An analysis of the pattern of mortgage foreclosures in Lucas County, Ohio

Xueying Chen

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A Thesis

entitled

An Analysis of the Pattern of Mortgage Foreclosures in Lucas County, Ohio

by

Xueying Chen

Submitted to the Graduate Faculty as partial fulfillment of the requirements

for the Master of Arts Degree in Geography

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College of Graduate Studies

The University of Toledo

December 2010
An Abstract of

An Analysis of the Pattern of Mortgage Foreclosures in Lucas County, Ohio

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Many factors lead to mortgage default and foreclosure; however, few scholars have systematically examined how different characteristics contribute to mortgage foreclosure. This research uses multiple datasets from Lucas County, Ohio to examine some of these previously omitted or understudied aspects of the issue. Particular attention has been paid to each census tract’s housing and loan characteristics like housing prices and subprime loan counts, as well as to the socio-economic characteristics like, income level and other demographic characteristics.

The study begins with descriptive statistics analysis, spatial autocorrelation analysis, and comparison of foreclosure patterns in the different time periods. OLS model, H-Robust model, and spatial regression models are used to explain the interaction between housing foreclosure and socio-economic characteristics, housing characteristics and loan characteristics. The study finds that foreclosures cluster in low to moderate income communities and inner-core cities, although suburban areas have seen an increase in recent years. As expected, loan characteristics are closely related to foreclosure patterns in Lucas County. Besides, average residential property values, median household income, and other factors also contribute to foreclosures in the Lucas County. The use of
spatial models and H-Robust OLS has reduced some errors related to spatial dependence and heteroscedasticity between foreclosure and the selected variables.

This study not only contributes to the literature and methodology in related topics, but also provides a better understanding of the relationship between socio-economic, housing and loan characteristics and foreclosure, and will assist in the creation of better policies to deal with the problem of foreclosure. At the end of the study, future studies of the issue are also discussed.
Acknowledgments

This thesis would not have been completed without my adviser, Dr. Daniel J. Hammel. I am grateful for his intellectual support, and enthusiasm that made this thesis possible, for his patience in correcting my grammar, stylistic and scientific errors, and for his guidance to make the methodology more appealing. I also want to thank Dr. Peter Lindquist, Dr. Sujata Shetty, and Dr. Kevin Czajkowski for their encouragement, guidance and support to make this thesis possible.

I wish to thank the Center for Urban and Regional Analysis (CURA) at the Ohio State University to provide the HMDA data in Lucas County, OH between 2004 and 2005.

I could not have this work completed without the love, support, and encouragement I received from my parents. Only now am I beginning to realize how much my parents sacrificed so that I could attend college. I wish to thank all my friends for their continuous prayers and love, though I do not have words to adequately describe my gratitude for all their support.
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List of Abbreviations

AMTPA ........................................... The Alternative Mortgage Transaction Parity Act
AREIS .............................................. Auditors Real Estate Information System
DIDMCA ............... The Depository Institutions Deregulation and Monetary Control Act
HMDA ............................................. Mortgage Disclosure Act Datasets
HUD ............................................. The Department of Housing and Urban Development
LISA ............................................. Local indicators of spatial association
MBA ............................................... The U.S. Mortgage Bankers Association
OLS ............................................... Ordinary Least Square
TIGER ................. Topologically Integrated Geographic Encoding and Referencing system
Chapter 1

Introduction

1.1 Problem Statement

The United States is undergoing the deepest recession since the Great Depression of the 1930s, and home foreclosures are one significant part of it. According to one study, more than 2.3 million properties are facing foreclosure in 2008, which represents an 81 percent increase from 2007 (RealtyTrac 2009). According to Policy Matters Ohio, the number of Sheriff’s sales statewide tripled between the middle of the 1990s and 2001 (Schiller, Meredith et al. 2004). Another survey conducted by the group indicates that there were 85,782 new foreclosure filings in 2008 statewide, which means that there was one foreclosure filing for every 60 housing units (Rothstein David 2009). In northwest Ohio, subprime lending has grown exponentially in recent years and is widely believed to have played an important role in the region’s foreclosure crisis.

It is critical for policy makers to understand the threat of foreclosures, and find ways to minimize the externalities. Given that it will be too late for local governments to implement cost-effective plans to prevent or minimize the spillover effects of foreclosures once they have happened, it is crucial that local governments can successfully predict where potential foreclosures are likely to occur before they happened.
A better understanding of the spatial characteristics of the foreclosure crisis, for instance, where and how foreclosures spread or recede, and in which neighborhoods foreclosures have been concentrated or dispersed, seems essential to an efficient and effective policy response to the crisis. Regardless of the findings that previous studies have confirmed, there has been limited research on the issue of the longitudinal and spatial characteristics of foreclosure. Thus, this study intends to analyze the connection between community socio-economic factors, housing characteristics, loan characteristics and foreclosure.

1.2 Objectives

The Objectives of this study are as follow:

1) Review literature on related studies;

2) Identify the spatial characteristics of mortgage foreclosures in Lucas County, OH;

3) Identify factors associated with mortgage foreclosures in Lucas County, OH;

4) Construct models to analyze the effects of socio-economic characteristics; housing characteristics, loan characteristics on mortgage foreclosures in the study area;
Chapter 2

Literature Review

2.1. Home Foreclosure since the 1970s

The U.S. housing market has been widely regarded to be in a state of crisis since the middle of 2007, with the collapse in house values and the default of many subprime mortgages. Consequently, increasing foreclosures and large declines in house prices are widespread throughout the nation, especially in California, Florida, Michigan, Ohio, and Arizona.

In spite of the crisis in recent years, foreclosure levels in the U.S. have significantly grown since the 1970s nationally. Foreclosure rates on conventional loans increased from about 0.4 percent up to around 0.8 percent by the end of the 1980s (Elmer and Seelig 1998). Between the 1990s and the early 2000s, foreclosures continued a generally upward trend, and were peaking at 1.3 percent in late 2003 before a slightly decline in 2004. However, foreclosures rates soared during the late 2000s across the entire country. According to the U.S. Foreclosure Index from ForeclosureS.com, a leading real estate information provider, about one million homes were foreclosed by the end of 2008.
Figure 2-1 shows all foreclosures started as a percent of outstanding number of loans from 1979 to 2007. There is a clear trend of increasing foreclosures started which accelerated dramatically after 2005.

![Figure 2-1 All Foreclosures Started: U.S. 1979-2007 Quarterly Data](image)

Source: Mortgage Banker Association; (Anderson, Capozza et al. 2008)

Ohio has experienced continuous increase in mortgage defaults and foreclosures during the last two decades. The default rate of all loan types increased from 0.67 percent by the end of 1995 to over 3.5 percent in 2004, and reached a historical high in 2007 (Kaplan and Sommers 2009). By contrast, the nation rate increased from 0.87 percent in 1995 to around 1.5 percent in 2004. In Ohio new foreclosure filings rate continued a solid trend of increase since the middle of the 1990s. Since 1995, the number of filings has more than quintupled statewide (Rothstein David 2009). Ohio was in the fourth place in national ranking in new foreclosures as of the last quarter of 2008, according to the
survey conducted by the U.S. Mortgage Bankers Association (2008). Although foreclosure filing data do not provide a complete picture of foreclosures, it remains a good source of information to illustrate the situation of foreclosure crisis in Ohio.

It seems that the large increase in mortgage default rates and foreclosure filing rates is closely related to Ohio’s poor economic performance and increasing job loss in recent years. For example, between 2001 and 2003, Ohio lost about 240,000 jobs statewide and about two thirds are in manufacturing industries. Further, home prices in Ohio have grown much slower than in the U.S. as a whole, and this may explain part of the increases in mortgage default and foreclosure rates.

![Figure 2-2 Ohio Foreclosure Filings: 1995-2007](source: Policy matters Ohio)
2.2 The Negative Impacts of Foreclosure

Home foreclosure occurs when the borrower is unable to meet mortgage payments, and defaults on a home loan. A foreclosure can be both time consuming and costly to both homeowner and lender. An early study by Moreno (1995) estimated that, the average loss to a foreclosed family is $7,200. Another study found that the estimated costs varied from $7,200 to $58,759 for each case (McCarthy, Vanzandt et al. 2001). Cutts and Green (2004) estimated that, the entire foreclosure process cost loan holders an average of $58,792, and takes them 18 months to resolve the problem, compared to the loans that involve a voluntary transfer of title, which cost an average of $44,000 and take 12 months to resolve.

Besides directly affecting those involved in it, foreclosures also create negative impacts to nearby properties and communities. Previous studies have found various forms of foreclosure spillover effects: lowering nearby property values, reducing local property tax base, disrupting social ties, increasing crime, resulting in negative neighborhood image, and so on (Moreno 1995; Baxter and Lauria 2000; Apgar, Duda et al. 2005; Immergluck and Smith 2006; Immergluck and Smith 2006). Some researchers have estimated the spillover effects of foreclosures on nearby property values and neighborhoods. Moreno (1995) found that, on average, each foreclosure costs the city $27,000 and neighborhood $10,000 directly, using operational data from local agencies that handled foreclosures. Simon et al. (1998) used property tax delinquency data as a proxy for foreclosure in Cleveland, and suggested that, a given residential property’s sale price decreased by $788 when the “nearby area” has one percentage point increase in property tax delinquency. Shlay and Whitman (2006)
concluded that the presence of abandoned properties has depressed property prices by $7,627; they also pointed out that this negative effect diminished with distance. Another study by Immergluck and Smith (2006) examined foreclosures’ externalities in Chicago using a sophisticated regression model. Their study estimated that, a foreclosure within 1/8 mile of a single-family home could lower its sale price by 0.9 percent on average. Lin et al. (2009) constructed a model with special attention to longitudinal and spatial aspects of foreclosures in Chicago, and found that property values drop between 1.2 to 1.7 percent for foreclosures liquidated within a 5 year period and a 0.6 mile radius. The negative effect is most severe on adjacent properties within 2 years of foreclosure, and the externalities diminish with both increased distance and time. The study also suggests the intensity of the spillover effects could be reduced during housing market boom years because it’s closely tied to housing cycles.

Socio-economic factors associated with high foreclosure rates also have been researched. Baxter and Lauria (2000) investigated the impact of economic change and the racial distribution of population on housing foreclosure in New Orleans. They suggested that housing foreclosure rates were high in predominantly black neighborhoods and in neighborhoods with smaller but growing black populations. Quercia et al. (2005) found that black borrowers, and borrowers with fewer resources relative to what they owe were less likely to avoid foreclosure. The study also suggested that borrowers with mortgages which have high interest rates and originated within two years of the default would be more likely to default on their loans.

Understanding the spatial characteristics of foreclosure crisis is essential to efficient and effective policy response. Some studies have suggested that home
foreclosures are highly concentrated in particular urban areas (Can 1998; Gramlich 2007). A study in Atlanta demonstrated that foreclosure filings concentrate in lower-income, and minority communities with older housing stock (Duda and Apgar 2005). A recent study in Minnesota by Grover et al. (Grover, Smith et al. 2008) found that most high foreclosure census tracts are located in the inner cities of Minneapolis and St. Paul. Another study in the New England region found that neighborhoods with more younger and larger families were most affected by foreclosures and the crisis was spreading to increasingly more black and Hispanic neighborhoods. Further, the degree of spatial association of foreclosure was increasing in the study area; neighborhoods with high foreclosure rates in the previous period continue to experienced relatively high levels of foreclosures (Laurie, Emilia et al. 2009).

In general, foreclosures not only lay negatively impacts on the borrowers and the lenders, but also have serious spillover effects to the community, like lowering property values and increasing crime. What’s worse, these harmful influences might last over years. Therefore, it is critical to understand the factors associated with foreclosure, as well as its spatial characteristics.

2.3 The Development of Subprime Mortgages

2.3.1 Definitions of Subprime Lending

It would be useful to define “subprime mortgage” for the purposes of this study. However, there is no universally accepted definition of the term. The first definition of subprime mortgage comes from the Department of Housing and Urban Development (HUD). HUD began tracking the subprime mortgage market in 1993 and created an
annual list of subprime lenders, who claim to make at least 50 percent of their loans to subprime borrowers as subprime lenders (Scheessele 1999). According to HUD, a “high-cost” loan is defined as a mortgage with an initial interest rate that is at least 300 basis points larger than the yield of a treasury bill with a comparable maturity period.

Another common definition for a subprime mortgages originates from the secondary mortgage market, which consists of investors who purchase securities that are collateralized by residential mortgages. In this context, a subprime mortgage refers to a loan placed in a pool of securitized mortgages that is labeled “subprime”. The third widely used definition of subprime mortgage refers to residential loans that do not conform to the criteria for “prime” mortgages. Subprime lending is largely determined by the borrower’s credit history and score in this context, and the subprime borrower refers to a borrower with low credit score, loan default or even bankruptcies, and thus has a lower probability to make full repayment. In this study, I will use the concept from HUD’s criteria for “subprime mortgage” and utilize the “high-cost” loans data created by HMDA as the proxy of subprime loans to examine the relationship between foreclosures and subprime lending in Lucas County.

2.3.2 The Development of Subprime Mortgages

Subprime lending is a relatively new segment of the home mortgage market that grew rapidly through the last fifteen years. From 1993 to 1999, the number of subprime loans reported under the HMDA sharply increased from 104,000 to one million in 1999. Subprime mortgages’ share of total mortgage origination was less than five percent in 1994, but had increased to almost 13 percent of the mortgage origination market by 1999.
In 2005, $665 billion of subprime loans were originated, and subprime mortgages’ share of total mortgage originations had grown to 23 percent in 2006 (Schloemer, Li et al. 2006).

Many factors have contributed to the dramatic growth of subprime loans and the changes in laws are fundamental. Two acts opened the door for the development of subprime mortgage market: the Depository Institutions Deregulation and Monetary Control Act (DIDMCA) and the Alternative Mortgage Transaction Parity Act (AMTPA). The DIDMCA preempted state interest rate caps. The latter act was adopted in 1982, and permitted the use of balloon payments and variable interest rates. However, not until the Tax Reform Act of 1986 (TRA), did the subprime lending became a large-scale lending alternative (Forrester 1994; Immergluck 2004).

The large growth in the number of independent mortgage brokers over the last two decades is another critical factor (Immergluck 2004). Kim-Sung and Hermanson (2003) found that broker-originated loans are twice as likely to be subprime as lender-originated loans (26 percent versus 12 percent). Changes in the market also contributed to the growth of subprime lending market. For instance, refinance loans are a major component of the subprime mortgage market. According to one study by HUD on data reported under HMDA, refinance loans by subprime lenders increased by more than 700,000 loans from 1993 to 1998, almost four times the rate for subprime home purchase loans. Further, refinance loans by subprime lenders increased by 890 percent, while refinances by prime lenders grew by only 2.5 percent, from 1983 to 1998 (Scheessele 1999).
2.3.3 Subprime Loans and Mortgage Default/Foreclosure

Subprime loans lead to delinquency and foreclosure at relatively high rates. Evidence shows that the probability of default of a subprime loan is at least five times higher than a prime loan. Besides, subprime loans are more sensitive to interest rate changes (Pennington-Cross 2003). One study indicated that seriously delinquent rates for all grades subprime loans increased from about five percent in early 2000 to more than eight percent by the end of 2001, while prime loan delinquency rates remained almost stable at around one percent over that period (Crews-Cutts 2003). According to an industry survey of 27 larger subprime lenders, ninety-day delinquency rates for C- and D-grade loans were 10 percent and 22 percent, compared to 0.25 percent for prime refinance loans (Phillips-Patrick, Hirschhorn et al. 2000).

Gerardi et al. (2009) demonstrated that, subprime mortgages played an important role in the foreclosure crisis in Massachusetts, by creating a group of homeowners who were sensitive to negative house price appreciation (HPA). Another study in Summit County, Ohio by Kaplan and Sommers (2009) identified a clear relationship between concentrated foreclosures and subprime lending, which is associated with Summit County’s racial patterns. Quercia et al. (2005) found that 20.7 percent of all first-lien subprime refinance mortgages originated in 1999 had foreclosed by 2003, which was more than 10 times than the rate for prime loans. Immergluck and Smith (2005) believed that subprime lending had a strong substantial effect on foreclosures in the case of refinance lending. They estimated that the effect of subprime loans on foreclosures was about 20 to 30 times the effect of prime lending.
The issue of impact of race on mortgage default and foreclosure has been examined. Many studies have shown that subprime lending is spatially uneven and is more likely clustered in low-income and minority neighborhoods; and the absence of mainstream lenders in those neighborhoods is another critical factor to the concentration of subprime loans (Immergluck 1999; Immergluck 2000; U.S. Department of Housing and Urban Development 2000). HUD (2000) analyzed lending patterns in the United States in 2000, and the results showed that black neighborhoods were dominated by subprime lenders nationwide by 1998. The study also found some shared patterns in five large cities: Atlanta, Philadelphia, New York, Chicago, and Baltimore. According to this study, home owners in black dominated neighborhoods were about twice as likely as home owners in low income white neighborhoods to receive subprime loans. Besides, while only 18 percent refinance borrowers in low income white neighborhoods received subprime loans, 39 percent borrowers in upper-income black census tracts got their refinance loans from subprime lenders. Scheessele (2002) conducted an analysis at census tract level throughout the country and concluded that, race, compared to income, was the stronger determinant of subprime loan patterns; and race had a stronger effect on the subprime lenders’ share with the controlling for a variety of neighborhood characteristics. Silver (2003) analyzed mortgage lending in six large cities—Detroit, Cleveland, Baltimore, Atlanta, Milwaukee and Houston--finding similar results with credit history data in his model.

2.3.4 Behaviors of Borrower and Creditor

The performance of a mortgage is typically characterized by whether it is prepaid or in default. In most cases, borrowers will prepay their mortgages if interest rates drop,
and the gain from doing so outbalances the cost. However, trigger events, like health
problems, can lead to loan defaults and subsequent foreclosure. Hence, the probability of
a loan delinquency and subsequent foreclosure is sensitive to the delay before foreclosure,
the loan to value (LTV) ratio and the variance of house prices. When borrowers become
unable to meet their payments, they may have the option to modify their loans with
higher interest rate, or to sell their properties to escape from direct foreclosure. When
house values decrease, however, borrowers may find their debt is greater than the value
of the property. In such situation, neither a pre-foreclosure or “short” sale nor refinancing
the loan is a cost efficient option.

A handful of studies have shown that the behaviors of the lender and borrower do
have a significant impact on mortgage delinquency and subsequent foreclosure (Capozza,
and Wyatt (1994) examined the moral hazard problem in commercial mortgage market.
Their analysis shown that lenders will only consider foreclosure alternatives when the
cost of foreclosure is higher than the cost of revealing information concerning the true
foreclosure costs to other borrowers, and thus encouraging additional defaults. Elmer and
Seeling (1999) examined mortgage default and foreclosure process by modeling the
impact of trigger events along with the amount of equity in the household by examining
properties price changes for borrowers. Pavlov (2001) constructed a model to estimate
borrowers’ behavior in mortgage termination using a flexible proportional-hazard
framework and individual mortgage data in Los Angeles. He found that the necessity to
sell the property was sensitive to the local economic condition but largely independent of
the value of the mortgage. On the other hand, Ambrose and Capone (1996) argued that
lenders’ behaviors were very insensitive to changes in a variety of factors, including interest rates, environments and time horizons according to the simulation results from his model. Baku and Smith (1998) interviewed leadership and staff from community lending originations and found that the performance of loans made by nonprofit lenders to low income households was sensitive to the incentive structure internal to the nonprofit agency. A later study by Ambrose et al (2001) examined the timing of mortgage defaults given home price and interest rate changes using FHA empirical data. The study showed that the cost of life events, such as unemployment and divorce, influenced the borrowers’ option but the existence of second mortgages played a significant role. In general, the behaviors of both borrowers and lenders do have an impact on mortgage default and subsequent foreclosure.

The issue of whether mortgage defaults led to foreclosure has been examined. A study by Capozza et al (1997) addressed that foreclosure becomes a necessary option when the LTV ratio is above 100 percent, combining with trigger events. Lauria, et al (2004) estimated the variables that determine the time that elapses between default and foreclosure. Using the relevant neighborhood property values, the study found that lower LTV ratios have significantly longer period of the foreclosure proceedings are initiated than high LTV’s. The results indicated that borrowers who defaulted because of trigger events were foreclosed at a significantly faster rate than those have a job but unable to afford the payments. Thus, lenders are not anxious to foreclose the property for the possibility to refinance a loan with a higher interest rate. Another study in Massachusetts, using a dataset during the early 1990s, found that most borrowers who lost their homes
have “negative equity”, meaning that the market prices of the properties are below borrowers’ mortgages (Foote, Gerardi et al. 2008).

Studies also found that credit score is a key element in explaining borrower’s option on mortgage default. A study conducted by Harrison et al. (2004) found that high credit score borrowers with a high likelihood of payment tend to select higher LTV mortgages and that low credit score borrowers with a high likelihood of payment select low LTV mortgages. Danis and Pennington-Cross (2005) examined the behavior of investments in subprime mortgages and found that low FICO credit scores and past delinquency rates significantly affect the likelihood of default by subprime borrowers.

State foreclosure laws also impact both borrower and creditor’s decision. Two studies examined the cost of foreclosure to borrower and lender. The study by Phillips and Rosenblatt (1996) found that the availability of deficiency judgments lowered foreclosure costs for the creditor. They suggested that the costs to the creditor are lower because the borrower seems more likely to agree to a quicker solution in exchange for the lender releasing its right to seek a deficiency judgment. Pennington-Cross (2004) found, in a latter study, that borrowers would be more willing to maintain their properties if that could reduce their potential liabilities, which would have to be satisfied out of other assets.

In summary, various factors, like demographic characteristics, housing cycles, policy changes, and so on, contributed to the widespread foreclosure crisis in the United States. Researchers from different disciplines have investigated the problem using both qualitative and quantitative methods. However, as many aspects of the problem still remain unknown due to its complexity, further research is needed. This study will focus
on the spatial characteristics of foreclosure, and how it relates to neighborhood characteristics, particularly subprime loans.
Chapter 3

Methodology

3.1 Datasets Used in This Study

3.1.1 Datasets Used in Foreclosure Studies

As mentioned in the last chapter, various datasets have been used in previous home mortgage default and foreclosure research. There is no perfect measure of foreclosures; each dataset has its own strengths and limitations, and this chapter will provide a brief review of these datasets. Due to the complexity of foreclosure processes, the following section will discuss some major datasets used in related studies.

(1) Home Mortgage Disclosure Act Datasets

The HMDA data is one of the most commonly used public datasets in mortgage studies, and it is monitored by the Federal Financial Institutions Examination Council (FFIEC). HMDA data includes both mortgage applicants’ and borrowers’ characteristics, and loan information at the origination of the mortgage.
However, there are some limitations of the HMDA datasets. For instance, loan information is not complete in the HMDA datasets. Some critical information, like LTV, and debt to loan ratio (DTL), are not collected. In addition, since HMDA only captures borrowers and their loan characteristics at the origination of the loan but not at the beginning of mortgage default, it might be misleading in measuring factors associated with the default and foreclosure. Also, as HMDA data are aggregated at census tract level, it is impossible to analyze loan performance at a more precise spatial scale.

(2) Foreclosure Filing Data

Generally, foreclosure filing data are generated and managed by the local civic court. These data are helpful in measuring factors that might cause default and foreclosure. However, such data cannot be used easily in academic studies, largely due to the format of the data. Because most information is in legal documentation format, it is not tabulated or computerized, and thus it is extremely time consuming to organize and format data.

Filing data might also be questionable if used as a proxy for foreclosure analysis even though they are well formatted. Once foreclosure is initiated, there are state-specific timetables regarding the length of time necessary to complete a property sale. In Ohio, the time from initial action to foreclosure sale takes around 252 days. Although filing data measure troubled loans which may end up with foreclosure process, about half of the borrowers successfully avoid Sheriff’s auction sales through refinancing, pre-foreclosure sale, and so on during the time to complete the foreclosure process. Therefore, using the foreclosure filing in foreclosure studies may overestimate the effect of the crisis because
the filing data only capture the foreclosure process at the first stage, but not capture exactly the number of families that lose their homes to foreclosure. For example, in Lucas County, Ohio, an average of only 46.8 percent of foreclosures filing cases ended up with foreclosure from 1994 to 2007.

Figure 3-1 1994-2007 Sheriff’s Sale and Foreclosure Filing in Lucas Co., OH

Source: Policy Matters Ohio (www.policymattersohio.org)

(3) Sheriff’s Sale Data

The recorder’s office or the auditor’s office in each county keeps records of deed transfer data, and thus there are sufficient historical data to do time series analysis. In addition, Sheriff’s sale data is useful in estimating the situation of foreclosure as it contains most foreclosed property records. However, if the recording process is not
required by the county, some buyers might not record the transfer, leading to an incomplete dataset. Another limitation of this type of data is that some properties are sold at sheriff’s sales due to obligations other than loan default, like tax delinquency, or mechanic’s liens. Using sheriff’s sale data might also underestimate the risk of the foreclosure crisis because the data contain records of the foreclosed properties but not properties with troubled loans.

(4) The U.S. Mortgage Bankers Association Datasets

The U.S. Mortgage Bankers Association (MBA) provides quarterly case counts for foreclosure at state level. The data present the quarterly foreclosure rates for prime loans, subprime loans, FHA-insured loans, and other types of loans since the late 1970s. The MBA also provides market-share data for different types of loans. Therefore, the MBA datasets are useful in time series analyses, exploring the status and trends of foreclosure at state and country level. One large shortcoming is that they do not contain any data below state level. In addition, many of the MBA data are expensive.

(5) Mortgage Loan Performance Data

Mortgage loan performance data datasets capture most of the subprime loans and many prime loans in the U.S. at individual level. The Loan Performance, Inc., a nationwide mortgage data provider, manages the data. These data were used in some studies (Danis and Pennington-cross 2008) to analyze the performance of subprime loans. But the loan performance datasets are not widely used in academic research due to their
high price. Instead, the data are widely used by some financial institutions in mortgage default risk analysis.

(6) Other Commercial Foreclosure Data

Properties with troubled loans have become attractive to some real estate investors, and some are sold before the foreclosure auction. Thus, some commercial organizations provide lists of properties in the foreclosure process, and such data can be found from the internet. But these lists are less useful for academic purposes because those lists do not cover all or even the most of the foreclosed properties.

The purpose of this study is to explore the relationships among neighborhood socio-economic characteristics, subprime loans and home foreclosures in a spatial context. Given that new foreclosure filings are just the beginning of the foreclosure process and over 50 percent of those filings in Lucas County, OH were withdrawn in the last 15 years, using the filing data will lead to biased results in this research. On the other hand, foreclosed properties sold at sheriff’s auctions sale are supposed to represent foreclosure status in Lucas County, and HMDA data contain high-cost loan records. Thus, the primary datasets in this study are the sheriff’s sales data and the HMDA data.

3.1.2 Summary of Datasets Used in This Study

This study uses datasets from different sources:

1) Historical sheriff’s sales in Lucas County, OH
2) HMDA Loan Application Register (LAR) Raw Data
3) Lucas County real estate data from AREIS (Auditors Real Estate Information System)

4) U.S. Census Bureau’s 2000 census SF3 dataset

5) TIGER street line GIS data

The sheriff’s sale data are retrieved from the AREIS dataset, which is managed by the Lucas County Auditor’s Office. Records can be traced back to 1987, and cases between 2004 and 2007 are used in this study.

The sheriff’s sale data contain property parcel ID numbers, and therefore this study visualized foreclosure cases based on the property parcel data. The geocoded datasets were then spatially aggregated at census tract level for further analysis. Some cases are lost during the process of geocoding and retrieving data. This study assumes that there is no significant difference between lost cases and the cases used in this research because the cases lost during this stage are less than one percent of the total cases.

To derive the yearly foreclosure rate, all foreclosure cases in each census tract are divided by the total owner-occupied housing units in the same census tract.

3.1.3 Variable Selection

Most of the selected variables are based on previous studies, and they are classified into three categories: socio-economic characteristics, housing characteristics, and loan characteristics. There are two sub groups of the socio-economic characteristics: demographic characteristics and economic characteristics.
(1) Socio-economic Characteristics

**Demographic Characteristics**

Demographic structure of a neighborhood usually describes the population composition, including gender, age, marital status, race, and education, as well as other information. Therefore, demographic characteristics are highly related to the social and economic structure of a neighborhood. A handful of studies find that racial composition plays a key role in mortgage default and concentrated foreclosures (Baxter and Lauria 2000; U.S. Department of Housing and Urban Development 2000; Laurie, Emilia et al. 2009). Immergluck and Smith (2006) used a subset of the young male population (14~24 years old) as a proxy in their study about the impact of foreclosure on violent crime rates. In addition, employment and marital status and changes in these characteristics are considered important because these factors influence the risk of mortgage default and subsequent foreclosure. In brief, race, marital status, age, and some other factors contribute to mortgage default and foreclosure.

**Economic Characteristics**

Economic characteristics are significant in home foreclosure. As mentioned in the last chapter, income and social class are commonly used in related studies. Median family or household income is one of the major indicators. The poverty rate and the unemployment rate are also important indicators since they represent the economic situation of the neighborhood to some extent. Therefore, these variables will be included in this study to investigate how they relate to concentrated foreclosures.
(2) Housing Characteristics

Housing characteristics contribute significantly to mortgage foreclosure. Homeownership rate, median/average value of homes, the vacancy rate, the local market situation, and so on, have a significant impact on mortgage default and foreclosure.

Housing value appreciation should be closely related to mortgage default risk. Borrowers are more likely to go through the foreclosure process when there is a negative equity (Foote, Gerardi et al. 2008). On the other hand, high foreclosure rates will lower housing appreciation values of both the foreclosed properties and the properties adjacent to them (Immergluck and Smith, 2005). Vacancy rate is supposed to be related to home foreclosure because foreclosed houses are often vacant. In addition, a high vacancy rate in a community may decrease local property values, resulting in more foreclosures in the area.

(3) Mortgage Characteristics

As discussed in the previous chapter, the risks of default and subsequent foreclosure differ greatly among different types of loan, and subprime loans are far riskier than prime loans. Therefore, home mortgage characteristics: like home mortgage rates per capita per census tract, should be considered. Given that high-cost loans are more risky and lead to default and foreclosure at a higher rate, the percentage of subprime loans out of the total loan originations in each census tract, average rate spread rates for subprime loan holders, as well as other characteristics of the subprime loan holders are also important factors.
3.2 Research Methodology

3.2.1 Explanatory Analyses

This study begins with an explanatory spatial analysis of foreclosures and associated factors in the study region.

(1) Descriptive analyses

Simple descriptive analysis is conducted after data cleaning to describe the distribution of foreclosure cases in Lucas County. The first step is geocoding each foreclosure case to the parcel address of the foreclosed property. All the cases are then aggregated at the census tract level, and then standardized into the foreclosure rate by dividing foreclosure cases by the total number of occupied housing units in the same census tract. Frequency analysis and univariate analysis are used in the next step in the descriptive analysis. Foreclosure rates during this period are classified into six categories and visualized in a thematic map.

(2) Spatial analyses

Spatial dependency is a common phenomenon for geographically distributed attributes. In housing studies, the most common example is that, a property’s value affects and is affected by the adjacent properties. Spatial autocorrelation exists when the spatial distribution of a variable is not random and the values of the variable at a set of locations depend on values of the same variable at other locations (Anselin 2003). The assumption of independence in OLS may be violated if spatial autocorrelation exists. Spatial autocorrelation may cause the OLS standard error estimates to be less efficient if it is significant (Griffith and Amrhein 1991). A latent positive spatial autocorrelation
tends to inflate the significance of the regression and suggests that certain covariates are more significant than they actually are. The latent negative spatial autocorrelation, on the other hand, tends to suppress the significance of the regression and makes certain covariates appear to be less significant than they actually are. Therefore, the error terms or spatial lag should be included in the model if spatial autocorrelation is significant.

A weight matrix has been created to measure the relative locations of pairs of places on the map. When polygon (census tract in this study) i and j share boundaries, the weight is equal to 1, otherwise it is 0. Thus, the weight matrix can be expressed as:

$$W_{ij} = \frac{C_{ij}}{C_{ij}}$$

After deriving the weight matrix, the spatial autocovariance can be calculated via the following function:

$$\sum \sum w_{ij}(x_i - \bar{x})(x_j - \bar{x})$$

Several statistics can be used to measure the level of spatial autocorrelation: Moran’s I, Geary’s Ratio C, and the G-statistic. Although may not hold true in reality, these statistics assume that the magnitude and the variables of the spatial autocorrelation are relatively stable across the study region. This study will use Moran’s I statistics to measure spatial autocorrelation. The Moran’s I statistic, developed by Moran (1948; 1950; 1950), is calculated by standardizing the spatial autocovariance. The Global Moran’s I can be expressed as:

$$I = \frac{n \sum \sum w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{W \sum (x_j - \bar{x})^2} ,$$
where \( x_i \) is the value of the variable in area unit I and \( W \) is the sum of all elements of the spatial weight matrix. The range of the Moran’s I index is -1 to 1. The study variable is randomly distributed when Moran’s I is close to zero. On the other hand, when the index is close to either 1 or -1, it indicates that the variable represents a clustered pattern.

This study will also use the local Moran statistics to examine spatial dependency at local scale. The local version of Moran’s I developed by Anselin (1995) is one of the local indicators of spatial association (LISA) and is useful in exploring how neighboring values are associated with each other.

### 3.2.2 Spatial Regression

It is important to recognize spatial autocorrelation in spatial data since the results of classical statistical analysis will be incorrect as the assumption of independence is violated when spatial autocorrelation exists and is significant (Anselin 2003). Initially, this study supposes there is spatial autocorrelation or spatial dependency of some variables when dealing with spatial datasets. Therefore, if the spatial dependency of the variables is significant, this study needs to include the spatial error or the spatial lag into the model. Otherwise, the general OLS model will be more appropriate for the study.

A general OLS model is expressed as:

\[
Y = X\beta + \varepsilon
\]

where \( Y \) is the matrix of the dependent variable, \( X \) is the matrix of the independent variables, and \( \varepsilon \) is the error term matrix.
The function listed above can be revised into two general spatial regressions, when considering the effect of spatial autocorrelation: spatial lag regression and spatial error regression.

The spatial lag regression is generated as follow:

\[ Y = X\beta + \rho W_y + \nu \]

where \( \rho \) is the spatial autoregressive coefficient, \( W_y \) is a spatially lagged variable of the dependent variable, and \( \nu \) is the error term.

The spatial error regression can be expressed as:

\[ Y = X\beta + \rho W\varepsilon + \nu \]

where \( \rho \) is the spatial autoregressive coefficient, \( W \) is the spatial weight matrix, \( \varepsilon \) is the spatial error term and the \( \nu \) is the error term of the model.

Two tests are helpful in determining which regression model is more appropriate for the study: the Lagrange Multiplier (LM) error test and the LM-lag test (Anselin 2003). If none of the tests is significant, there is no need to use any spatial regression models. If only the LM-error test is significant, the spatial error model is appropriate. On the other hand, if only the LM-lag test is significant, the spatial lag model should be chosen. If both tests are significant, which spatial model will be more appropriate should be based on the Robust LM-error diagnostic. The spatial lag model will be used if the Robust LM-lag is significant; otherwise, the spatial error model will be chosen.

3.2.3 Heteroscedasticity and H-Robust OLS

_Heteroscedasticity_
Heteroscedasticity results from improper model specification, for example, non-constant coefficient, omitted variables, non-linearity and data aggregation. Although there are several tests to determine whether heteroscedasticity is present or not in a model, it’s difficult to tell the cause of the problem from these tests. If heteroscedasticity exists and is significant, then OLS estimates are no longer BLUE (best linear unbiased estimator), which means that among all the unbiased estimators, OLS does not provide the estimate with the smallest variance. Therefore, significance tests can be either too high or too low, and the direction of the bias depends on the nature of the heteroscedasticity.

Robust Standard Errors

Heteroscedasticity arises from the violation of the assumption that the variances of error terms are constant. When this problem is present, robust standard errors tend to be more trustworthy as robust standard errors relax either or both of the OLS assumptions that errors are both independent and identically distributed. The use of robust standard errors does not change coefficient estimates, but the test statistics will give a reasonably accurate p values. On the other hand, the use of Weighted Least Squares (WLS) will also correct the problem of bias in the standard errors, and will also give more efficient estimates. However, WLS requires more assumptions and is more difficult to implement. Hence, in this study, robust standard errors seem to be a more practicable method for dealing with the issue of heteroscedasticity.

The HC0 estimator proposed by Huber (1967) and White (1980) is the classic correction for heteroscedasticity problem. Three improvements, HC1, HC2, and HC3 are
discussed latter in MacKimon and White's study (1985). Long and Ervin (2000) suggests that HC0 is likely to result in incorrect inference when the sample size is small than 250, and HC3 is the best estimator in small samples. Therefore, this study will use HC3 in Robust OLS if heteroscedasticity is significant.

This study will utilize different statistical packages to construct models. Stata 10, a leading statistical program will be used in constructing OLS and H-Robust OLS models. In addition, a widely used spatial statistical package, GeoDa, will be used for spatial dependency analysis and spatial modeling.
Chapter 4

Foreclosure in Lucas County

4.1 The Content of Lucas County

4.1.1 Social Economic Characteristics of the Research Area

Lucas County is located in the northwest section of the state of Ohio, and borders the state of Michigan. According to the U.S. Census Bureau, the county has a total area of 596 square miles. As of the 2000 census, there were 455,054 people, 182,847 households, and 116,290 families residing in the county. The population density was 1,337 people per square mile. The average family size was 3.06 and the average household size was 2.44.

Lucas County has been losing population since the 1970s, due to the depression of America’s manufacturing industry. From 1970 to 2000, Lucas County lost 6 percent of its population accumulatively. According to the U.S. Census Bureau’s estimation, Lucas County had a population of 441,970 in 2007, losing about three percent of its population since 2000. Obviously, losing population is not a good signal for the local housing market.
As of the 2000 census, racial composition in Lucas County was 77.50 percent White, 16.98 percent Black or African American, 0.26 percent Native American, 1.21 percent Asian, 0.02 percent Pacific Islander, 1.86 percent from other races, and 2.16 percent from two or more races.

The median household income was $38,004, and the median income for a family was $48,190, according to the 2000 census. And the capital income for the county was $20,518. About 10.70 percent of families and 13.90 percent of the population were below the poverty line, including 19.70 percent of those under age 18 and 8.70 percent of those age 65 or over.

The job market in Lucas County has been in a relatively weak condition compared to the national job market since the early 2000s. Unemployment rates presented an overall increasing trend after 2000, though they dropped slightly between 2004 and 2006.
Figure 4-2 Unemployment Rate: Lucas vs. United States (1990-2009)

Source: The U.S. Department of Labor (http://www.dol.gov/)

4.1.2 Housing Characteristics of the Research Area

As of the 2000 census, there were 196,259 housing units at an average density of 576 per square mile in Lucas County. The median value of owner-occupied homes was $90,700, and the homeownership rate was 65.35 percent, in terms of 2000 census data. In addition, home prices in Lucas County have grown much slower than in the United States as a whole. The median value of residential properties in 2006 was $92,600, calculated from Lucas County ARIES 2006 data. Therefore, such relatively poor growth in house equity certainly contributes to rising problem mortgages in the county to some extent.
4.2 Foreclosure in Lucas County

4.2.1 Foreclosure process in Ohio

There are two kinds of foreclosure processes in the United States, the first one requires a judicial process while the other does not; and it depends on each state’s foreclosure laws. In Ohio, only judicial foreclosure is allowed; and there are several critical points in the foreclosure process.

The foreclosure process begins when the lender files a civil lawsuit against the borrower who is behind in payments, usually for more than 90 days. The case will be dismissed if the borrower repays the loan, sells the property and then pays off the loan, refines the mortgage, successfully files for bankruptcy; or becomes current on the loan in some way. If none of the above happens, then the property and the mortgage will be put onto a civic sale, which are usually conducted by the County Sheriff’s Office. However, if the property is sold, the loan is fully paid, or the borrower files bankruptcy before the auction, it will be withdrawn from the sale. Properties sold at the Sheriff’s sales are recorded at each county’s auditor’s office as Sheriff’s Deeds. If the property is not sold during the Sheriff’s sale, typically, the lenders will take the title of the property and sell it at some point in the future.

Since the entire process can last as long as 262 days under Ohio’s foreclosure laws, there is no perfect dataset to describe the foreclosure situation. Thus, the choice of dataset largely depends on the objective of the research and the availability of data. As discussed before, it is more appropriate to use the Sheriff’s Sale data for this study.
4.2.2 Lucas County’s foreclosure crisis

In terms of new foreclosure filings, Lucas County showed a steady increasing trend since the mid 1990s. There were 4,491 foreclosure filings in Lucas County in 2009, which increased over 250 percent from 1995. And according to Policy Matters Ohio, Lucas County continued in the second place in state ranking in new foreclosures filing per 1,000 population in 2009 (Rothstein 2010).

![Figure 4-3 Lucas County Foreclosure Filings: 1995-2009](image)

In Lucas County, the residential mortgage foreclosure rate remained relatively stable before the mid 1990s. However, it has risen rapidly since the early 2000s, except 2002 and 2006. The Sheriff’s sale totals jumped from 768 cases in 2000 to 2,142 cases by the end of 2007, an increase of over 170 percent. Sheriff’s sales reached historical high in 2008, when there were 2,402 cases, more than triple the number in 1990.
Figure 4-4 Sheriff’s Sale from 1988 to 2009, Lucas County, OH

Sources: ARIES, Lucas County

4.3 Summary

Regardless of sharing common characteristics of population size, infrastructure
and a large dependence on manufacturing with other mid-west industrial cities, Lucas
County has continually been falling behind in both economy development and population
growth during the last decade.

Table 4.1 Selected Characteristics of Lucas County

<table>
<thead>
<tr>
<th>Demographic:</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Population</td>
<td>455,054</td>
</tr>
<tr>
<td>White</td>
<td>352,678</td>
</tr>
<tr>
<td>Black or African American</td>
<td>77,268</td>
</tr>
<tr>
<td>Number</td>
<td>Percent</td>
</tr>
<tr>
<td>77.50%</td>
<td>-</td>
</tr>
</tbody>
</table>


<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>American Indian and Alaska Native</td>
<td>1,179</td>
<td>0.26%</td>
</tr>
<tr>
<td>Asian</td>
<td>5,527</td>
<td>1.21%</td>
</tr>
<tr>
<td>Native Hawaiian and Other Pacific Islander</td>
<td>92</td>
<td>0.02%</td>
</tr>
<tr>
<td>Some other race</td>
<td>8,468</td>
<td>1.86%</td>
</tr>
<tr>
<td>Two or more races</td>
<td>9,842</td>
<td>2.16%</td>
</tr>
<tr>
<td>Median age</td>
<td>35</td>
<td>-</td>
</tr>
<tr>
<td>Average family size</td>
<td>3.06</td>
<td>-</td>
</tr>
<tr>
<td>Average household size</td>
<td>2.44</td>
<td>-</td>
</tr>
<tr>
<td>Female householder, no husband present</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school graduate or higher, percent of persons age 25+</td>
<td>14.70%</td>
<td>83.0%</td>
</tr>
<tr>
<td>Bachelor's degree or higher, percent of persons age 25+</td>
<td></td>
<td>21.10%</td>
</tr>
<tr>
<td>Economic:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median household income</td>
<td>$38,004</td>
<td>-</td>
</tr>
<tr>
<td>Median family income</td>
<td>$48,190</td>
<td>-</td>
</tr>
<tr>
<td>Median family income(in 2007 inflation-adjusted dollars)</td>
<td>$52,713</td>
<td>-</td>
</tr>
<tr>
<td>Capital income</td>
<td>$20,518</td>
<td>-</td>
</tr>
<tr>
<td>Individuals below poverty level</td>
<td>13.90%</td>
<td></td>
</tr>
<tr>
<td>Families below poverty level</td>
<td>10.70%</td>
<td></td>
</tr>
<tr>
<td>In labor force(&gt;=16 years old)</td>
<td>65.00%</td>
<td></td>
</tr>
<tr>
<td>Unemployed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Housing:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total housing units</td>
<td>196,259</td>
<td>-</td>
</tr>
<tr>
<td>Occupied housing units</td>
<td>182,847</td>
<td>93.17%</td>
</tr>
<tr>
<td>Owner-occupied housing units</td>
<td>119,492</td>
<td>60.88%</td>
</tr>
<tr>
<td>Renter-occupied housing units</td>
<td>63,355</td>
<td>32.28%</td>
</tr>
<tr>
<td>Vacant housing units</td>
<td>13,412</td>
<td>6.83%</td>
</tr>
<tr>
<td>Median value of owner-occupied homes ($)</td>
<td>90,700</td>
<td>-</td>
</tr>
<tr>
<td>Median owner costs with a mortgage($)</td>
<td>900</td>
<td>-</td>
</tr>
<tr>
<td>Median owner costs without mortgage($)</td>
<td>294</td>
<td>-</td>
</tr>
<tr>
<td>Average value of residential properties (2006)</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Average value of residential properties (2008)</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

Chapter 5

Explanatory Analyses

5.1 Data Description

When looking at the spatial patterns of these sheriff’s sales records, this study found that many cases are highly concentrated in certain areas, especially clustered around the inner-city areas, and the pattern is relatively stable over time. However, these cases began to scatter to surrounding suburbs (see Figure 5-1). Given that households in distressed inner-city areas suffer more during economic recession, this pattern is not surprising. On the other hand, houses in wealthier communities might end up with a pre-foreclosure sale. Houses located in these distressed areas, however, might be less attractive to pre-foreclosure buyers and, thus, many of them have to go the Sheriff’s auction. Therefore, the dataset may over represent the problem in these areas.
Figure 5-1 Spatial Distribution of Sheriff’s Sales in Lucas County, OH (2000-2009)
Figure 5-1 continued
Figure 5-2 Total Residential Sheriff’s Sales in Lucas County, OH (2000-2009)

There is a total number of 9,045 sheriff’s sales from 2004 to 2008, 84 of which are eliminated due to inaccurate parcel IDs. Thus, 8,931 (99.07 percent) cases are geocoded with property parcel information, then; those cases are aggregated at the census tract level and standardized by total occupied housing units to derive a foreclosure rate in each census tract. There are 128 census tracts in Lucas County in total, and the average foreclosure rate measured by the accumulated Sheriff’s Sales data between 2004 and 2008 is five percent, with a standard deviation of 3.6 percent (the highest value is 15.58 percent and the lowest value is 0.43 percent). More than half of the census tracts (55.47 percent) have a foreclosure rate lower than five percent, and 87 percent have a foreclosure rate lower than 10.00 percent and the rest have a foreclosure rate from 10 percent to 16 percent.
Figure 5-3 Foreclosure Rates (2004-08) Distribution at the Census Tract Level

Figure 5-4 Accumulated Foreclosure Rates (2004-08) Distribution Map
Subprime loan data are combined into a two years period in this study for analysis as Shetty and Hammel (2010) in their study found that the normal length of time to go through the foreclosure process in Lucas County is about 12 to 18 months in recent years. The length of time from filing to confirmation of Sheriff’s Sale in Lucas County between 2004 and 2008 is listed as follows:

Table 5.1 Length of Time from Filing to Confirmation of Sale or Dismissal

<table>
<thead>
<tr>
<th></th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of confirmations</td>
<td>24</td>
<td>28</td>
<td>35</td>
<td>36</td>
<td>35</td>
</tr>
<tr>
<td>Mean time in days</td>
<td>460</td>
<td>486</td>
<td>421</td>
<td>382</td>
<td>341</td>
</tr>
<tr>
<td>Median time in days</td>
<td>377</td>
<td>447</td>
<td>375</td>
<td>352</td>
<td>322</td>
</tr>
<tr>
<td>95% confidence interval in days</td>
<td>367-552</td>
<td>397-575</td>
<td>367-476</td>
<td>323-441</td>
<td>301-381</td>
</tr>
</tbody>
</table>

Source: Mortgage foreclosures: characteristics and patterns in Lucas County, Ohio, 2009

5.2 Spatial Autocorrelation Analysis

5.2.1 Connectivity of census tracts in Lucas County

There are many ways to define a spatial relationship, and this paper defines neighborhood based on queen’s adjacency criterion and uses the first order of contiguity to create the spatial weights matrixes. And the connectivity of different census tracts is the basis of calculating the spatial weights matrices. The connectivity of census tracts is shown below in Figure 5-5. Each bar in the histogram denotes the number of neighboring census tracts for any given census tract. Most of the census tracts have six neighboring...
census tracts. And only one census tract has one neighboring census tract. The connectivity of census tracts in Lucas County is illustrated as in Figure 5-5:

![Figure 5-5 Connectivity of Census Tracts in Lucas County](image)

There are two common spatial autocorrelation analyses: univariate and multivariate spatial autocorrelation analysis. The first one explores whether a variable is spatially autocorrelated with the same variable in adjacent neighborhoods while the latter one explores the autocorrelation between two or more variables in adjacent neighborhoods.

Both univariate and multivariate spatial autocorrelation are used in this section to explore the spatial autocorrelation for the foreclosure rate itself, and the dependency between the foreclosure rate and other social economic characteristics. All univariate and bivariate autocorrelation tests are based on local and global autocorrelation analyses and all variables are standardized in this section.
5.2.2 Local Spatial Autocorrelation

The analysis of local spatial autocorrelation of the foreclosure rate in Lucas County shows that there is a high-high spatial autocorrelation in the inner city areas. Census tracts that have high foreclosure rates in those areas are surrounded by other census tracts also with high foreclosure rates. This study also found that, census tracts in the western part of the county show a low-low spatial autocorrelation, indicating that communities with low foreclosure rates are surrounded by neighboring census tracts also with low foreclosure rates.

Figure 5-6 Local Spatial Relationships of Foreclosure Rates (2007)
5.2.3 Global Spatial Autocorrelation

**Foreclosure Rates**

The spatial autocorrelation of foreclosure rates in different census tracts in 2007 is significant with a Moran’s Index of 0.4232. It suggests that foreclosure rates are autocorrelated themselves in neighboring census tracts. Thus, the spatial distribution of foreclosure rates in Lucas County is not random but is highly clustered.

**Foreclosure rates and average residential property values**

When looking at the relationship between foreclosure rates in 2007 with mean residential property values in 2006, I found that these variables are negatively autocorrelated with Moran’s I of -0.4592. This suggests that foreclosure rate per census tract is negatively autocorrelated with the average residential property values in neighboring census tracts. While looking at foreclosure rates in 2006, a similar result is found. These simple relationships between foreclosure rates and average residential property values mean that these two variables are closely related spatially.

**Foreclosure rates and homeownership rates**

Homeownership rates and foreclosure rates in 2007 show a negative relationship with the Moran’s I of -0.2298. This indicates that homeownership rates in 2000 auto correlates with foreclosure rates in 2007. Meanwhile, housing vacancy rates have been found positively related to foreclosure rates with the Moran’s I of 0.2581.
Foreclosure rates and subprime loan shares rates

When looking at the relationship between foreclosure rates in 2007 and subprime loan to total loan ratio between 2005 and 2006, a positive relation is found (Moran’s I=0.3853). Similarly, foreclosure rates in 2006 are also positively related to subprime loan to total loan ratio between 2004 and 2005. Therefore, foreclosure rates and subprime loan shares rate are not only closely related, but they also have a spatial relationship.

5.3 Summary

Simple statistical and spatial analysis show that foreclosure became a broader county-wide issue and foreclosure rates measured in this section have increased since the 1990s. Although suburban areas have seen some increases in recent years, foreclosures are more concentrated in low to moderate income and inner-city areas in Lucas County. Only about a third to half out of the new foreclosure filings finished the foreclosure process, the reason why a large amount of new filings did not terminate as foreclosed properties remains unclear.

Housing vacancy rates have been found to be positively related to the foreclosure rates. On the other hand, homeownership rate is negatively related to the foreclosure rate. The decrease in housing values in recent years has led to more people becoming more vulnerable to foreclosures.

Foreclosures show a clustered pattern in certain areas in the spatial autocorrelation analysis. Foreclosures in one census tract are autocorrelated with neighboring census tracts’ foreclosures. Besides, foreclosures are positively autocorrelated with subprime loans and housing vacancy rate in neighboring census tracts. Foreclosures are negatively
autocorrelated with homeownership rates, median household income (2000), and average residential property values in neighboring census tracts. The above findings provide the evidence that spatial dependency exists among foreclosures and some social economic characteristics.
Chapter 6

Models Results and Analysis

This study built several different models to estimate the subprime lending, housing and socio-economic effects on foreclosures using 2007 Sheriff’s sale data. These models include OLS, spatial models and H-Robust OLS to correct heteroscedasticity. This study also runs models containing only housing and socio-economic characteristics on foreclosures. By comparing two groups of models, this study will illustrate the importance of loan effects on housing foreclosure.

The following sections will discuss the results about of these models. In the first part, this study will compare model results and develop the best prediction of the relationships between loan characteristics, housing characteristics, socio-economic characteristics and foreclosure. Models discussed here include OLS, spatial models and heteroscedasticity-corrected regression models.

After running the OLS model I did the Bresuch-Pagan test and found that heteroscedasticity is highly significant. Hence, this thesis used robust standard errors (HC3) to correct the problem. After that, this study compared the results with the spatial models. Therefore, this study will report results from an OLS model, a model corrected for heteroscedasticity, and a model corrected for spatial autocorrelation.
At present this study is unable to correct both spatial autocorrelation and heteroscedasticity in one model; thus, this section will focus on the analysis of the variables that are significant in both the Heteroscedasticity-Robust OLS model and the spatial model. Since there is a difference in the levels of significance between OLS and Heteroscedasticity-Robust OLS, if the significance level of a specific variable changed dramatically in different models, the study will discuss it. Otherwise, the discussion versus the spatial model will be based on the Heteroscedasticity-Robust OLS model.

Moreover, since this study corrects heteroscedasticity and spatial autocorrelation separately, future work should formally correct both heteroscedasticity and spatial autocorrelation at the same time.

6.1 Data summary

Basic descriptive statistics for all the variables used in the analysis of the relationships between foreclosures, subprime lending, and community social economic characteristics are listed in Table 6.1.
Table 6.1 Descriptive Statistics of Selected Variables

<table>
<thead>
<tr>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Confidence Level (95.0%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable:</strong></td>
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<td></td>
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<tr>
<td>Rate07</td>
<td>128</td>
<td>0.010</td>
<td>0.009</td>
<td>0</td>
<td>0.042</td>
</tr>
<tr>
<td><strong>Socio-economic Characteristics:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BOWNRT</td>
<td>128</td>
<td>0.078</td>
<td>0.136</td>
<td>0</td>
<td>0.541</td>
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<tr>
<td>HHINCOME ($1,000)</td>
<td>128</td>
<td>37.382</td>
<td>16.243</td>
<td>9.256</td>
<td>99.908</td>
</tr>
<tr>
<td><strong>Housing Characteristics:</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AVGREVAL06($1,000)</td>
<td>128</td>
<td>95.442</td>
<td>60.375</td>
<td>14.353</td>
<td>306.386</td>
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<tr>
<td>HSE_UNITS</td>
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<td>1533.273</td>
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<td>3388</td>
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<td>VACRATE</td>
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<td>0.064</td>
<td>0.012</td>
<td>0.440</td>
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<tr>
<td>SALE0506</td>
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<td>23.289</td>
<td>18.201</td>
<td>0</td>
<td>97</td>
</tr>
<tr>
<td><strong>Loan Characteristics:</strong></td>
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<td></td>
<td></td>
<td></td>
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<tr>
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<td>48.020</td>
<td>0</td>
<td>244</td>
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<tr>
<td>AM2IN_56</td>
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<td>0</td>
<td>4.878</td>
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<tr>
<td>TOTLOAN57</td>
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<td>671.008</td>
<td>392.778</td>
<td>15.000</td>
<td>2279</td>
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</tbody>
</table>

Community socio-economic variables include median age, median household income, black alone homeownership rate, and population. This study assumes, other than minority percentage, the black alone homeownership rate could be a better proxy in measuring the effects of racial composition on foreclosure rate. Thus, the black alone homeownership rate was used in these models instead of minority percentage. The variables listed above are measured by the 2000 census tract values. Housing characteristics include the average value of housing units, housing vacancy rate, and cumulated foreclosure rate in a two year period before the study year. Loan characteristics include loan to population ratio, subprime loan to total loan ratio, accumulated loan cases, accumulated subprime loan cases and average subprime loan amount to income ratio. All loan characteristics are aggregated into a two year period at census tract level. For detailed narratives and statistical descriptions of the selected variables, please refer to the previous sections.
Given that the sample size is not large enough (128 census tracts), this study has to control the number of independent variables; otherwise, including large amount of independent variables will not only inflate the R-squared, but will also lead to redundancy. Therefore, this study omitted variables which were not significant, highly correlated to other independent variables, or had other problems. After omitting such variables, I reran the analysis to obtain trimmed model coefficients.

6.2 Summary of OLS and Spatial Regression Models

Models with loan data

The OLS results from the model with loan data (Table 6.2) suggest a relatively high R-squared of 0.68. Both multicollinearity (p=0.000) and heteroscedasticity (p= 0.002) are present in the model. Therefore, the error term does not have a constant variance, and R-squared might be improved if multicollinearity can be reduced. The significant heteroscedasticity has violated one assumption of OLS. Although it is usually difficult to determine the nature of the bias, the significant heteroscedasticity will not yield unbiased coefficient estimates. As mentioned in previous sections, robust standard error is used to provide more accurate standard errors.

Spatial dependence is apparent in this regression (p=0.04), and only the Lagrange Multiplier (lag) error test is significant (p=0.04). Thus, spatial autocorrelation (lag) is probably a bigger issue than spatial error in this case. Hence, the spatial lag model is used to see if it can provide a better fit or not. The R-squared from the spatial lag model is increased to 0.70, which is relatively high, and the log likelihood is also increased from 493.26 to 495.49, indicating that the spatial lag model yields a better fit compared to the
OLS model. Additionally, the likelihood ratio test, which compares the OLS model to the alternative spatial lag model, gives a value of 4.46 (p=0.03), confirming the strong significance of the spatial autoregressive value. The heteroscedasticity problem, though still significant at the 90 percent significant level (p=0.07), is much less serious than in the OLS model. Therefore, the spatial lag model provides a better fit than the OLS model. Since the spatial lag model is the strongest model, the parameter estimates from this model will be analyzed to see what variables significantly affect the foreclosure rate in Lucas County.

Notice that loan amount to income ratio (subprime loan alone) does not affect foreclosure rates in the H-Robust OLS model while it does in the spatial lag model. This is important because when the spatial autocorrelation of foreclosures is controlled, the loan amount to income ratio (subprime loan alone) is significantly related to foreclosure rates.

Models without loan data

This research also generated another group of models with only socio-economic and housing variables. A better understanding of the effects of loan characteristics can be gained by comparing two groups of models. The OLS results from the model without HMDA data indicate that the R-squared is 0.66, which is lower than the model with loan data. The Jarque-Bera test was used to check for multicollinearity, and the result is significant, suggesting that the R-squared might improve if multicollinearity is reduced. Heteroscedasticity is also significant via Breusch-Pagan test. Thus, the H-Robust OLS is built to correct heteroscedasticity.
Since spatial dependence was detected in this model again, both the spatial lag model and the spatial error model are generated to see which can provide a better fit. This study found out, however, only the Lagrange Multiplier (lag) test is significant (p=0.08), meaning that the spatial lag model should be selected. The spatial lag model has improved the R-squared slightly to 0.67, and the log likelihood also increased from 488.357 to 488.973. Therefore, the spatial lag model yields a better fit than the OLS model. Although these models yield very similar results, the spatial dependence tests confirm that spatial lag error is highly significant in the OLS model; therefore, the spatial lag model is again the best fit among these four models.

Comparing two groups of models this study found that including loan data in the models can yield better results. Loan data is closely related to the foreclosure rates in Lucas County as well as other socio-economic and housing characteristics. Also, this study found that spatial models have significantly improved the model fit by increasing the log likelihood. Therefore, using spatial models can yield more efficient estimates by accounting for spatial effects and the effects of related omitted variables. Also, spatial models can provide another view of the variables’ effects on foreclosures.
<table>
<thead>
<tr>
<th></th>
<th>OLS Model</th>
<th>H-Robust OLS Model</th>
<th>Spatial Lag Model</th>
<th>Spatial Error Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>No. of Observations</strong></td>
<td>128</td>
<td>128</td>
<td>128</td>
<td>128</td>
</tr>
<tr>
<td><strong>Variables</strong></td>
<td>10</td>
<td>10</td>
<td>11</td>
<td>10</td>
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<tr>
<td><strong>R-Square</strong></td>
<td>0.68</td>
<td>0.68</td>
<td>0.70</td>
<td>0.69</td>
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<td><strong>Log Likelihood</strong></td>
<td>493.259</td>
<td>495.491</td>
<td>494.355</td>
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<table>
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<tr>
<th></th>
<th>Coef.</th>
<th>Std. error</th>
<th>p value</th>
<th>Coef.</th>
<th>Std. error</th>
<th>p value</th>
<th>Coef.</th>
<th>Std. error</th>
<th>p value</th>
<th>Coef.</th>
<th>Std. error</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
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<td>0.0030</td>
<td>0.040</td>
<td>0.0063</td>
<td>0.0036</td>
<td>0.079</td>
<td>0.0029</td>
<td>0.0033</td>
<td>0.381</td>
<td>0.0071</td>
<td>0.0030</td>
<td>0.017</td>
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<td><strong>HHINCOME($1,000)</strong></td>
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<td>6.54E-05</td>
<td>0.030</td>
<td>0.0001</td>
<td>0.0000</td>
<td>0.023</td>
<td>0.0001</td>
<td>6.16E-05</td>
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<td>0.0001</td>
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<td>2.00E-05</td>
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<td>-4.00E-05</td>
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<td><strong>TOTLOAN56</strong></td>
<td>-1.14E-06</td>
<td>3.64E-05</td>
<td>0.755</td>
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<td>-1.43E-06</td>
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<td>0.0110</td>
<td>0.024</td>
<td>0.0252</td>
<td>0.0133</td>
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<td>4.97E-05</td>
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<td>0.000</td>
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<td><strong>SUB0506</strong></td>
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<td>5.63E-05</td>
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<td>0.0017</td>
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<td>0.000</td>
<td>-5.27E-06</td>
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<td>0.000</td>
<td>-4.92E-06</td>
<td>1.19E-06</td>
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<td>-5.48E-06</td>
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<td><strong>W_RATE07</strong></td>
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**Diagnostics for Multicollinearity**

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<tr>
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<tbody>
<tr>
<td>Jarque-Bera test</td>
<td>31.67*** 0.000</td>
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</table>

**Diagnoses for Heteroscedasticity**

<p>| | | | |</p>
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<tr>
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</thead>
<tbody>
<tr>
<td>Breusch-Pagan test</td>
<td>26.48** 0.002</td>
<td>15.87* 0.07</td>
<td>13.24 0.15</td>
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<tr>
<td>White test</td>
<td>50.17 0.602</td>
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<td></td>
</tr>
<tr>
<td>Diagnostics for Spatial Dependence</td>
<td>Value 1</td>
<td>Value 2</td>
<td></td>
</tr>
<tr>
<td>-----------------------------------------------------------</td>
<td>---------</td>
<td>---------</td>
<td></td>
</tr>
<tr>
<td>Moran's I (error)</td>
<td>2.02**</td>
<td>0.044</td>
<td></td>
</tr>
<tr>
<td>Lagrange Multiplier(lag)</td>
<td>4.08**</td>
<td>0.043</td>
<td></td>
</tr>
<tr>
<td>Robust LM (lag)</td>
<td>2.14</td>
<td>0.143</td>
<td></td>
</tr>
<tr>
<td>Lagrange Multiplier(error)</td>
<td>1.94</td>
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<tr>
<td>Robust LM (error)</td>
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<td>0.968</td>
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<tr>
<td>Lagrange Multiplier(SARMA)</td>
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<td></td>
<td>4.46**</td>
<td>2.19</td>
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</table>

Table 6.2 Continued.

*** 0.001 significant level

** .005 significant level

*.010 significant level

+.015 significant level
Table 6.3 Comparison of models without loan data

<table>
<thead>
<tr>
<th></th>
<th>OLS Model</th>
<th>H-Robust OLS Model</th>
<th>Spatial Lag Model</th>
<th>Spatial Error Model</th>
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<td><strong>No. of Observations</strong></td>
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<td>128</td>
<td>128</td>
<td>128</td>
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<td><strong>Variables</strong></td>
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<td>7</td>
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<td><strong>R-Square</strong></td>
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<td>0.66</td>
<td>0.67</td>
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Diagnostics for Multicollinearity

| Jarque-Bera test | 30.19*** | 0.000 |

Diagnostics for Heteroscedasticity

| Breusch-Pagan test | 27.78*** | 0.000 |
### Diagnostics for Spatial Dependence

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Table 6.3 Continued

*** 0.001 significant level

** .005 significant level

* .010 significant level

+.015 significant level
6.3 Comparison between Models

The following section will discuss the variables that are significant in the Heteroscedasticity-Robust OLS and the spatial lag model. The median household income, average housing property values (2006), housing vacancy rate, housing units, two year period Sheriff’s sale counts, and two year period subprime loan counts are all significant at 90 percent confidential level in both H-Robust and spatial lag models.

Housing values and housing units are negatively related to foreclosures while vacancy rate, subprime loan counts, and Sheriff’s sale counts are positively related to foreclosure rates as predicted. This means that communities with higher property values are more attractive in the housing market and are less vulnerable to the foreclosure crisis. In contrast, communities with higher vacancy rates and more Sheriff’s sales may imply an unstable and less dynamic housing market, resulting in more foreclosures. Notice that, in the second group of models without loan variables, house vacancy rate no longer affects foreclosure in Lucas County.

All loan variables except the total loans counts have an effect on foreclosure rates in Lucas County based on the spatial lag model, as the study assumed. Subprime loan counts are positively correlated with foreclosure, indicating that communities with more subprime loan counts suggest that more risky mortgages exist. And this in turn implies higher potential for high foreclosure rates. Additionally, the loan amount to income ratio (subprime loan alone) is significant in the spatial lag model but does not affect foreclosure in the H-Robust OLS model.

Housing characteristics have more significant impacts on foreclosure rates in Lucas County than demographic or economic variables. The median household income
was expected to be negatively related to foreclosure rate. However, it is positively affecting foreclosure rates in the H-Robust OLS. Instead of using minority percentage, this study utilized black alone homeownership rates to examine racial effects on foreclosure, as this study assumes the race of homeowners is more important in exploring the racial effects on foreclosure. However, black alone homeownership rate, which was assumed to affect foreclosures, is not significant for Lucas County when controlling for other factors in all models. This finding suggests that besides racial effects, other socio-economic or housing factors contribute more on foreclosures.

6.4 Interpretation of the Spatial Lag Model

Residuals form the spatial lag model were mapped out to see if any pattern exists. There are two types of residuals from the spatial lag model. One is the model residual, which accounts for the spatial lag term, and the other is the prediction error, which accounts for \((y - \hat{y})\). The range of the model residuals is between -0.0130 and 0.0205, and the model residuals are close to normal distribution (Figure 6-1).

![Figure 6-1: Distribution of Model Residuals from Spatial Lag Model](image)

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The Moran’s I scatter plot for the prediction error and model residual are shown in Figure 6-2. The Moran’s I for the model residual is 0.009, or nearly zero, indicating that the spatially lagged dependent variable term has eliminated all spatial autocorrelation. On the other hand, the Moran’s I index for prediction error (Moran’s I=0.093) is similar to the Moran’s I statistic for residual of the OLS model (Moran’s I= 0.075). Since the prediction errors are an estimate for the spatially transform errors, it is not a surprise that they are spatially correlated.

Figure 6-2 (a) Moran Scatter Plot for spatial lag prediction errors  
(b) Moran Scatter Plot for spatial lag residuals

Residuals from the spatial lag model appear randomly distributed on the standard deviation map (Figure 6-3), confirming that the influence of neighboring tracts has been incorporated into the model. The standard deviation map of the model prediction error highlights where the variables were least effective in predicting foreclosures rate (Figure 6-3).
The negative values indicate the foreclosure rates are lower than expected while positive values suggest foreclosure rates are higher than expected.

Figure 6-3 Spatial Distribution of Residuals from the Spatial Lag Model
Compared to the model residuals map, the prediction errors map shows more clustering of error values, indicating that the spatial factors are important in the spatial lag model. Therefore, the randomly distributed residual, or remaining error, indicates that the spatial lag model has largely accounted for spatial differences. Hence, this study demonstrates that spatial factors are important in foreclosure rates in Lucas County.

6.5 Common Variables affecting foreclosures in both models

*The Median Household Income*

The median household income is positively associated with foreclosure in Lucas County. Although contrary to expectation, it might be that householders with lower income living in a higher income community might be more likely to default on their
mortgages, and therefore inflate the foreclosure rates in that census tract. Additionally, census tracts with much lower median household income might also indicate that there are more rental households in these communities as those households cannot afford to purchase a house with their income. Therefore, communities with lower median household income might have lower foreclosure rates. But it might also be the effect of omitted variables and other factors in the model.

**Housing Vacancy Rate**

The housing vacancy rate is found to be positively associated with the foreclosure rate in the study area. Housing vacancy rate is one of the most important indicators of the health of a housing market. Higher housing vacancy rates usually suggest a surplus of housing supply compared to housing demand. Housing vacancy is necessary in the housing market since the housing absorption rate cannot be as high as 100 percent in most situations. Hence, a low to moderate housing vacancy rate will not have a significant negative effect on the housing market in most cases. However, a high housing vacancy rate is the evidence that the market is unhealthy. This indicates that more foreclosures will occur in communities with a relatively weak housing market.

**Average Residential Property Values**

Previous studies have found that property values have a strong impact on foreclosures, especially for homeowners. A handful of scholars (Foote, Gerardi, and Willen 2008) believe that negative home equity is one of the major factors leading to mortgage default decisions of the borrowers, and negative home equity usually comes
from the decrease of property value or a weak housing market condition. Given the fact that the housing market in Lucas County has been relatively weak due to the slow growth in both the economy and in population during the last few years, I believe that communities with higher average housing values are less vulnerable to the problem. In other words, the more dynamic a local housing market is the less likely the community will have a serious foreclosure problem.

*Housing Units*

The total housing units in each census tract is negatively related to foreclosure rates in Lucas County. This is not a surprise since the larger the base the lower foreclosure rates might be.

*Sheriff’s Sales*

Since foreclosures present certain patterns cross space and time in Lucas County, Sheriff’s sales of previous years can be a relatively good estimator in predicting foreclosures in the following year. As predicted, the two year period Sheriff’s sales data is positively related to foreclosure rates in Lucas County. In other words, neighborhoods with high foreclosure rates previously continue to experience a relative high level of foreclosure rates. Concentrated Sheriff’s sale cases might also lower property values and result in physical dilapidated infrastructures in those neighborhoods. In addition, communities with clustered Sheriff’s sales suggest a less vibrant local housing market, and lead to an unstable social structure among neighborhoods.
Subprime loans

As predicted, subprime loan counts are significantly related to foreclosure in Lucas County. Given the fact that a subprime mortgage is much more risky than conventional mortgages, it is not a surprise that borrowers with subprime loans are more likely to have foreclosure problems. Therefore, subprime loan counts can be a relatively good estimator in forecasting foreclosure. Based on the spatial lag model, when subprime loan cases increase every 18 cases, the foreclosure rate will increase 0.01 percent when controlling other factors.

In summary, a healthy housing market is fundamental for a vital community, and a vibrant local housing market is the evidence of both financial and figurative investment to the neighborhoods. A city with strong communities lays the foundation for economic growth itself. However, foreclosure not only negatively affects the homeowner, but also weakens the local housing market, resulting in a weak housing market and unstable social structure, which could foretell a city in despair.
Chapter 7

Conclusion and Discussion

7.1 Conclusions

As mentioned before, the relationship between community socio-economic characteristics, housing characteristics, loan characteristics and residential mortgage foreclosure is complicated. This study considers and analyzes the impacts of these factors in both OLS and spatial econometric models. Hence, the current approach will not only estimate the related variables’ effects on foreclosure, but will also distinguish between each of those effects and any spatial influence, which were left unaddressed in previous studies.

A sequence of four models was estimated, revealing the relationships between communities’ socio-economic characteristics, housing characteristics, loan characteristics, and foreclosure in Lucas County. While the specific regression coefficients estimated in this study will pertain to the study area only, the demonstrated modeling approach can apply universally.

When examining whether and how those factors affect foreclosure, this study found that there are six variables that are significantly related to foreclosure: median household income, average residential property values, housing vacancy rate, housing
units counts, Sheriff’s sale counts and subprime loan counts. Among those relationships the median household income is different from what I expected. Data collection errors, the correlation between the variables, the relatively long time span between different data sets, omitted variables, and spatial effects might somehow, make the estimated results difficult to interpret. Besides, this study argues that, gentrification, neighborhood renovation of the previous foreclosed properties, or neighborhood redevelopment might lead to such relationship.

This study finds some interesting results among the relationship and the some of the results contradict some previous studies on the topic. This study used black alone homeownership rate as a proxy to the racial effects on foreclosure and found that racial composition is not a significant explanation of foreclosure in Lucas County in all models. This finding is different from what previous research found (Baxter and Lauria 2000; Kaplan and Sommers 2009). But it is difficult to determine which finding is more appropriate since there are many differences in socio-economic characteristics in different places. Such findings also suggest that local context is very important to the impact on foreclosure. Therefore, the reason why such differences exist needs further exploration.

Challenges of time and data are a major limitation of this study. Although court records can be easily accessed, most of them do not have the format that can be easily coded or utilized in statistical packages. Thus, reorganizing such data is time consuming. If court foreclosure records can be merged with Sheriff’s sale data individually, then further investigation to find out how housing and loan characteristics, as well as individual borrower’s characteristics can affect foreclosure will become possible. This
will be much more accurate than using HMDA data, which is aggregated at the census tract level.

7.2 Future Study

Many of the study results are really interesting, though further investigation is needed. For example, finding an approach for running the spatial regression models controlling for spatial autocorrelation and heteroscedasticity at the same time would allow an interesting comparison of the results with those from this study. Therefore, by comparing the results from two methods, I can see whether controlling heteroscedasticity and spatial autocorrelation together or not will yield different results. Attention should be also paid to other issues associated with the spatial regression models, such as the level of data aggregation and multicollinearity.

Further research may focus on investigating how foreclosures affect demographic and neighborhood changes. Although previous studies have found that foreclosures have spillover effects on both nearby property values and the neighborhood, what community socio-economic and housing characteristics are being affected still remains unclear. Therefore, it is interesting to find out at what point foreclosures will contribute to socio-economic and housing characteristics, either positively or negatively. On the other hand, capturing the “threshold effects” of foreclosure is also worth further investigation. Since there’s a possibility that not until a particular variable met a threshold will its effect on foreclosure becomes relatively large, it would be useful to figure out, for instance, at what point will a particular socio-economic or housing characteristics become significant to foreclosures.
In addition, it is interesting to find out why some socio-economic characteristics affect foreclosures and others do not. If focusing on only one factor, then the future study can explore the relationship of an individual factor and foreclosures, for example, the relationship between single parent family rate and foreclosure, and the relationship between educational attainment and foreclosure.

Another issue of the future study is conducting a survey with the borrowers whose houses were foreclosed, and track their changes of addresses after the foreclosure. Through conducting survey or interviews, the future study can explore the reasons why borrowers default and the impact of the default on them, both financially and psychologically. It is also really interesting to know where those suffering foreclosure moved: are they going to rent a house or buy another property in neighborhoods with lower average house prices, or maybe they become homeless after their properties foreclosed. These will be very helpful to learn how borrower characteristics affect default decisions, foreclosure risks, and identify people most in need of help. Therefore, exploring questions above is useful to set up new assistance or educational programs in helping homeowners to move forward from their foreclosures. In addition, the findings can provide the lenders with more reliable underwriting standards. Also, given to the fact that the negative impacts of foreclosure on homeowner are critical, their solutions after the foreclosure and moving decisions will not only affect the family itself, but also influence their previous and future neighborhoods. Hence, it will be useful to get to know how these homeowners are affecting the neighborhoods.

Besides, the relationship between foreclosure filings and Sheriff’s sale cases need further study. It would be helpful once we get to know what happens to the filings
properties which do not go to Sheriff’s auction, and how these properties might affect communities’ variables. For instance, pre-foreclosure sale properties may lower the sale values of nearby properties as the seller would like to avoid foreclosure from a quick sell with a much lower price comparing other properties’ on the market. Hence, even those pre-foreclosure properties did not go to Sheriff’s auctions, they might also negatively affect the local housing market in another way.
References


Appendix A:

Local Spatial Autocorrelation of

Selected Variable
Figure A-1 Local Spatial Autocorrelation of Sheriff’s Sales and Foreclosure Rates
Figure A-2 Local Autocorrelation Map of Median Household Income and Foreclosure Rates (2007)
Figure A-3 Local Spatial Autocorrelation Map of Average Residential Property Values and Foreclosure Rates (2007)
Figure A-4 Local Autocorrelation Map of Minority Percentage vs. Foreclosure Rates (2007)
Appendix B:

Prediction Values and Residuals from Selected Models
Figure B-1 Spatial Distribution of Prediction errors from the Spatial Lag Model (without Loan Data)
Figure B-2 Spatial Distribution of Residuals from the Spatial Lag Model (without Loan Data)
Figure B-3 Spatial Distribution of the Prediction Values from the OLS Model (with Loan Data)
Figure B-4 Spatial Distribution of Residuals from the OLS Model (with Loan Data)
Figure B-5 Spatial Distribution of the Prediction Values from the OLS Model (without Loan Data)
Figure B-6 Spatial Distribution of the Residuals from the OLS Model (without Loan Data)
Appendix C:

Distribution Maps of Selected Factors
Figure C-1 Spatial Distribution of the Accumulated Foreclosure Rates: 2005-06
Figure C-2 Spatial Distribution of the Black Homeownership Rates
Figure C-3 Spatial Distribution of the Housing Vacancy Rates
Figure C-4 Spatial Distribution of the Accumulated Subprime Loan Counts: 2005-06
Figure C-5 Spatial Distribution of Sheriff’s Sale Counts 2005-06
Figure C-6 Spatial Distribution of the Loan Amount to Income Ratio (Subprime loan alone): 2005-06
Figure C-7 Spatial Distribution of the Median Household Income (2000)
Figure C-8 Spatial Distribution of the Average Residential Property Values (2006)
Figure C-9 Spatial Distribution of Total Housing Units (2000)
Figure C-10 Spatial Distribution of the Total Loan Counts: 2005-06