy rate (VACRATE), median vacant residential houses (VACRES), percentage of people below poverty level (%PINCPOV), total vacant addresses (TOTVAC), and percentage of income less than $10,000 (%INC<10,000) have the highest positive correlation, which are significant at the .01 level (r = .469, r = .438, r = .392, r = .258, and r = .250 respectively).

Table 12. *Correlation result between crime and neighborhood characteristics*

Variable	Description	Violent Crime	Property Crime	Total Crime
TOTPOP	Overall total population	.138	.241**	.235*
MEDFINC	Median family income (dollars)	-.353**	-.290**	-.316**
%PINCPOV	Percentage of all people whose income in the past 12 months is below the poverty level	.512**	.392**	.433**
MALE 15 - 24	Male 15 – 24	.250**	.249**	.261**
%WHITE	% White	-.562**	-.303**	-.362**
%AFA	% Black or African American	.548**	.260**	.321**
%HISP	% Hispanic or Latino	-.334**	-.172	-.208*
VACRES	Median vacant residential addresses	.411**	.438**	.458**
VACBUS	Median vacant business addresses	-.088	-.026	-.038
TOTVAC	total vacant addresses	.193*	.258**	.262**
VACRATE	vacancy rate	.292**	.469**	.471**
%INC<10,000	Income - Less than $10,000	.379**	.250**	.286**
%INC200,000>	Income - $200,000 or more	-.317**	-.289**	-.309**
FORATE	foreclosure rate	.163	.157	.163

**. Correlation is significant at 0.01 level (2-tailed). *. Correlation is significant at 0.05 level (2-tailed).

The results of the correlation analysis showed that most of the variables are significant with both violent, and property crime, but the result of the correlations are, of course, only indicative of the relationships that must be investigated by using a multiple regression model. Correlation analysis tests the strength of the relationship between two variables, regression analysis, on the other hand, make a stronger claim; they attempt to demonstrate the degree to which one or more variables potentially promote positive or negative change in another variable.

Examining the relationship between foreclosure-led vacant houses, and crime in the city of Miami required the incorporation of the regression model discussed in the methodology ($C_i = a + b_1P_i + b_2V_i + b_3Z_i + b_4F_i + \varepsilon_i$) to test for H2, and to explain the effect of crime on foreclosure. Using the index crime in the city of Miami as the dependent variables, both violent, and property crime were examined separately to run the regression. Violent and property crime are both regarded as index crimes, but they both require separate types of attention. A total of 75,159 index crimes were collected for this study, 6,727 comprised of violent crimes, while 68,432 were property crimes. Although the total number of violent crimes appears considerably lesser in comparison to property crimes, violent crimes tends to attract more attention. In most cases, violent crimes have a better chance of being reported when related to vacant and abandoned buildings. Also, the effect of property crime may be greater in lower income neighborhoods, but high income neighborhoods have a higher chance of reporting such crimes that may be considered of less consequence in low income neighborhoods (Immergluck, and Smith, 2006). To further examine crime, foreclosure, and vacant houses, the Enter Linear Regression was conducted on violent crime, property crime, and a combination of both (total crime) The independent variables consisted of the vacant properties data (residential, and commercial), demographic characteristics, foreclosure rate, and socioeconomic variables for all 117 census tracts in the city of Miami.

From the regression result, the model r^2 for violent crime (r^2 = .414) and property crime (r^2 = .449) shows a measure of how much of the variability in the outcome is accounted for by the predictor (Table 13). This means that all of the independent variables accounted for 41.4% of the variation in violent crime and 44.9% in property crime. The regression result with total crime as the dependent variable is a combination of both violent and property crime. In total crime, VACRATE, VACRES, %PINCPOV, and %AFA have the highest positive correlation, which are significant at the .01 level (r = .471, r = .458, r = .433, and r = .321 respectively). The model r^2 (r^2 = .462) for total crime shows a measure of how much of the variability in the outcome is accounted for by the predictor. This means that all of the independent variables accounted for 46.2% of the variation in total crime.

Violent crime result shows an insignificant result on all counts with the exception of the %AFA population leading to a 1.04 increase in crime with a significance level of .062. The result could be argued as a non-contributive factor for influencing crime in the real world.

In property crime, six of the demographic variables were statistically significant to neighborhood crime. These include total population (TOTPOP), VACRATE, VACBUS, percent of income above $200,000 (%INC200000>), %HISP and %AFA. All of the above mentioned indicators were significant at the 0.01 level with the exception of percent of income above $200,000 and percent of African American population. The result showed that for every unit increase in VACRATE and TOTPOP, there would be a

45.686 and .087 unit increase in property crime respectively. Also, for every unit increase in VACBUS, %INC200, 000>, and the %HISP, there would be a unit decrease of 1.734, 23.343, and 10.109 in property crime respectively.

From the total crime result in the regression analysis, TOTPOP, VACRATE, and VACBUS are all significant at the .01 level. %INC200000> and %HISP are both significant at $P \geq .01$ but < 0.05. The result showed that for every unit increase in TOTPOP, and VACRATE, there would be a .093 and 48.594 unit increase in total crime respectively. Also, for every unit increase in VACBUS, %INC200000>, and %HISP, there would be a unit decrease of 1.885, 24.010, and 9.911 in total crime respectively.

Table 13. *Regression of crime on neighborhood characteristics and foreclosure rate in the city of Miami*

	Violent Crime				Property Crime				Total Crime			
	Coeff.	Std. Error	Stdzd Coeff.	Sig.	Coeff.	Std. Error	Stdzd Coeff.	Sig.	Coeff.	Std. Error	Stdzd Coeff.	Sig.
(Constant)	-12.922	46.191		.780	**905.165**	**293.078**		**.003**	**886.734**	**322.759**		**.007**
% of all people below poverty level	.808	.811	.163	.321	4.792	5.143	.148	.354	5.465	5.664	.151	.337
Median family income	.000	.000	-.049	.719	.000	.002	-.022	.867	.000	.002	-.025	.849
Total population	.005	.004	.140	.178	**.087**	**.024**	**.359**	**.000**	**.093**	**.027**	**.343**	**.001**
vacancy rate	1.675	1.842	.129	.365	**45.686**	**11.688**	**.538**	**.000**	**48.594**	**12.872**	**.513**	**.000**
foreclosure rate	-25.713	119.644	-.018	.830	622.780	759.129	.066	.414	563.340	836.009	.054	.502
Vacant residential addresses	.065	.154	.059	.675	-.381	.975	-.053	.697	-.349	1.073	-.044	.746
Vacant business addresses	-.101	.093	-.116	.279	**-1.734**	**.589**	**-.305**	**.004**	**-1.885**	**.648**	**-.297**	**.004**
% Income Less than $10,000	-.129	1.043	-.017	.902	-6.341	6.620	-.130	.340	-6.275	7.291	-.115	.391
% Income $200,000 or more	-.567	1.505	-.055	.707	**-23.343**	**9.548**	**-.346**	**.016**	**-24.010**	**10.515**	**-.320**	**.024**
% Male 15 – 24	.178	1.040	.014	.864	-6.846	6.600	-.083	.302	-6.660	7.268	-.073	.362
% Hispanic or Latino	.123	.574	.048	.830	**-10.109**	**3.640**	**-.599**	**.007**	**-9.911**	**4.009**	**-.527**	**.015**
% Black or African American	1.040	.552	.419	.062	**-7.454**	**3.505**	**-.458**	**.036**	-6.121	3.860	-.338	.116
N			117				117				117	
R^2			0.414				0.449				0.462	

Bold and underlined = Sig at P < 0.01; Bold = Sig at P ≥ 0.01 but p < 0.05; Underlined = Sig at P ≥ 0.05 but < 0.1

CHAPTER 5

DISCUSSIONS

5.1 Introduction

This chapter discusses the findings of this study based on the results gotten from both spatial, and statistical analysis in relation to foreclosure in MMA, and the city of Miami.

5.2 Foreclosure and Neighborhood Characteristics in MMA

The spatial analysis showed a concentration of foreclosure on the eastern part of MMA. Most of the foreclosure listings were clustered on the municipalities surrounding the city of Miami (see figure 6). The western part of the county had little or no cases of foreclosure whatsoever. The northern part of MMA showed a high concentration of random distribution of foreclosed houses. Areas where concentrations of high market value foreclosed houses were surrounded by similar values consist of the city of Miami and Miami Beach. The reason for the concentration of high market value foreclosed houses in the city of Miami and the surrounding areas could be associated with the geographic location. The geographic location of Miami and the beachside communities north of Miami Beach: Surfside, Bal Harbour, Sunny Isles Beach, etc. attracts a higher price of houses than other areas. These areas are considered among the top ten least affordable housing options for moderate-income families in the nation’s 25 largest metropolitan areas (Bandell, 2012; Kolko, 2014.)

The spatial analysis showed a pattern for foreclosure cases in MMA, the statistical analysis on the other hand showed that foreclosure rate and most of the neighborhood characteristics were not correlated at a significant level. The foreclosure rate showed a negative correlation with the population of people in owner-occupied housing units (-.200), and a positive correlation with percentage of people below poverty level (.119). This means that an increase in foreclosure rate indicates a decrease in the population of people in owner occupied housing unit, and an increase in foreclosure rate indicates an increase in percentage of people below the poverty level. The negative correlation between foreclosure rate and the population of people in owner-occupied housing units is understandable. An increase in foreclosure is expected to reduce the number of people still entitled to a house, especially in an area like the MMA where foreclosure cases are well above average. Looking at the rest of the variables in the study to address H1, disparities exist when relating the three observed racial compositions and the socioeconomic variables. From the correlation analysis, the poverty rate of people 25 years and above, the percent of all people whose income is below the poverty level, and the percentage of people whose income are less than $10,000 all have a positive correlation with the African American population, and a negative correlation with the White and Asian population. Whereas the percentage of people whose income are more than $200,000, the median household income, and the percentage of people who attained a bachelor degree and higher level of education all have a positive correlation with the White and Asian population, but a negative correlation with the African American population (see Table 4). This shows that in MMA, the socioeconomic status of the

African American population is less favorable compared to that of the Whites, or the Asian population. This result on household income and race is somewhat similar to a study conducted on the relationship between housing foreclosure, lending practice, and neighborhood ecology (Kaplan & Sommers, 2009). Kaplan and Sommers (2009) categorized the minority percentage in Summit County, Ohio as African American, White Hispanic, and Asian American groups. In their correlation result between foreclosure rate and the minority neighborhoods, the Hispanic and the Asian percentage were small (1.1% and 1.8% respectively compared to the 14% for African American). Their results showed that neighborhoods where subprime activity is exceptionally high (over 22%) share a number of characteristics: they all have a high minority proportion which primarily consists of the African American population. Generally, levels of income are lower and poverty rates are higher. Like the studies referenced in H1 (Baxter & Lauria, 1998; Chan et al., 2013; U.S. Department of Housing and Urban Development, 2000), the correlation analysis on individual variables in this study showed that among the three racial compositions examined, the African American variable alone had negative correlation with those socioeconomic variables that provides positive re-enforcements which strengthens the social and economic status in their neighborhood. This shows that the African American neighborhoods, being one of the dominant racial groups in MMA, are a primary focus to be further observed in relation to the foreclosure study.

The spatial output of the three components derived from the PCA analysis also points that the African American population in the north showed deficiency in socioeconomic stimulus. From the EI result, the northern part of MMA showed the lowest score whereas the areas surrounding the city of Miami portrayed a much better economic standard. This could explain why the city of Miami and its surrounding areas displayed a higher concentration of high market valued foreclosed houses that the rest of the county. The regression result generated from EI, CI, and, RI showed an unfavorable insignificant relationship with foreclosure rate. The regression results with violent crime and property crime as the dependent variables provided a much better model where $r^2 = .414$, and .449 respectively. Foreclosure rate and foreclosure rate squared which both used the PCA component results as the independent variables, portrayed a model where $r^2 = .022$, and .009 respectively. A possible explanation for the poor r^2 model could be because of the combination of variables used. When consideration is given to the initial correlation between the foreclosure rate and the same variables which made up those three components, the poor regression results comes as no surprise.

The foreclosure rate variable from the high risk sample had a higher correlation with the majority of the variables used. Variables with low correlation from the initial analysis showed a much higher correlation when repeated with the fewer census tracts from the high risk sample. There was an improvement in the high risk sample regression r^2 value where $r^2= .168$, yet the changes in the high risk sample result still did not improve the regression between foreclosure rate and the 3 component score. The result still showed an insignificant relationship with the selected independent variables. Unlike the correlation analysis, the PCA from the high risk sample did not show much improvement. Although the communalities result for the high risk sample showed that all the 26 variables were accounted for, the cumulative percent of variance for the initial PCA was higher than that of the high risk sample. Similar variables were identified in the RI results for the two PCA analyses. EI and CI showed more variables in the initial PCA than that of the high risk sample PCA. These changes did not account for much improvement from that of the initial PCA, and they also did not assist in improving the relationship between foreclosure rate and its independent variables as seen from the regression analysis result. Previous studies conducted by Kaplan and Sommers (2009) in Summit County, Ohio, and Mikelbank (2009) in Columbus, Ohio showed a more significant regression model for foreclosure rate where $r^2 = .47$, and $r^2 = .65$ respectively. In this study, three regressions were carried out using the un-squared MMA study area with 519 census tracts, the squared MMA study area with 519 census tracts, and a high risk sample from the northern part of MMA with 68 census tracts, but the result acquired from all three proved insignificant to the relationship between foreclosure rate and the PCA scores. The insignificant relationship in this study's foreclosure cases could be as a result of the deviation from the approach adopted by other studies, or it could simply mean that unlike other study areas like Summit County, Ohio and Columbus, Ohio, foreclosure cases in MMA have no significant relationship with its neighborhood characteristics. Perhaps a possibility exists where the error lies with the variables used for this study.

Observing both the spatial and statistical analysis, the following can be said about the northern part of Miami-Dade County. First, The EI is at its lowest in the north. Secondly, there is a concentration of foreclosure cases at the northern part of Miami-Dade County, and finally, the African American population appears to be heavily dominant in the north.

With the exception of the African American population, no other race or ethnic group exhibited a high population in the northern part of Miami-Dade County. The spatial representation of the African American population puts a large proportion of the population in an area that shows a clustering of foreclosure and also a deficit in EI. Also, the result from the correlation analysis shows African American populations as the only race in Miami-Dade County to have a positive correlation with the percentage of people living below poverty level and also a positive correlation with percentage income below $10,000. All these contribute to the fact that amidst other races, the African American population has a socioeconomic deficiency coupled with a higher case of foreclosure than any other racial groups in MMA.

The correlation between %African American and foreclosure rates showed a weak positive relationship, which at first seems surprising (Table 8). But foreclosure rate was defined as the number of repossessed houses divided by owner occupied houses. If the rates of home ownership are low for African Americans, the foreclosure rates could be high but not affect the neighborhood. High rates of defaulting on mortgages may be part of the story, but low rates of home ownership may override that relationship. Black inner-city neighborhoods have been a prominent topic of discussion among social scientists and criminologists (Shaw & McKay, 1942; Sampson & Wilson, 1995). These neighborhoods have disproportionately suffered severe population and housing loss up to the point that it begins to disrupt the social and institutional order (Sampson & Wilson, 1995). The theory of concentrated disadvantage by Sampson and Wilson discusses on how the racial differences in poverty and family disruption is so strong that the worst urban context in which Whites resides are considerably better than the average context of Black communities. Even when given the same objective socioeconomic status, Blacks and Whites face vastly different environments in which to live, work, and raise their children (Sampson & Wilson, 1995). The findings from this study fits in line with Sampson and Wilson's theory. It appears that the results strongly indicate that the African American population are concentrated and residentially segregated in impoverished neighborhoods. Several studies have proven that block groups or tracts with high proportions of foreclosure are commonly present among clusters of African American populations and low income neighborhoods (Chan et al., 2013; U.S. Department of Housing and Urban Development, 2000). Spatial analysis in this study shows that in the case of MMA, both tend to be located in the same area. A study on foreclosure conducted in Oakland showed that foreclosure houses tend to be concentrated in minority neighborhoods with "higher-than-typical crime rates and poor schools" (Williams, Weinheimer, & Brooks, 2011). Oakland's foreclosure problems was characterized by low income, high crime rates, poor living conditions, etc. that were persuaded through predatory lending practices (Williams et al., 2011). However, whether or not the concentration of foreclosure in the African American neighborhood can be attributed to predatory lending through subprime mortgage is beyond the scope of this study.

5.3 Foreclosure and Crime in the City of Miami

Both violent and property crime were statistically correlated with the majority of the variables used in the study. Foreclosure rate and crime showed a weak relationship compared to most of the variables (see Table 12). Foreclosure rate was significant at r = .163, and .157 with violent and property crime respectively. The result between crime and vacancy rate showed a better correlation than that of crime and foreclosure rate. Crime and vacancy rate correlation showed r = .292 for violent crime, and r = .469 for property crime, both which were significant at .01 level. The highest correlation with violent crime were with %White, and %AFA. %White showed a negative correlation with violent and property crime with r = -.562, and r = -303 respectively. The %AFA on the other hand showed a positive correlation with r = .548 for violent crime, and r = .260 for property crime. The result from the correlation analysis indicates that increase in the percentage of African American population leads to an increase in crime while the percentage of White population has an inverse relationship with crime. The finding that %AFA is one of the strongest correlates of crime is consistent with the theory of concentrated disadvantage by Sampson and Wilson (1995). The concentrated disadvantage theory, an updated version of Shaw and McKay's social disorganization theory, argues that a disproportionate amount of crime is associated with the concentration of African Americans into communities, neighborhoods, housing projects, etc. where poverty and unemployment rates are high, income levels are low, and divorce rates and out of wedlock births are high. The regression analysis also explained a great deal of the variance for all three crime index: violent crime with r^2 = .414, property crime with r^2 = .449, and total crime with r^2 = .462. From the regression result, violent crime in general exhibited a statistically insignificant relationship with every variable in the study except the African American variable. The analysis revealed a relationship between the

African American population and Crime, with a 1% increase in the Black or African American population leading to 1% increase in violent crime. Yet the relationship among the two variables had a significant level of .062 which does not incite confidence of the outcome being a contributive factor in the real world. The result for violent crime in previous studies showed a more significant relationship with variables such as the number of businesses, unemployment rate, median family income, percentage low education etc. (Immergluck & Smith, 2006; Katz et al., 2011). Property crime on the other hand had a significant relationship with numerous variables such as the Hispanic population, the African American population, the number of people whose income are over $200, 000, and vacancy rate. With the exception of the vacancy rate, every other significant demographic variable listed above indicated an inverse relationship with property crime. Despite the strong positive correlation between crime and the African American population, both variables representing the dominant minority group in the city of Miami (Hispanic, and the African American) also indicated a negative relationship with property crime. This indicates that the minority populations in the city of Miami are not statistically significant determinants of property crime.

Investigating the relationship between foreclosure, vacancy, and crime in the city of Miami was part of the primary objective of this study. The result from the regression analysis shows that foreclosure rate, a primary variable for this analysis, indicated an insignificant relationship with crime; both violent, and property. Immergluck and Smith's (2006) study on Chicago, Illinois revealed a direct relationship between foreclosure and violent crime, whereas no relationship was observed between foreclosure and property crime. Besides the insignificant relationship with foreclosure and crime in this study, no relationship was observed between the variables on vacant houses and violent crime. In property crime, vacancy rate was a statistical determinant with a 1% increase in vacancy rate leading to a 45% increase in property crime. The rest of the variables representing vacant houses in this study (vacant residential addresses, and vacant business addresses) were statistically insignificant with property crime.

The result retrieved for the relationship between the vacant houses and crime were an unexpected deviation from the expected outcome. Then again several factors needs to be considered when attempting to relate different variables. It is possible that a better result could still be achieved if a more consistent, standardized set of data was used throughout the course of this study. The data used consisted of the total form (TOTPOP, TOTMED, TOTHH, TOTHU), the percentage form (%AFA, %WHITE, %ASIAN, %TPH), and the density form (POPDEN, FORATE, VACRATE) for the various variables. It is also possible that a different result could be achieved if proper consideration were given to the underlying size of the tracts in this study. The results may be biased simply because the size of the tracts was not clued into the outcome of the analysis. The reason for pointing all these out is to note that there are several factors at play which could be responsible for the insignificant relationship between the foreclosure, crime, vacant data, and the vector of neighborhood characteristics discussed in this study. Future studies could shed more light on these points to explore the possibility of improving the results, especially after the r^2 result for the regression analysis in MMA proved to be poor on all fronts.

CHAPTER 6

CONCLUSIONS

6.1 Introduction

This chapter concludes the study by addressing the objectives and the hypotheses introduced in Chapter 1, and the future direction which could be taken to further this study. Also addressed are the limitations and the challenges encountered during the course of this research, from data processing to analysis.

6.2 Conclusion

The purpose of this study was to (1) observe the clustering pattern of foreclosure in MMA, (2) research the relationship between foreclosure and other neighborhood characteristics at the census tract level and, (3) study the relationship between foreclosure and crime in the city of Miami. For the purpose of this study, data of foreclosed houses in Miami-Dade County was collected between 2010-2013 along with 2011-2012 crime data and a census tract level database for the year 2010 containing information on neighborhood characteristics. These were set up to achieve the following objectives:

1. Run nearest neighbor analysis, spatial autocorrelation, and cluster and outlier analysis on the MMA to show its foreclosure distribution pattern.
2. Use correlation analysis, PCA, and regression analysis to check the relationships between housing foreclosures and the 26 selected neighborhood attributes to determine if any relationship exists in the MMA.

3. Run a regression analysis with the selected neighborhood attributes and also with the vacancy period of the foreclosure process to study the relationship between foreclosure, vacancy, and crime in the city of Miami, Florida.

Hypothesis 1 states that there is a higher concentration of foreclosure among the African American neighborhoods and low income neighborhoods. In MMA, foreclosure cases showed a clustering pattern. The city of Miami showed a concentration of high market value foreclosure cases in MMA; an area predominantly occupied by the Whites and Hispanic population. The entire northern part of MMA also showed a concentration of foreclosure which appears to be the result of a random distribution. Unlike the city of Miami which represents one of many areas with a high density population of White or Hispanic population, the northern part of MMA represents a concentration of foreclosure in neighborhoods predominantly occupied by the African Americans population. The statistical analysis (correlation, PCA, and regression) showed that the foreclosure rate observed in this study had no statistical significant relationship with the neighborhood characteristics in MMA. Among other variables however, correlation, and PCA both showed that the economic conditions in the White, and the Asian neighborhoods have high positive correlation with variables depicting a better socioeconomic standing in MMA. The African American neighborhood appeared to be significantly correlated with characteristics showing that the area exhibits deficit in income and education attainment. The visual representation of the different racial composition in MMA made it possible to identify the segregation among the races, and to identify where each of the three racial groups observed where dominant in number. This study accepts H1 which indicates an increased presence of foreclosure in the African American neighborhood and low income neighborhoods.

Hypothesis 2 states that the increase in foreclosure-led vacant houses leads to an increase in crime. The result from the regression analysis showed that foreclosure was not statistically significant with crime in the city of Miami, but the vacancy rate showed a statistically significant relationship with property crime. Foreclosure rate and vacancy rate showed no relationship whatsoever with violent crime. The vacant residential addresses and the vacant business addresses both indicated a statistically insignificant relationship with violent crime and property crime. This study rejects H2 which indicates that an increase in foreclosure-led vacant houses leads to an increase in crime.

6.3 Limitations

While the researches carried out in this study were separated into categories, it is crucial to state the shortcomings identified during the course of the whole thesis. Several limitations were confronted, the greatest being the lack of accessible foreclosure data. A total of 18,155 foreclosure data were downloaded for this study, but this was not the total number of foreclosure filings in Miami-Dade County. Limitations placed on the number of available downloads per day hindered the purchase of all of the foreclosure data. Also, a time constraint and the inaccessibility of adequate and affordable foreclosure data for a long period of time hindered the study of a temporal analysis showing the spatial distribution of foreclosure.

Some foreclosure cases appeared for more than one foreclosure status. This means that an address could show as an upcoming foreclosure and as a cancelled or sold foreclosure at the same time. On a similar note, the foreclosure data descriptions were specific. It recorded the date of foreclosure, the address, the foreclosure status, the type of property that was foreclosed, etc. The vacancy data on the other hand showed less precise information. There was no way to know the specific date a property became vacant, or if all the vacant and abandoned properties were as a result of foreclosure. It is important to note that not all foreclosed properties become vacant and abandoned, and not all vacant and abandoned properties are the direct result of foreclosure. Despite the difficulty of obtaining and processing of the foreclosure data, an accurate data on vacant and abandoned buildings as a result of foreclosure proved to be more difficult to acquire. To this end, the aggregate quarterly data at the census tract level of all the vacant houses in the city of Miami was used.

6.4 Future Directions

This study leaves paths to be explored for further research and two are discussed here. Justin Clark, an attorney who specializes in foreclosure cases believes that the foreclosure recovery in Florida lags because unlike some other states, Florida's legal system prolongs the foreclosure process. "Florida is a 'judicial state, meaning all foreclosures have to go through the court." In addition, a Floridian's debt mounts quickly. “During a three-year foreclosure process, a homeowner with a $1,500 monthly payment can quickly incur $54,000 of late payments, plus legal fees and expenses. So while prices may be rising, the amount owed increases even faster," Clark said (Shanklin, 2014). Considering the different interest rates applied to mortgage holders, the expenses accrued from the home loans that may inadvertently lead to foreclosure will be exponential for subprime loan owners. A future study into foreclosure using data from home loans in MMA (both prime and subprime loans) will examine the impact of subprime and predatory lending mortgage and the possibility of an existing area or demography targeted for subprime lending.

Besides the large scale effect of foreclosure on the economy, and the real estate market in the United States, foreclosure also dealt a devastating blow on families, and also brought distress to communities and municipalities. Addressing those communities affected with foreclosure, little systematic researches have been conducted on metropolitan responses to the foreclosure threat, and steps to be taken towards property recovery. Property recovery is the new initiative adopted by many housing systems in major metropolitan areas (Williams et al., 2011; Swanstrom, Chapple, & Immergluck, 2009). Both studies by Williams et al., (2011), and Swanstrom et al., (2009) were funded by the MacArthur Foundation’s Building Resilient Regions (BBR) project to explore regional solutions to foreclosure crisis. A similar method should be adopted in MMA to assist in Federal and State policies towards mitigating foreclosure in the municipalities in MMA.

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APPENDIX A

METROPOLITAN FORECLOSURE RATE RANKING

Metropolitan Statistical Area Name	**Rank in Foreclosure Rate**	**Foreclosure Rate**	**Prime Foreclosure Rate**	**Subprime Foreclosure Rate**
Vineland-Millville-Bridgeton, NJ Metropolitan Statistical Area	1	16.0%	10.4%	42.7%
Atlantic City-Hammonton, NJ Metropolitan Statistical Area	2	12.0%	8.6%	40.3%
Kingston, NY Metropolitan Statistical Area	3	11.8%	7.9%	34.5%
Miami-Fort Lauderdale-Pompano Beach, FL Metropolitan Statistical Area	4	11.6%	8.4%	27.2%
Tampa-St. Petersburg-Clearwater, FL Metropolitan Statistical Area	5	10.9%	7.6%	29.3%
Poughkeepsie-Newburgh-Middletown, NY Metropolitan Statistical Area	6	10.7%	7.4%	34.4%
Deltona-Daytona Beach-Ormond Beach, FL Metropolitan Statistical Area	7	10.4%	7.3%	26.2%
Orlando-Kissimmee, FL Metropolitan Statistical Area	8	10.0%	7.2%	26.4%
Lakeland-Winter Haven, FL Metropolitan Statistical Area	9	9.7%	6.6%	23.7%
Port St. Lucie, FL Metropolitan Statistical Area	10	9.7%	7.0%	26.0%
Palm Coast, FL Metropolitan Statistical Area	11	9.5%	6.7%	28.2%
Ocala, FL Metropolitan Statistical Area	12	9.4%	6.6%	23.7%
Glens Falls, NY Metropolitan Statistical Area	13	9.3%	6.0%	29.0%
Punta Gorda, FL Metropolitan Statistical Area	14	8.8%	6.8%	21.3%
Trenton-Ewing, NJ Metropolitan Statistical Area	15	8.7%	5.9%	35.8%
Jacksonville, FL Metropolitan Statistical Area	16	8.6%	5.8%	24.5%
Bradenton-Sarasota-Venice, FL Metropolitan Statistical Area	17	8.6%	6.3%	26.6%
Cape Coral-Fort Myers, FL Metropolitan Statistical Area	18	8.3%	6.3%	24.2%
Palm Bay-Melbourne-Titusville, FL Metropolitan Statistical Area	19	8.2%	5.9%	26.1%
Albany-Schenectady-Troy, NY Metropolitan Statistical Area	20	8.2%	5.0%	35.2%
Pine Bluff, AR Metropolitan Statistical Area	21	8.1%	5.5%	27.8%
Las Vegas-Paradise, NV Metropolitan Statistical Area	22	7.9%	5.5%	24.5%

Lewiston-Auburn, ME Metropolitan Statistical Area	23	7.9%	5.0%	28.7%
Utica-Rome, NY Metropolitan Statistical Area	24	7.9%	4.8%	26.1%
Binghamton, NY Metropolitan Statistical Area	25	7.9%	5.1%	26.8%
Bangor, ME Metropolitan Statistical Area	26	7.7%	4.9%	27.6%
New York-Northern New Jersey-Long Island, NY-NJ-PA Metropolitan Statistical Area	27	7.6%	5.1%	32.3%
Youngstown-Warren-Boardman, OH-PA Metropolitan Statistical Area	28	7.6%	5.2%	20.9%
Sebastian-Vero Beach, FL Metropolitan Statistical Area	29	7.5%	5.5%	22.6%
Elmira, NY Metropolitan Statistical Area	30	7.5%	4.4%	21.5%
Syracuse, NY Metropolitan Statistical Area	31	7.4%	4.6%	28.6%
Mobile, AL Metropolitan Statistical Area	32	7.4%	5.5%	24.0%
Shreveport-Bossier City, LA Metropolitan Statistical Area	33	7.4%	5.1%	26.2%
Kankakee-Bradley, IL Metropolitan Statistical Area	34	7.2%	4.7%	20.8%
Memphis, TN-MS-AR Metropolitan Statistical Area	35	6.9%	4.2%	21.8%
Panama City-Lynn Haven-Panama City Beach, FL Metropolitan Statistical Area	36	6.9%	4.9%	26.2%
Terre Haute, IN Metropolitan Statistical Area	37	6.9%	4.9%	22.1%
Tallahassee, FL Metropolitan Statistical Area	38	6.6%	4.4%	22.9%
Jackson, TN Metropolitan Statistical Area	39	6.6%	4.3%	22.8%
Naples-Marco Island, FL Metropolitan Statistical Area	40	6.6%	5.0%	26.4%
Rockford, IL Metropolitan Statistical Area	41	6.5%	4.6%	20.7%
New Haven-Milford, CT Metropolitan Statistical Area	42	6.4%	3.9%	24.1%
Norwich-New London, CT Metropolitan Statistical Area	43	6.3%	4.1%	24.0%
Tuscaloosa, AL Metropolitan Statistical Area	44	6.3%	4.4%	31.4%
Danville, IL Metropolitan Statistical Area	45	6.3%	3.7%	23.1%
Pensacola-Ferry Pass-Brent, FL Metropolitan Statistical Area	46	6.3%	4.1%	21.4%
Cleveland-Elyria-Mentor, OH Metropolitan Statistical Area	47	6.2%	4.2%	19.5%
Fort Walton Beach-Crestview-Destin, FL Metropolitan Statistical Area	48	6.2%	4.3%	28.0%
Alexandria, LA Metropolitan Statistical Area	49	6.2%	4.1%	24.7%
Rochester, NY Metropolitan Statistical	50	6.2%	3.9%	24.9%

Area				
Kokomo, IN Metropolitan Statistical Area	51	6.1%	4.0%	21.1%
Monroe, LA Metropolitan Statistical Area	52	6.1%	4.7%	23.0%
Chicago-Naperville-Joliet, IL-IN-WI Metropolitan Statistical Area	53	6.0%	4.3%	23.7%
Montgomery, AL Metropolitan Statistical Area	54	6.0%	4.3%	24.7%
Akron, OH Metropolitan Statistical Area	55	6.0%	4.3%	20.1%
Anderson, IN Metropolitan Statistical Area	56	5.8%	4.1%	17.9%
Scranton--Wilkes-Barre, PA Metropolitan Statistical Area	57	5.8%	3.8%	18.8%
Buffalo-Niagara Falls, NY Metropolitan Statistical Area	58	5.8%	3.8%	24.5%
Dover, DE Metropolitan Statistical Area	59	5.8%	3.8%	25.1%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metropolitan Statistical Area	60	5.7%	3.7%	23.7%
Gainesville, FL Metropolitan Statistical Area	61	5.7%	3.8%	20.7%
Allentown-Bethlehem-Easton, PA-NJ Metropolitan Statistical Area	62	5.6%	4.0%	23.2%
Topeka, KS Metropolitan Statistical Area	63	5.5%	3.8%	22.9%
Cleveland, TN Metropolitan Statistical Area	64	5.5%	3.9%	22.0%
Salem, OR Metropolitan Statistical Area	65	5.5%	3.8%	22.7%
Salisbury, MD Metropolitan Statistical Area	66	5.4%	3.6%	18.6%
Medford, OR Metropolitan Statistical Area	67	5.4%	4.1%	22.9%
Ocean City, NJ Metropolitan Statistical Area	68	5.4%	3.7%	36.4%
Mansfield, OH Metropolitan Statistical Area	69	5.4%	3.5%	17.6%
Ithaca, NY Metropolitan Statistical Area	70	5.3%	4.0%	19.1%
Reno-Sparks, NV Metropolitan Statistical Area	71	5.3%	3.9%	21.5%
Jackson, MS Metropolitan Statistical Area	72	5.3%	3.1%	18.1%
Albany, GA Metropolitan Statistical Area	73	5.2%	3.6%	16.1%
Rocky Mount, NC Metropolitan Statistical Area	74	5.2%	3.4%	16.2%
Chattanooga, TN-GA Metropolitan Statistical Area	75	5.1%	3.2%	20.8%
Peoria, IL Metropolitan Statistical Area	76	5.1%	3.3%	22.4%
Pittsfield, MA Metropolitan Statistical Area	77	5.1%	2.9%	18.5%
Springfield, MA Metropolitan Statistical Area	78	5.1%	2.8%	17.6%
Hinesville-Fort Stewart, GA Metropolitan Statistical Area	79	5.1%	4.0%	19.4%
Flint, MI Metropolitan Statistical Area	80	5.1%	3.6%	13.8%
Erie, PA Metropolitan Statistical Area	81	5.1%	3.1%	19.2%

Dayton, OH Metropolitan Statistical Area	82	5.0%	3.6%	19.7%
Baltimore-Towson, MD Metropolitan Statistical Area	83	5.0%	3.2%	22.3%
Cumberland, MD-WV Metropolitan Statistical Area	84	5.0%	3.2%	17.9%
Columbus, OH Metropolitan Statistical Area	85	5.0%	3.4%	21.7%
Johnstown, PA Metropolitan Statistical Area	86	5.0%	3.0%	22.4%
Portland-South Portland-Biddeford, ME Metropolitan Statistical Area	87	5.0%	3.4%	24.8%
Dothan, AL Metropolitan Statistical Area	88	5.0%	3.9%	22.6%
Bridgeport-Stamford-Norwalk, CT Metropolitan Statistical Area	89	5.0%	3.3%	22.3%
Indianapolis-Carmel, IN Metropolitan Statistical Area	90	4.9%	3.3%	20.8%
Cincinnati-Middletown, OH-KY-IN Metropolitan Statistical Area	91	4.9%	3.6%	20.0%
Michigan City-La Porte, IN Metropolitan Statistical Area	92	4.9%	3.2%	17.6%
Wichita Falls, TX Metropolitan Statistical Area	93	4.9%	3.8%	19.5%
Springfield, OH Metropolitan Statistical Area	94	4.9%	3.4%	16.6%
Providence-New Bedford-Fall River, RI-MA Metropolitan Statistical Area	95	4.9%	3.3%	18.1%
Sandusky, OH Metropolitan Statistical Area	96	4.9%	3.4%	18.1%
Macon, GA Metropolitan Statistical Area	97	4.8%	3.3%	14.5%
Little Rock-North Little Rock-Conway, AR Metropolitan Statistical Area	98	4.8%	3.3%	25.1%
Muncie, IN Metropolitan Statistical Area	99	4.8%	3.3%	15.1%
Worcester, MA Metropolitan Statistical Area	100	4.8%	2.9%	20.5%
Lima, OH Metropolitan Statistical Area	101	4.8%	3.0%	12.6%
Honolulu, HI Metropolitan Statistical Area	102	4.8%	3.1%	26.0%
Lawton, OK Metropolitan Statistical Area	103	4.8%	3.3%	20.6%
New Orleans-Metairie-Kenner, LA Metropolitan Statistical Area	104	4.7%	3.0%	19.3%
Bend, OR Metropolitan Statistical Area	105	4.7%	3.5%	26.1%
Janesville, WI Metropolitan Statistical Area	106	4.7%	3.2%	17.7%
Reading, PA Metropolitan Statistical Area	107	4.7%	3.3%	20.9%
Dalton, GA Metropolitan Statistical Area	108	4.6%	3.3%	17.2%
South Bend-Mishawaka, IN-MI Metropolitan Statistical Area	109	4.6%	2.9%	14.8%
Weirton-Steubenville, WV-OH Metropolitan Statistical Area	110	4.6%	3.3%	11.9%
Decatur, IL Metropolitan Statistical Area	111	4.5%	2.7%	18.5%

York-Hanover, PA Metropolitan Statistical Area	112	4.5%	3.1%	22.0%
Sumter, SC Metropolitan Statistical Area	113	4.5%	2.9%	16.0%
Goldsboro, NC Metropolitan Statistical Area	114	4.4%	3.1%	18.0%
Fort Smith, AR-OK Metropolitan Statistical Area	115	4.4%	3.0%	18.6%
Milwaukee-Waukesha-West Allis, WI Metropolitan Statistical Area	116	4.4%	2.9%	21.6%
Racine, WI Metropolitan Statistical Area	117	4.4%	3.1%	18.7%
Evansville, IN-KY Metropolitan Statistical Area	118	4.4%	3.0%	19.9%
Columbia, SC Metropolitan Statistical Area	119	4.4%	2.9%	18.1%
Brunswick, GA Metropolitan Statistical Area	120	4.3%	3.4%	15.6%
Columbus, GA-AL Metropolitan Statistical Area	121	4.3%	3.0%	18.1%
Augusta-Richmond County, GA-SC Metropolitan Statistical Area	122	4.3%	3.0%	19.5%
Rome, GA Metropolitan Statistical Area	123	4.3%	3.4%	16.2%
Elkhart-Goshen, IN Metropolitan Statistical Area	124	4.3%	2.8%	16.6%
Hartford-West Hartford-East Hartford, CT Metropolitan Statistical Area	125	4.3%	2.6%	20.5%
LouisvilleJefferson County, KY-IN Metropolitan Statistical Area	126	4.3%	2.9%	20.6%
Saginaw-Saginaw Township North, MI Metropolitan Statistical Area	127	4.2%	3.1%	11.9%
Anniston-Oxford, AL Metropolitan Statistical Area	128	4.2%	2.9%	19.6%
Elizabethtown, KY Metropolitan Statistical Area	129	4.2%	3.0%	19.3%
Fort Wayne, IN Metropolitan Statistical Area	130	4.2%	2.9%	17.8%
Savannah, GA Metropolitan Statistical Area	131	4.2%	3.0%	16.6%
Pascagoula, MS Metropolitan Statistical Area	132	4.1%	2.7%	15.6%
Hagerstown-Martinsburg, MD-WV Metropolitan Statistical Area	133	4.1%	3.0%	17.5%
Eugene-Springfield, OR Metropolitan Statistical Area	134	4.1%	2.8%	21.4%
Birmingham-Hoover, AL Metropolitan Statistical Area	135	4.1%	2.7%	18.3%
Yakima, WA Metropolitan Statistical Area	136	4.1%	2.7%	16.3%
Canton-Massillon, OH Metropolitan Statistical Area	137	4.1%	3.0%	13.2%
Valdosta, GA Metropolitan Statistical Area	138	4.1%	2.8%	23.0%
Lake Charles, LA Metropolitan Statistical Area	139	4.1%	2.8%	20.0%

Toledo, OH Metropolitan Statistical Area	140	4.0%	2.9%	15.1%
Hot Springs, AR Metropolitan Statistical Area	141	4.0%	3.1%	22.4%
Longview, WA Metropolitan Statistical Area	142	4.0%	2.8%	18.6%
Carson City, NV Metropolitan Statistical Area	143	4.0%	3.1%	14.6%
Pittsburgh, PA Metropolitan Statistical Area	144	4.0%	2.5%	17.5%
Gulfport-Biloxi, MS Metropolitan Statistical Area	145	4.0%	2.9%	15.2%
Mount Vernon-Anacortes, WA Metropolitan Statistical Area	146	3.9%	2.7%	21.8%
Atlanta-Sandy Springs-Marietta, GA Metropolitan Statistical Area	147	3.9%	2.7%	15.9%
El Paso, TX Metropolitan Statistical Area	148	3.9%	2.6%	13.9%
Wheeling, WV-OH Metropolitan Statistical Area	149	3.9%	2.8%	14.1%
Harrisburg-Carlisle, PA Metropolitan Statistical Area	150	3.9%	2.6%	20.5%
Danville, VA Metropolitan Statistical Area	151	3.9%	2.8%	11.2%
Springfield, IL Metropolitan Statistical Area	152	3.9%	2.6%	14.9%
Salinas, CA Metropolitan Statistical Area	153	3.9%	2.9%	16.9%
Portland-Vancouver-Beaverton, OR-WA Metropolitan Statistical Area	154	3.9%	2.6%	21.4%
Charleston-North Charleston-Summerville, SC Metropolitan Statistical Area	155	3.8%	2.6%	19.0%
Olympia, WA Metropolitan Statistical Area	156	3.8%	2.6%	19.9%
Clarksville, TN-KY Metropolitan Statistical Area	157	3.8%	2.6%	19.1%
Florence, SC Metropolitan Statistical Area	158	3.8%	2.3%	14.3%
Fond du Lac, WI Metropolitan Statistical Area	159	3.8%	2.5%	21.7%
Davenport-Moline-Rock Island, IA-IL Metropolitan Statistical Area	160	3.8%	2.5%	18.5%
Oklahoma City, OK Metropolitan Statistical Area	161	3.8%	2.3%	18.7%
Lafayette, IN Metropolitan Statistical Area	162	3.8%	2.7%	17.4%
Spartanburg, SC Metropolitan Statistical Area	163	3.7%	2.5%	15.3%
Huntington-Ashland, WV-KY-OH Metropolitan Statistical Area	164	3.7%	2.5%	14.7%
Barnstable Town, MA Metropolitan Statistical Area	165	3.7%	2.4%	19.9%
Albuquerque, NM Metropolitan Statistical Area	166	3.7%	2.7%	18.8%
Pueblo, CO Metropolitan Statistical Area	167	3.7%	2.4%	12.8%
Greenville, NC Metropolitan Statistical Area	168	3.7%	2.6%	16.3%

Texarkana, TX-Texarkana, AR Metropolitan Statistical Area	169	3.7%	2.2%	18.4%
Vallejo-Fairfield, CA Metropolitan Statistical Area	170	3.7%	2.5%	14.3%
Bloomington, IN Metropolitan Statistical Area	171	3.7%	2.5%	18.6%
Bay City, MI Metropolitan Statistical Area	172	3.6%	2.1%	16.2%
Lebanon, PA Metropolitan Statistical Area	173	3.6%	2.4%	20.9%
Decatur, AL Metropolitan Statistical Area	174	3.6%	2.5%	20.3%
Burlington-South Burlington, VT Metropolitan Statistical Area	175	3.5%	2.6%	24.4%
Seattle-Tacoma-Bellevue, WA Metropolitan Statistical Area	176	3.5%	2.4%	20.4%
Fayetteville-Springdale-Rogers, AR-MO Metropolitan Statistical Area	177	3.5%	2.7%	19.2%
Altoona, PA Metropolitan Statistical Area	178	3.5%	2.0%	14.1%
Auburn-Opelika, AL Metropolitan Statistical Area	179	3.5%	2.5%	23.9%
Santa Fe, NM Metropolitan Statistical Area	180	3.5%	2.6%	21.0%
Beaumont-Port Arthur, TX Metropolitan Statistical Area	181	3.5%	2.0%	14.2%
St. Louis, MO-IL Metropolitan Statistical Area	182	3.5%	2.3%	15.4%
Tulsa, OK Metropolitan Statistical Area	183	3.5%	2.3%	16.1%
Richmond, VA Metropolitan Statistical Area	184	3.4%	2.3%	14.2%
Jonesboro, AR Metropolitan Statistical Area	185	3.4%	2.4%	22.3%
Salt Lake City, UT Metropolitan Statistical Area	186	3.4%	2.3%	19.0%
Muskegon-Norton Shores, MI Metropolitan Statistical Area	187	3.4%	2.3%	11.6%
Nashville-Davidson--Murfreesboro--Franklin, TN Metropolitan Statistical Area	188	3.4%	2.2%	17.8%
El Centro, CA Metropolitan Statistical Area	189	3.4%	2.1%	8.9%
Brownsville-Harlingen, TX Metropolitan Statistical Area	190	3.3%	2.1%	10.6%
Parkersburg-Marietta-Vienna, WV-OH Metropolitan Statistical Area	191	3.3%	2.5%	11.5%
Bremerton-Silverdale, WA Metropolitan Statistical Area	192	3.3%	2.1%	21.4%
Gadsden, AL Metropolitan Statistical Area	193	3.3%	2.6%	13.2%
Wichita, KS Metropolitan Statistical Area	194	3.3%	2.4%	14.6%
Detroit-Warren-Livonia, MI Metropolitan Statistical Area	195	3.3%	2.3%	10.2%
Gainesville, GA Metropolitan Statistical Area	196	3.3%	2.4%	12.8%
Baton Rouge, LA Metropolitan Statistical Area	197	3.3%	2.1%	14.7%

Houma-Bayou Cane-Thibodaux, LA Metropolitan Statistical Area	198	3.2%	2.2%	16.3%
Spokane, WA Metropolitan Statistical Area	199	3.2%	2.2%	17.2%
Fayetteville, NC Metropolitan Statistical Area	200	3.2%	2.1%	16.2%
Myrtle Beach-North Myrtle Beach-Conway, SC Metropolitan Statistical Area	201	3.2%	2.6%	14.8%
Omaha-Council Bluffs, NE-IA Metropolitan Statistical Area	202	3.2%	2.1%	14.8%
Williamsport, PA Metropolitan Statistical Area	203	3.2%	1.9%	15.3%
Jefferson City, MO Metropolitan Statistical Area	204	3.2%	2.4%	12.6%
Wilmington, NC Metropolitan Statistical Area	205	3.2%	2.6%	15.3%
Burlington, NC Metropolitan Statistical Area	206	3.2%	2.2%	13.6%
Riverside-San Bernardino-Ontario, CA Metropolitan Statistical Area	207	3.2%	2.1%	10.0%
Lynchburg, VA Metropolitan Statistical Area	208	3.1%	2.2%	14.9%
Ogden-Clearfield, UT Metropolitan Statistical Area	209	3.1%	2.2%	18.6%
Morristown, TN Metropolitan Statistical Area	210	3.1%	2.2%	12.1%
Hanford-Corcoran, CA Metropolitan Statistical Area	211	3.1%	1.9%	9.8%
McAllen-Edinburg-Mission, TX Metropolitan Statistical Area	212	3.1%	1.8%	8.6%
Coeur d'Alene, ID Metropolitan Statistical Area	213	3.1%	2.4%	15.5%
Kansas City, MO-KS Metropolitan Statistical Area	214	3.1%	2.1%	14.3%
Lexington-Fayette, KY Metropolitan Statistical Area	215	3.1%	2.2%	18.9%
Columbus, IN Metropolitan Statistical Area	216	3.1%	2.1%	18.8%
Durham-Chapel Hill, NC Metropolitan Statistical Area	217	3.1%	2.0%	15.7%
Yuba City, CA Metropolitan Statistical Area	218	3.1%	2.4%	9.2%
Wausau, WI Metropolitan Statistical Area	219	3.1%	2.4%	14.4%
Dallas-Fort Worth-Arlington, TX Metropolitan Statistical Area	220	3.1%	1.8%	14.9%
Madera-Chowchilla, CA Metropolitan Statistical Area	221	3.1%	2.1%	9.1%
Stockton, CA Metropolitan Statistical Area	222	3.1%	2.2%	10.6%
Greensboro-High Point, NC Metropolitan Statistical Area	223	3.1%	2.1%	13.0%
Pocatello, ID Metropolitan Statistical Area	224	3.1%	2.1%	17.0%
Lawrence, KS Metropolitan Statistical Area	225	3.1%	2.4%	16.1%

Winston-Salem, NC Metropolitan Statistical Area	226	3.0%	2.1%	13.8%
Sherman-Denison, TX Metropolitan Statistical Area	227	3.0%	2.0%	14.2%
Champaign-Urbana, IL Metropolitan Statistical Area	228	3.0%	2.0%	18.5%
Anderson, SC Metropolitan Statistical Area	229	3.0%	2.1%	11.7%
Battle Creek, MI Metropolitan Statistical Area	230	3.0%	2.2%	7.3%
Modesto, CA Metropolitan Statistical Area	231	3.0%	2.1%	10.8%
Idaho Falls, ID Metropolitan Statistical Area	232	3.0%	2.0%	18.8%
Hattiesburg, MS Metropolitan Statistical Area	233	3.0%	1.9%	15.6%
Boston-Cambridge-Quincy, MA-NH Metropolitan Statistical Area	234	3.0%	1.9%	17.1%
Laredo, TX Metropolitan Statistical Area	235	2.9%	1.5%	9.7%
Charlotte-Gastonia-Concord, NC-SC Metropolitan Statistical Area	236	2.9%	2.0%	14.1%
Huntsville, AL Metropolitan Statistical Area	237	2.9%	2.2%	19.2%
Boise City-Nampa, ID Metropolitan Statistical Area	238	2.9%	2.1%	14.8%
Greenville-Mauldin-Easley, SC Metropolitan Statistical Area	239	2.9%	2.0%	13.7%
Florence-Muscle Shoals, AL Metropolitan Statistical Area	240	2.9%	2.0%	14.1%
Lewiston, ID-WA Metropolitan Statistical Area	241	2.9%	1.8%	19.5%
Washington-Arlington-Alexandria, DC-VA-MD-WV Metropolitan Statistical Area	242	2.9%	1.9%	16.6%
St. Joseph, MO-KS Metropolitan Statistical Area	243	2.8%	2.0%	10.9%
Yuma, AZ Metropolitan Statistical Area	244	2.8%	2.0%	8.9%
Hickory-Lenoir-Morganton, NC Metropolitan Statistical Area	245	2.8%	2.0%	11.3%
Oshkosh-Neenah, WI Metropolitan Statistical Area	246	2.8%	2.0%	19.5%
Corpus Christi, TX Metropolitan Statistical Area	247	2.8%	1.6%	12.5%
Tucson, AZ Metropolitan Statistical Area	248	2.8%	1.9%	11.5%
Grand Junction, CO Metropolitan Statistical Area	249	2.8%	2.0%	14.8%
Des Moines-West Des Moines, IA Metropolitan Statistical Area	250	2.8%	2.1%	19.1%
Kingsport-Bristol-Bristol, TN-VA Metropolitan Statistical Area	251	2.7%	2.0%	10.5%
La Crosse, WI-MN Metropolitan Statistical Area	252	2.7%	2.1%	13.8%
Sheboygan, WI Metropolitan Statistical	253	2.7%	2.2%	15.9%

Area				
Jackson, MI Metropolitan Statistical Area	254	2.7%	1.9%	9.9%
Sacramento--Arden-Arcade--Roseville, CA Metropolitan Statistical Area	255	2.7%	1.9%	11.9%
Owensboro, KY Metropolitan Statistical Area	256	2.7%	1.9%	13.5%
Bowling Green, KY Metropolitan Statistical Area	257	2.7%	2.0%	13.8%
Amarillo, TX Metropolitan Statistical Area	258	2.7%	1.6%	13.9%
Virginia Beach-Norfolk-Newport News, VA-NC Metropolitan Statistical Area	259	2.6%	1.8%	13.5%
Merced, CA Metropolitan Statistical Area	260	2.6%	1.9%	8.9%
Manchester-Nashua, NH Metropolitan Statistical Area	261	2.6%	1.8%	12.6%
Denver-Aurora-Broomfield, CO Metropolitan Statistical Area	262	2.6%	1.8%	13.9%
Jacksonville, NC Metropolitan Statistical Area	263	2.6%	2.1%	15.6%
Los Angeles-Long Beach-Santa Ana, CA Metropolitan Statistical Area	264	2.6%	1.8%	10.9%
Lansing-East Lansing, MI Metropolitan Statistical Area	265	2.6%	1.9%	9.4%
Athens-Clarke County, GA Metropolitan Statistical Area	266	2.6%	1.8%	15.1%
Lafayette, LA Metropolitan Statistical Area	267	2.6%	1.7%	15.6%
St. George, UT Metropolitan Statistical Area	268	2.6%	2.0%	14.7%
Bloomington-Normal, IL Metropolitan Statistical Area	269	2.6%	1.8%	17.2%
Farmington, NM Metropolitan Statistical Area	270	2.6%	1.7%	15.3%
San Antonio, TX Metropolitan Statistical Area	271	2.6%	1.5%	12.6%
Lancaster, PA Metropolitan Statistical Area	272	2.6%	1.7%	18.3%
Warner Robins, GA Metropolitan Statistical Area	273	2.6%	1.8%	13.2%
Niles-Benton Harbor, MI Metropolitan Statistical Area	274	2.6%	1.7%	8.2%
Redding, CA Metropolitan Statistical Area	275	2.6%	1.9%	9.4%
Madison, WI Metropolitan Statistical Area	276	2.6%	2.1%	17.3%
Fresno, CA Metropolitan Statistical Area	277	2.6%	1.7%	8.0%
Santa Cruz-Watsonville, CA Metropolitan Statistical Area	278	2.6%	1.8%	14.6%
Knoxville, TN Metropolitan Statistical Area	279	2.6%	1.7%	12.9%
Fairbanks, AK Metropolitan Statistical Area	280	2.6%	1.3%	15.7%
Greeley, CO Metropolitan Statistical Area	281	2.6%	1.9%	10.1%
Kalamazoo-Portage, MI Metropolitan Statistical Area	282	2.5%	1.6%	12.1%

Bakersfield, CA Metropolitan Statistical Area	283	2.5%	1.6%	7.9%
St. Cloud, MN Metropolitan Statistical Area	284	2.5%	1.9%	15.2%
Monroe, MI Metropolitan Statistical Area	285	2.5%	1.9%	10.9%
Phoenix-Mesa-Scottsdale, AZ Metropolitan Statistical Area	286	2.5%	1.7%	9.6%
Raleigh-Cary, NC Metropolitan Statistical Area	287	2.5%	1.7%	15.3%
Appleton, WI Metropolitan Statistical Area	288	2.5%	1.8%	18.9%
Houston-Sugar Land-Baytown, TX Metropolitan Statistical Area	289	2.5%	1.3%	11.8%
Las Cruces, NM Metropolitan Statistical Area	290	2.5%	1.8%	12.8%
Visalia-Porterville, CA Metropolitan Statistical Area	291	2.5%	1.6%	7.6%
Cedar Rapids, IA Metropolitan Statistical Area	292	2.5%	1.8%	20.7%
Dubuque, IA Metropolitan Statistical Area	293	2.4%	1.8%	14.4%
Johnson City, TN Metropolitan Statistical Area	294	2.4%	1.7%	10.4%
San Diego-Carlsbad-San Marcos, CA Metropolitan Statistical Area	295	2.4%	1.7%	12.7%
Santa Rosa-Petaluma, CA Metropolitan Statistical Area	296	2.4%	1.8%	13.2%
Grand Rapids-Wyoming, MI Metropolitan Statistical Area	297	2.4%	1.7%	10.2%
Bellingham, WA Metropolitan Statistical Area	298	2.4%	1.6%	19.0%
Green Bay, WI Metropolitan Statistical Area	299	2.4%	1.9%	16.1%
Chico, CA Metropolitan Statistical Area	300	2.4%	1.7%	9.3%
Roanoke, VA Metropolitan Statistical Area	301	2.4%	1.7%	11.8%
Kennewick-Pasco-Richland, WA Metropolitan Statistical Area	302	2.4%	1.6%	14.2%
Eau Claire, WI Metropolitan Statistical Area	303	2.4%	1.8%	12.3%
Provo-Orem, UT Metropolitan Statistical Area	304	2.4%	1.7%	15.1%
Abilene, TX Metropolitan Statistical Area	305	2.4%	1.6%	13.9%
Longview, TX Metropolitan Statistical Area	306	2.4%	1.4%	11.4%
Sioux City, IA-NE-SD Metropolitan Statistical Area	307	2.4%	1.7%	11.1%
Wenatchee-East Wenatchee, WA Metropolitan Statistical Area	308	2.3%	1.5%	15.5%
Charleston, WV Metropolitan Statistical Area	309	2.3%	1.6%	10.4%
Joplin, MO Metropolitan Statistical Area	310	2.3%	1.8%	7.8%
San Jose-Sunnyvale-Santa Clara, CA Metropolitan Statistical Area	311	2.3%	1.7%	15.5%

Colorado Springs, CO Metropolitan Statistical Area	312	2.3%	1.6%	13.1%
Tyler, TX Metropolitan Statistical Area	313	2.3%	1.4%	12.0%
Killeen-Temple-Fort Hood, TX Metropolitan Statistical Area	314	2.3%	1.5%	13.2%
Lincoln, NE Metropolitan Statistical Area	315	2.3%	1.6%	14.9%
Lake Havasu City-Kingman, AZ Metropolitan Statistical Area	316	2.3%	1.7%	7.6%
San Francisco-Oakland-Fremont, CA Metropolitan Statistical Area	317	2.3%	1.6%	12.7%
Prescott, AZ Metropolitan Statistical Area	318	2.2%	1.5%	11.7%
Springfield, MO Metropolitan Statistical Area	319	2.2%	1.7%	10.6%
Napa, CA Metropolitan Statistical Area	320	2.2%	1.6%	11.2%
Manhattan, KS Metropolitan Statistical Area	321	2.2%	1.6%	14.5%
Great Falls, MT Metropolitan Statistical Area	322	2.1%	1.6%	16.7%
Waco, TX Metropolitan Statistical Area	323	2.1%	1.2%	12.1%
Oxnard-Thousand Oaks-Ventura, CA Metropolitan Statistical Area	324	2.0%	1.5%	9.6%
Waterloo-Cedar Falls, IA Metropolitan Statistical Area	325	2.0%	1.4%	13.5%
Asheville, NC Metropolitan Statistical Area	326	2.0%	1.5%	11.5%
Columbia, MO Metropolitan Statistical Area	327	2.0%	1.4%	13.6%
State College, PA Metropolitan Statistical Area	328	1.9%	1.4%	15.4%
Logan, UT-ID Metropolitan Statistical Area	329	1.9%	1.5%	12.0%
Duluth, MN-WI Metropolitan Statistical Area	330	1.9%	1.5%	8.2%
Minneapolis-St. Paul-Bloomington, MN-WI Metropolitan Statistical Area	331	1.9%	1.4%	11.0%
Ann Arbor, MI Metropolitan Statistical Area	332	1.8%	1.3%	11.7%
Victoria, TX Metropolitan Statistical Area	333	1.8%	0.9%	10.6%
Cape Girardeau-Jackson, MO-IL Metropolitan Statistical Area	334	1.8%	1.2%	10.6%
Charlottesville, VA Metropolitan Statistical Area	335	1.8%	1.3%	11.6%
Billings, MT Metropolitan Statistical Area	336	1.7%	1.3%	15.0%
Santa Barbara-Santa Maria-Goleta, CA Metropolitan Statistical Area	337	1.7%	1.3%	8.6%
Lubbock, TX Metropolitan Statistical Area	338	1.7%	1.0%	11.3%
Rochester, MN Metropolitan Statistical Area	339	1.7%	1.1%	11.5%
Blacksburg-Christiansburg-Radford, VA Metropolitan Statistical Area	340	1.7%	1.2%	10.2%

Rapid City, SD Metropolitan Statistical Area	341	1.7%	1.2%	14.9%
Flagstaff, AZ Metropolitan Statistical Area	342	1.6%	1.2%	8.8%
Holland-Grand Haven, MI Metropolitan Statistical Area	343	1.6%	1.2%	9.4%
Sioux Falls, SD Metropolitan Statistical Area	344	1.6%	1.3%	11.9%
Missoula, MT Metropolitan Statistical Area	345	1.6%	1.2%	13.1%
Mankato-North Mankato, MN Metropolitan Statistical Area	346	1.5%	1.2%	7.7%
Corvallis, OR Metropolitan Statistical Area	347	1.5%	1.0%	14.8%
Winchester, VA-WV Metropolitan Statistical Area	348	1.5%	1.1%	6.5%
San Angelo, TX Metropolitan Statistical Area	349	1.5%	0.8%	10.6%
Iowa City, IA Metropolitan Statistical Area	350	1.4%	1.2%	12.5%
Ames, IA Metropolitan Statistical Area	351	1.4%	1.2%	12.0%
Casper, WY Metropolitan Statistical Area	352	1.4%	1.0%	8.7%
Odessa, TX Metropolitan Statistical Area	353	1.4%	0.8%	6.4%
Austin-Round Rock, TX Metropolitan Statistical Area	354	1.3%	0.8%	10.3%
Anchorage, AK Metropolitan Statistical Area	355	1.3%	0.7%	9.5%
Fort Collins-Loveland, CO Metropolitan Statistical Area	356	1.3%	0.9%	9.0%
Fargo, ND-MN Metropolitan Statistical Area	357	1.3%	1.0%	9.5%
Boulder, CO Metropolitan Statistical Area	358	1.3%	1.0%	7.8%
San Luis Obispo-Paso Robles, CA Metropolitan Statistical Area	359	1.3%	0.9%	8.0%
Cheyenne, WY Metropolitan Statistical Area	360	1.2%	0.9%	10.4%
Morgantown, WV Metropolitan Statistical Area	361	1.2%	0.7%	10.7%
Grand Forks, ND-MN Metropolitan Statistical Area	362	1.1%	0.7%	9.7%
Harrisonburg, VA Metropolitan Statistical Area	363	1.0%	0.8%	5.2%
College Station-Bryan, TX Metropolitan Statistical Area	364	0.9%	0.5%	9.1%
Midland, TX Metropolitan Statistical Area	365	0.9%	0.6%	6.2%
Bismarck, ND Metropolitan Statistical Area	366	0.7%	0.5%	9.5%

APPENDIX B

INCORPORATED COMMUNITIES IN MIAMI DADE COUNTY

Map reference	Incorporated Community	Designation	Date incorporated	Population
2	Aventura	City	7-Nov-95	35,762
7	Bal Harbour	Village	16-Jun-47	2,513
8	Bay Harbor Islands	Town	Apr-47	5,628
11	Biscayne Park	Village	1933	3,055
28	Coral Gables	City	1925	46,780
32	Cutler Bay	Town	9-Nov-05	40,286
20	Doral	City	24-Jun-03	45,704
13	El Portal	Village	7-Dec-37	2,325
34	Florida City	City	1914	11,245
3	Golden Beach	Town	1929	919
17	Hialeah	City	1925	224,669
18	Hialeah Gardens	City	Dec-48	21,744
33	Homestead	City	1913	60,512
9	Indian Creek	Village	1939	86
26	Key Biscayne	Village	1991	12,344
19	Medley	Town	1949	838
24	Miami	City	July 28, 1896	413,892
25	Miami Beach	City	26-Mar-15	87,779
1	Miami Gardens	City	13-May-03	107,167
16	Miami Lakes	Town	5-Dec-00	29,361
12	Miami Shores	Village	2-Jan-32	10,493
21	Miami Springs	City	1926	13,809
14	North Bay Village	City	1945	7,137
6	North Miami	City	27-May-53	58,786
5	North Miami Beach	City	1927	41,523
15	Opa-locka	City	1926	15,219
31	Palmetto Bay	Village	10-Sep-02	23,410
30	Pinecrest	Village	12-Mar-96	18,223
29	South Miami	City	24-Jun-27	11,657
4	Sunny Isles Beach	City	1997	20,832
10	Surfside	Town	18-May-35	5,744
23	Sweetwater	City	1941	13,499
22	Virginia Gardens	Village	10-Jul-47	2,375
27	West Miami	City	1947	5,965

APPENDIX C

FORECLOSURE PROCESSING STAGES IN FLORIDA STATE

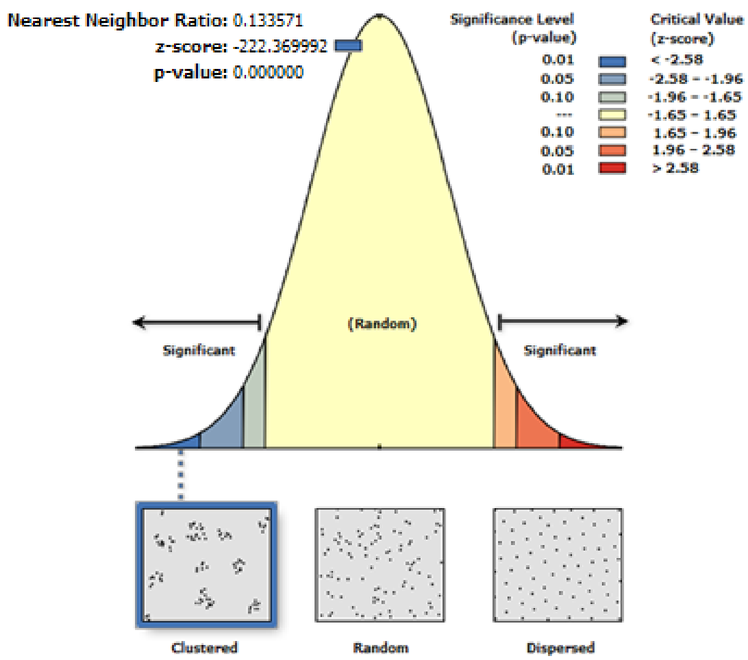
The type of foreclosure process carried out in Florida is known as Judicial Foreclosure Process where the lender files suit with the judicial system and the property is sold through auction to the highest bidder. The bidding is carried out by the court or the local sheriff. It is difficult to estimate the maximum amount of time needed to foreclose on a business or individual property because it differs from place to place and it depends on the property being sold. The foreclosure of a property currently takes about 600 days to run its course from the first notice until the date of sale. Foreclosure process in Florida begins when you miss out on 3-4 mortgage payment; this usually takes about 6 months before a Notice for foreclosure will be sent out to the mortgage holder. At this stage the mortgage holder is late with payment but remain in the property while the foreclosure proceedings progress. After notice for foreclosure on a property has been received, the foreclosure process has officially begun. This early stage falls under the pre-foreclosure period. During the proceedings the mortgage holder receives a Notice of Default indicating that he/she is late on payment. Notice of Default is a written notice sent to the mortgage holder by the mortgage lender, it will state how much money is owed, how late the payment is, and what needs to be done to prevent foreclosure from happening. Notice of Action is the next step in the foreclosure process. When a mortgage holder goes further in delinquency and cannot pay the terms stated in the Notice of Default, a Notice of Action stating the lender’s written demands and their intent to take back the property if the payment is not made is declared. Once the Notice of Action is posted, the formal foreclosure process takes place.

The lender will then file a Lis Pendens. The term "Lis Pendens" means “litigation pending” which is the document filed into public record by the lender notifying real estate and interested parties to the legal claim of a property. This is published on the local newspaper to put the public on notice that a law suit has been filed against the mortgage holder. The lawsuit which will be filed under Miami-Dade County where the property is located will state the intention of the mortgage lender to evict the residents and take over ownership of the property. The date and time of the auction will be posted and the property will be sold anywhere from three to six weeks in the future. Up until this point the mortgage holder is still able to contend for his property if he is able to come up with the appropriate payment owed to the lender until the set date of auction. Sherriff sale is the last step of the foreclosure process. This is where the property is auctioned off to the highest bidder at Miami-Dade county courthouse. Like any auction, the price is low to begin, but can escalate depending on the location and the demand of the property. Once a bidder has won the auction for the property, the former mortgage holder has terminated all of their rights to the property and is evicted after the sheriff sale. The foreclosed property stays vacant until it is sold to a new permanent owner. Title to the property is transferred to the winning bidder and the newly purchased property could be vacant for weeks or months depending on how long it will take the new owner to move in or in some cases where such properties are bought by a bank or a mortgage company (REO,) it may be vacant for up to a year until it is rented out or sold to another owner.

APPENDIX D

NEAREST NEIGHBOUR ANALYSIS AND SPATIAL AUTOCORRELATION SUMMARY

Average Nearest Neighbor Summary



Given the z-score of -222.37, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

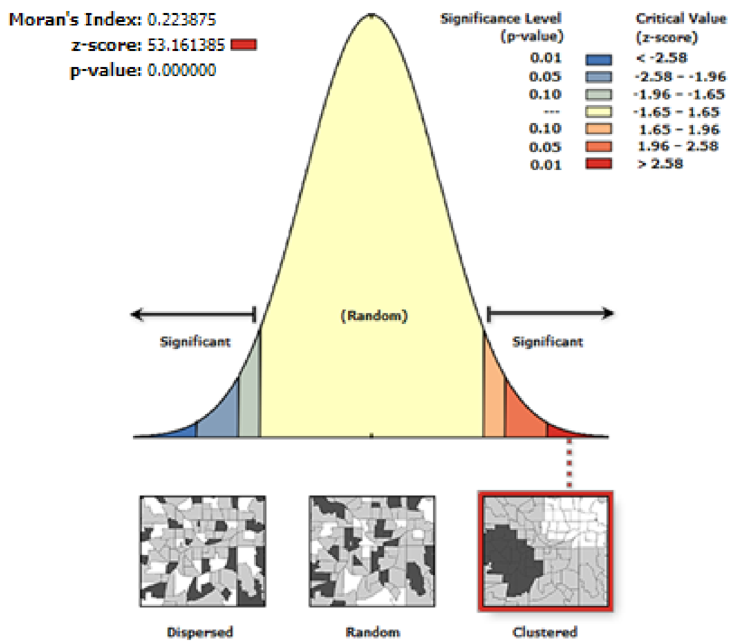
Average Nearest Neighbor Summary

Observed Mean Distance:	26.615245 Meters
Expected Mean Distance:	199.259731 Meters
Nearest Neighbor Ratio:	0.133571
z-score:	-222.369992
p-value:	0.000000

Dataset Information

Input Feature Class:	foreclosure_clip
Distance Method:	EUCLIDEAN
Study Area:	2858402079.285918
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 53.16, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Global Moran's I Summary

Moran's Index:	0.223875
Expected Index:	-0.000111
Variance:	0.000018
z-score:	53.161385
p-value:	0.000000

Dataset Information

Input Feature Class:	Sold
Input Field:	WIN_BID
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	5662.947963 Meters
Weights Matrix File:	None
Selection Set:	True