A Thesis
Entitled
Denied: A 2006 and 2009 Comparison of Mortgage Lending in the Toledo Metropolitan Statistical Area
By
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Submitted to the Graduate Faculty as partial fulfillment of the requirements for the
Master of Art Degree in Geography

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An Abstract of


by

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Obtaining a home loan is a vital component to acquiring the ‘American Dream’. There are many factors that determine the action taken on a home loan application by a lending institution. The Home Mortgage Disclosure Act (HMDA) mandates publicly available data which, among other things, allows academics to study which variables are significant in determining the acceptance or denial of a mortgage application. This study examines which variables were important in the denial of a home purchase loan in the years of 2006 and 2009. These years were selected to examine the effects the housing market collapse created in home purchase denials. Binary logistic regression models were run on HMDA variables, and the outcomes suggest that certain characteristics included in the model were more significant than others in determining home purchase application denial. Some of the results suggest discrimination based on race, ethnicity and sex. HMDA variables were also analyzed for spatial autocorrelation to determine the spatial patterns associated with home mortgage lending in the Toledo MSA in 2006 and 2009. The observed patterns suggest disinvestment in inner city Toledo, with higher denial rates and subprime loans centered in the City of Toledo. Spatial changes between the two years
reflects changes in lending practices as lending practices seemed to have drastically changed from 2006 to 2009.
This thesis is dedicated to my mother, Patricia Ann Moore and my late father, Kim Michael Moore. Their hard work and sacrifices have afforded me the opportunity to pursue whatever dreams I can possibly conjure. To both of them I am greatly indebted. To my sister, Lynsey Ann Corwin, and my brothers, Andrew, Kiel, and Matthew Moore: Thanks for your support.
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Table of Contents

Abstract ..................................................................................................................................................... iii
Acknowledgements ...................................................................................................................................... vi
Table of Contents ...................................................................................................................................... vii
List of Tables ............................................................................................................................................... ix
List of Figures ............................................................................................................................................. x
1 Introduction .............................................................................................................................................. 1
  1.1 Housing Collapse and Financial Turmoil in 2008 ................................................................. 1
  1.2 Spatial Patterns in Mortgage Lending ..................................................................................... 2
  1.3 Characteristics of Home Mortgage Lending ........................................................................... 4
  1.4 Problem Statement ...................................................................................................................... 5
  1.5 Study area ...................................................................................................................................... 7
2 Literature Review ...................................................................................................................................... 8
  2.1 General History of Modern Lending in the United States ....................................................... 8
  2.2 Deregulation and the Housing Collapse ................................................................................ 11
  2.3 Collapse ......................................................................................................................................... 13
  2.4 After the Collapse ......................................................................................................................... 14
  2.5 Discrimination in the Lending Arena ......................................................................................... 16
  2.6 Statistical Methods and HMDA Data in Home Mortgage Studies ......................................... 20
      2.6.1 Studies Using HMDA Data ................................................................................................. 20
### Table of Contents

2.6.2 Omitted Variable Bias

2.6.3 Studies Using Other Datasets

3 Data and Methodology

3.1 Combination of Methods

3.2 Home Mortgage Disclosure Act Data

3.3 Binary Logistic Regression

3.4 Spatial Autocorrelation

4 Discussion of Pattern in Raw HMDA Data

4.1 Spatial Autocorrelation Map Outputs and Patterns

4.1.1 Global Moran’s I

4.1.2 Local Anselin Moran’s I

4.2 Discussion of Raw Data Tables

5 Logistic Regression Results

5.1 2006 Model Statistical Analysis

5.2 2009 Model Statistical Analysis

5.3 Changes between 2006 and 2009

6 Conclusion

References
List of Tables

2.1: Homeownership Rates by Ethnic Group from 1994 to 2004..............................19
3.1: List of Variables in the 2006 and 2009 Regression Models ............................29
3.2: Census Tracts with No Data by Year and Variable .....................................32
4.1: Demographic Characteristics of 2006 and 2009 HMDA Data .........................49
4.2: Denial and Approval Counts and Percentages of 2006 and 2009 HMDA Data ....50
4.3: Loan Characteristics Counts and Percentages of 2006 and 2009 HMDA Data ......51
5.1: Control Variables for 2006 and 2009 Models ............................................54
5.2: SPSS Output for 2006 ..............................................................................55
5.3: SPSS Output for 2009 ..............................................................................58
List of Figures

1-1: Study Area: Toledo Metropolitan Statistical Area .......................................................... 7
2-1: Subprime Lending Origination Volume and Percentage 1999-2008 ............................. 15
2-2: Foreclosure and Delinquency Rates 1995-2011 .............................................................. 16
2-3: HOLC 1937 Redlining Map of Philadelphia ................................................................. 18
4-1: 2006 Global Moran’s I Output for Average Rate Spread .............................................. 36
4-2: 2009 Global Moran’s I Output for Average Rate Spread .............................................. 36
4-3: 2006 Global Moran’s I Output for Average Debt-to-Income ......................................... 37
4-4: 2009 Global Moran’s I Output for Average Debt-to-Income ......................................... 37
4-5: 2006 Global Moran’s I Output for Percent Denied ...................................................... 38
4-6: 2009 Global Moran’s I Output for Percent Denied ...................................................... 38
4-7: 2006 Global Moran’s I Output for Percent Subprime .................................................... 39
4-8: 2009 Global Moran’s I Output for Percent Subprime .................................................... 39
4-9: 2006 Anselin Local Moran’s I Output for Average Rate Spread ................................. 42
4-10: 2009 Anselin Local Moran’s I Output for Average Rate Spread ................................. 42
4-11: 2006 Anselin Local Moran’s I Output for Average Debt-to-Income ............................. 43
4-12: 2009 Anselin Local Moran’s I Output for Average Debt-to-Income ............................. 43
4-13: 2006 Anselin Local Moran’s I Output for Percent Denied .......................................... 44
4-14: 2009 Anselin Local Moran’s I Output for Percent Denied .......................................... 44
4-15: 2006 Anselin Local Moran’s I Output for Percent Subprime .......................45
4-16: 2009 Anselin Local Moran’s I Output for Percent Subprime .......................45
Chapter 1

Introduction

1.1 Housing Collapse and Financial Turmoil in 2008

The year of 2008 was a year full of historic benchmarks for the United States. In February, long time U.S. nemesis Cuban dictator Fidel Castro relinquished his power to his younger brother, Raul, changing the dynamic of a highly tumultuous relationship between the United States and Cuba. In August, United States Olympic swimmer Michael Phelps won a record setting eight gold medals in a single Olympics in Beijing. In November, the nation elected Barack Obama as its 44th President, making him the first Black man in history to hold the highest office in the country. Regardless of the significance of each of these events, 2008 will be remembered for the financial whirlwind that accumulated into a full blown economic catastrophe in September of that year.

In the first weeks of September 2008, the United States government had to take over two of the largest institutions in the home lending arena, Fannie Mae and Freddie Mac, in order to help keep them solvent. The liquidity of the housing market froze in place as financial institutions like JP Morgan Chase and Goldman Sachs scrambled to find injections of capital to keep from going bankrupt. As toxic assets from subprime
loans became too much for financial institutions to bear, the financial market needed a series of bailouts from the United States tax payers. The collapse of the housing market and the failure of the financial institutions that fuel the market with capital shed light on the importance of the solvency and integrity of said institutions to provide safe and secure loans to qualified applicants. Years of risky lending practices, in the form of subprime loans and credit default swaps, essentially unregulated by the federal government, led to an eventual breakdown of the housing market, which had major consequences on the national and global economy.

After the collapse of the housing market and the subsequent bailouts from the tax payers, lending institutions held on to their money and became more reluctant to originate loans, even to qualified applicants. Applicants would have to put much more money towards a down payment and credit restrictions became more stringent. The lending practices that created the housing collapse, such as subprime lending and no documentation loans, diminished significantly as banks tried to clean up the destruction caused by years of bad decision making.

1.2 Spatial Patterns in Mortgage Lending

Historically, home lending has had a spatial component. Academic research has shown that urban areas often suffer from capital disinvestment, higher rates of loan denial, and are more often affected by foreclosures brought upon by subprime, adjustable rate financial instruments compared to suburban locals.
Redlining, the act of denying loans based upon geographic boundaries (usually in predominantly Black or Hispanic neighborhoods), has been a focus of many academic studies over the last 50 years. Academic researchers such as Elvin Wyly, Stephen Holloway, Dan Immergluck, and Daniel Hammel have concluded that racism in home mortgage lending does persist and can be backed by empirical evidence and positivist regression models. Disinvestment in minority neighborhoods has been a long standing issue in the home lending arena. The Community Reinvestment Act of 1977 was Congress’s attempt to combat the issue of neighborhood exclusion from home mortgage lending, forcing banks to lend in neighborhoods from which they accepted deposits (Dymski 2009). Over the past 25 years, the lending pattern has shifted from place based (redlining) to applicant based (reverse redlining), a situation where lenders give minority applicants a loan with a higher interest compared to a similar, White applicant (Dymski 2009).

The subprime loan was an instrument created to extract capital out of minority neighborhoods, after years of blatant exclusion by lending institutions. Starting in the mid 1990s, lending institutions decided that underserved minority neighborhoods were markets which merited investment. Though home ownership rates in minority areas increased in the 1990s, the loans that increased home ownership in minority neighborhoods were far different from loans originated to applicants in White neighborhoods and suburban areas (Dymski 2009). Loans awarded to minorities were often characterized by high and adjustable interest rates.

Foreclosures associated with subprime loans also show signs of spatial pattern. Urban locales seem to be most affected by foreclosures and the adverse effects of
foreclosures, such as blight, crime, and property devaluation. The correlation between subprime loans and foreclosures is high, most often affecting minority, inner city locals (Rugh & Massey 2010).

1.3 Characteristics of Home Mortgage Lending

Home mortgage lenders use a litany of information to determine an applicant’s creditworthiness and the amount of money an applicant can afford to pay back. The Home Mortgage Data Act (HMDA) of 1975 was passed by Congress and created a layer of transparency in home lending practices (Wyly & Holloway 2002). This forced lending institutions to make information public for every loan transaction in a given year. Information included in the HMDA data is respondent information, property location (down to the census tract), loan information (loan type; property type; loan purpose; owner-occupancy; loan amount; preapproval; action type), applicant information (ethnicity; race; sex; gross annual income); purchaser and denial information (type of purchaser; reasons for denial), and demographic data at the census tract level (population; minority population percent; HUD median family income; tract to MSA median family income percentage; number of owner-occupied units, number of 1-to-4-family units).

Lenders are forbidden by federal law from making loan decisions based on race, ethnicity, gender, and nation of origin. Characteristics lending institutions can use to make loan decisions are debt-to-income ratio, employment history, credit history, collateral, sufficient cash for a down payment or closing costs, completeness of the application, and verification of information presented on the loan application. On the
HMDA form, lenders have the option of selecting “other”, giving lenders the option to mask discriminatory practices. Also, HMDA forms do not force lenders to divulge information pertaining to applicant credit scores, causing much debate among academics and social justice advocates.

1.4 Problem Statement

Lending practices undertaken by financial institutions can affect an individual’s ability to obtain the financial resources needed to fulfill the ‘American Dream’: home ownership. It means the difference between living in high density quarters or having the opportunity to own and maintain your own equitable property. The acceptance or denial of a home loan application depends on many characteristics, such as income, credit history, and work history. Applicant race and ethnicity are characteristics upon which lenders are prohibited from judging applicants. Many institutions emphasize that discriminatory lending practices are a thing of the past. Many academics suggest that home mortgage discrimination still takes place, but more subtly in comparison to practices in the past.

The Toledo Metropolitan Statistical Area (MSA), comprised of the counties of Fulton, Lucas, Ottawa, and Wood, like the rest of the United States, has been affected by weak housing markets. In the 1990s, ‘markets’ were opened up to include lower income, minority populations. Lenders saw an opportunity to take capital from populations that had been left out of the lending arena. The year 2006 brought the beginning of a drastic change. Before the collapse of the housing market in late 2008, lenders were lax with
loan requirements and many home buyers took advantage. After the collapse, lenders become more stringent with lending practices.

Changes in lending practices after the housing collapse have been described as drastic. How drastic were the changes before and after the collapse? This research will attempt to explain the changes in lending practice in the Toledo Metropolitan Statistical Area before and after the collapse, using 2006 and 2009 Home Mortgage Disclosure Act data. These years were picked due to their place in the chronology of the housing collapse: 2006 being the peak of subprime lending and 2009 being the beginning of the capital freeze applied by lending institutions.

Home mortgage lending follows a spatial pattern. Typically, Black and Hispanic neighborhoods have higher rates of denial than White neighborhoods, they are more likely to be affected by subprime loans, and they are more likely to be affected by foreclosures and vacancies (Holloway 1998). This research aims to identify the spatial patterns in the Toledo MSA for 2006 and 2009 and compare and contrast the changes in lending practices between the two years. The expected outcome of the 2006 regression model should line up with previous home lending models, in which Black applicants will show significance in home mortgage denials, along with female applicants and financial variables. The outcome of the 2009 regression model is somewhat unpredictable considering the instability of the housing market at the time.
1.5 Study Area

Located in northwest Ohio, the Toledo Metropolitan Statistical Area includes Lucas (129 census tracts), Wood (26 census tracts), Fulton (9 census tracts) and Ottawa (12 census tracts) counties and has a population of 651,429 as of the 2010 Census (U.S Census 2010). It is bordered to the north by Michigan, to the east by Lake Erie and Erie County, to the west by Williams and Henry counties, and to the south by Hancock, Sandusky, and Seneca counties. The area covers 1,623 square miles and has a population density of 402 people per square mile (Census-Charts.com 2007). Populous cities within the MSA include Toledo, Perrysburg, and Bowling Green.

Figure 1-1: Study Area, Toledo MSA
Chapter 2

Literature Review

2.1 General History of Modern Lending in the United States

Housing has played an integral part in the perceived “American Dream.” Homeownership represents more than just shelter for many Americans. It often means upward social mobility and economic and tax benefits, and it provides personal freedoms not available to renters (structural changes, pets, etc.). One’s ability to obtain a home mortgage is the major deciding factor in the fulfillment of this “American Dream.”

Throughout the last one hundred years, numerous policies, laws, and incentives have been enacted which have impacted the way the housing market operates. In 1934, as part of President Roosevelt’s New Deal policies, Congress enacted the National Housing Act, which created the Federal Housing Administration (FHA) (Gotham 2000). The purpose of the National Housing Act of 1934 was to help industries, namely home construction and finance companies, regain footing during the Great Depression (Gotham 2000). Additionally, this act allowed the FHA to insure privately held loans for new home purchases, making the down payments smaller for purchasers, guaranteeing fixed-rate loans with moderate interest rate loans, and making second loans unnecessary.
(Gotham 2000). The creation of the Federal Housing Administration made home ownership possible for many American families, namely the working class.

The Federal National Mortgage Association (Fannie Mae) was created in 1938. Later established as a government sponsored enterprise (GSE) in 1968, Fannie Mae was created as a secondary market for FHA insured loans (Van Order 2000). The role of the created secondary market was to give lending institutions and loan originators more options for funding mortgages (Passmore, Shurland & Burgess 2005). In 1948, Fannie Mae extended its operation to include Veterans Affairs (VA) mortgages which were becoming more prevalent following World War II (Owens 1998).

Congress enacted Title VII (the Fair Housing Act) as part of the Civil Rights Act of 1968. This law prohibits the discrimination of home mortgage applicants and rental applicants based on race, color, religion, or nation of origin (Yinger 1999). This law exempts the sale or rental of a single-family home as long as the owner is not going through an agent or the home has no more than four units, one in which the owner resides (Yinger 1999). This is the first major step taken by the United States Congress to curb discrimination in the home lending arena.

In 1970, Congress created the Federal Home Loan Mortgage Corporation (Freddie Mac) as a secondary market for the savings and loans industry (Van Order 2000). A GSE, Freddie Mac, pools together mortgages and bundles them from sale on the open market (Van Order 2000). This helps free up more money for home lending. This coincided with FNMA officially being renamed Fannie Mae. Fannie Mae also acts as a secondary market for a variety of loans (Van Order 2000).
The Home Mortgage Disclosure Act of 1975 (HMDA) was a continuation on the part of Congress to further rein in discrimination in home lending on the basis of race, color, gender, and nation of origin. This law forces lending institution to make public characteristics and the geographic distribution of all mortgage transactions made for each year (Guy, Pol, & Ryker 1982). This helps keep mortgage practices transparent and makes data publicly available for academics and community organizations. HMDA has been modified over the years to extend the coverage of transparency over larger amounts of loans. In 1992 and 1993, HMDA was modified by acts of Congress through the Federal Deposit Insurance Corporation Improvement Act and the Housing and Community Development Act which extended coverage of HMDA mandates to independent mortgage lenders and made HMDA more readily available to the public (FFIEC 2011). Starting in 2004, high cost loan data was collected for loans that were considered above the prime-interest for the time period (FFIEC 2011). This meant that subprime loans could be identified and studied.

In 1977, Congress enacted the Community Reinvestment Act (CRA). This act gave incentives to banks and savings and loans to lend money in low- to moderate-income neighborhoods from which they took deposits (Pindell 2009). Congress hoped to curb the practice of redlining, the act of not lending to applicants based on geographic areas along lines of race, a practice that was undertaken by many lending institutions for decades (McKinely 1994).
2.2 Deregulation and the Home Lending Crisis

Starting in the 1970s, many of the laws and regulations established by Congress to protect consumers and borrowers began to be repealed. The deregulation of the lending industry, e.g. the repeal of state level usury laws, the removal of interest rate ceilings, the deregulation of the derivatives market, and the philosophy of self-regulated markets came full circle in 2008 with the collapse of the United States housing market. A global, financial ripple affect can still be seen with the domino collapse of foreign markets across the globe.

Historically, usury laws have been established to assure that lenders are not applying unwarranted or excessive interest rates to borrowers. In the United States, usury laws date back to colonial times, when both maximum rates and penalties for borrowing were established through regulation (Rockoff 2003). In 1978, the Supreme Court set precedent for deregulation of the housing market through changes in federal usury laws. In Marquette National Bank vs. First of Omaha Service Corp., the Supreme Court ruled that nationally-chartered banks can apply the legal interest rates of the state in which it is headquartered to their banks in other states (Sherman 2009). This gave the incentive for nationally-chartered banks to relocate to states with usury laws that were industry friendly, creating competition amongst the states to attract such banks. This decision undermined the stability created by state usury laws which had helped protect consumers against unnecessarily high interest rates, and made possible subprime loans which would eventually contribute to the downfall of the housing market in 2008.
In 1980, Congress continued the systemic dismantling of banking regulation when it passed the Depository Institution Deregulatory and Monetary Control Act. This act of Congress eliminated all interest rate ceilings and opened the door for the tide of sub-prime lending that would become a capital extracting tool for the lending industry in the upcoming decades (Atlas, Dreier, & Squires 2008). This allowed depository banks to give out accounts with market rates of return (Sherman 2009).

The Garn-St. Germain Depository Act of 1982 deregulated the savings and loans institutions and allowed the use of adjustable-rate mortgages (Sherman 2009). This act was an attempt by the Reagan Administration to help the savings and loan industry, but profits for savings and loans steadily dropped throughout the 1980s.

The Riegle-Neil Interstate Banking and Branching Efficiency Act of 1994 (IBBEA) repealed regulation established by the Bank Holding Act of 1956, which restricted bank holding companies from acquiring banks from other states and merging together banking and non-banking operations (Sherman 2009). This action by Congress made way for interstate banking acquisitions, interstate agency operations, interstate branching, and de novo branching (Johnson & Rice 2007). This gave banks extraordinary amounts of power and eliminated competition through acquisitions and mergers. This is the origin of the phrase, “too big to fail.”

The Gramm-Leach-Bliley Act (or Financial Modernization Act) of 1999 essentially repealed the Glass-Steagall Act of 1933, a law which was designed to separate security brokers from bankers to help cure the ailments which created the “Great Depression” (Grant 2010). This law exempted derivatives, in the form of credit default swaps, from regulation in the market (Sherman 2009). This allowed for investors to
gamble on the repayment of bundled mortgages on the market, of which many went into default around the same time between 2006 and 2008. A majority of bundled assets were toxic in nature, and they were traded back and forth in a game of financial hot potato.

The final piece of deregulating legislation came in 2000 with the passing of the Commodity Futures Modernization Act. This act prohibited any regulation on derivatives or the trading of derivatives on the market (Sherman 2009). This piece of legislation was the last major piece of deregulatory law Congress passed before the housing market started showing signs of failure in 2007.

2.3 Collapse

The excessive amount of subprime, adjustable-rate loans (and other high risk mortgage products such as No-Doc, Balloons, Non-Amortizing, Alt-A, and Exotic loans) going into default from 2006 to 2008 created a catastrophic situation of global implications. A majority of lending institutions had bundled mortgage backed securities on their books, which were toxic and had no value (Sherman 2009). As interest rates adjusted, many borrowers became incapable of meeting monthly payments, setting in motion a mass default of home mortgages (Sherman 2009). At the same time, housing values started to decline creating a situation where many borrowers owed more on the mortgage than their homes were worth. All of these factors came together to create a perfect storm of such, resulting in a collapse of the housing market, which subsequently
resulted in the failure of lending institutions, both national and transnational in scope. Most importantly, this collapse put many hardworking, honest families in the streets.

In order to keep the economy from full collapse, both President George W. Bush and his successor, President Barack Obama, had to sign laws to inject certain institutions with capital in order to keep them solvent and functional. The list of institutions who received bailouts is lengthy (including GSEs Freddie Mac and Fannie Mae, and financial institutions Bear Stearns, A.I.G.; and automotive companies such as General Motors and Chrysler), with the initial Troubled Asset Relief Program (TARP) amount totaling $700 billion and a total commitment of around $12.2 trillion as of April 30th of 2011 (New York Times 2011).

2.4 After the Collapse

In 2009, lending for home purchases came to a near stand-still as banks and mortgage lending institutions froze their assets as they weathered the storm and fall out of the initial wave of defaults, mergers, and bank closures. Borrowers had to meet strict lending criteria, such as a 20 percent down payment and an exceptionally high credit score in order to secure a loan. In a majority of cases, borrowers had to acquire a FHA secured loan because lending institutions wanted the loan to be guaranteed in the situation of default.

Subprime lending had already started to decrease, peaking in 2005. Experts had already been aware of the damage subprime loans were doing to the market and many
Institutions scaled back the amount of subprime loans that were being originated (Bondadd 2010).

In 2010, President Obama signed into law the Frank-Dodd Wall Street Reform and Consumer Protection Act. This law separated banking from investment banking, essentially filling the gap left after the repeal of Glass-Steagall. This act called for more transparency in mortgage lending and calls for the creation of watchdog groups and consumer protection agencies on the federal level.
Foreclosures became prevalent in years following the crisis, peaking in 2009. As seen in this chart, foreclosures began to rise in 2006, the first signs that the housing market was unstable and heading towards eventual collapse (Quercia & Radcliffe 2008).

Figure 2-2: Foreclosure and Delinquency Rates 1995-2011
(Calculated Risk 2012: Lending Process Services)

2.5 Discrimination in the Lending Arena

From redlining to subprime loans, many academics believe that discrimination is still prevalent in home mortgage lending. Discrimination based on race happens on two different levels: individual and neighborhood levels. Stephen Holloway states in the
article “Exploring the Neighborhood Contingency of Race Discrimination in Mortgage Lending in Columbus, OH.” that “when we proclaim that discrimination no longer exists universally, we ignore or trivialize discrimination in specific locales against specific groups of people” (1998: 253). Within this article, Holloway also explains that place based discrimination and individual discrimination are both distinct and that research leading up to that point seemed to polarize the two different forms (Holloway 1998).

Wyly and Hammel state that “much of the history of urban studies can be read through the rich and contentious literature on banking discrimination and racial redlining” (2004: 1218). They describe how subprime lending, targeting ‘new markets’, drained capital out of the pockets of low income residents, in once redlined, inner-city neighborhoods (Wyly & Hammel 2004).

Redlining, as defined by Gregory Squires, is “the practice of refusing to provide financial services (primarily mortgage loans or property insurance) or of providing them on more stringent terms in selected neighborhoods for reasons not related to any reasonable definition of risk” (Encyclopedia of Urban American 1998: 630). The term redlining comes from the actual marking of boundaries on a map to delineate where loans would not be originated. The Home Owners’ Loan Corporation (HOLC), an agency set up as part of President Franklin Roosevelt’s New Deal legislation, through the Home Owners’ Loan Corporation Act of 1933, essentially institutionalized discrimination in the home lending arena (Aalbers 2011). This plan allowed for distressed homeowners to refinance into long-term, self-amortizing loans, replacing the five year, non-amortizing loans of the times (Aalbers 2011). This was offered to homeowners in neighborhoods in
which the government deemed fit for investment. Four types of neighborhoods, using a color code, were identified to determine the fitness for refinancing (Aalbers 2011):

Green: Grade A; homogenous neighborhoods; American business professionals; stable in good and bad times (White)

Blue: Grade B; stable, still good; reached their peak (White)

Yellow: Grade C; declining; heterogeneous; infiltrated by lower grade people (Black)

Red: Grade D; has already went through Grade C through the powers of detrimental influence of the pronounced degree due to colored element that now controls the area (Black)

Figure 2-3: HOLC 1937 Redlining Map of Philadelphia (Sharp 2012)
Reverse redlining is the practice of giving minority individuals home loans at higher costs compared to similar, White applicants. This phenomenon started in the early to mid 1990s and helped contribute the collapse of the housing market in 2007 (Gerardi & Wilkin 2009). Subprime, adjustable rate loans were the main products used in reverse redlining around this time. Lenders saw an opportunity to capitalize on minority markets which were neglected in decades past, so instead of giving minorities prime-rate loans they gave them higher interest rates which would adjust to higher rates at any given time during the loan. A 2006 study showed that over half of mortgages taken out by African Americans in 2005 had subprime features (Avery, Brevoort, & Canner 2006). United States Census data from a 2005 Housing Vacancy Survey shows that homeownership for African Americans rose 16.1% between 1994 and 2004 (Garriga, Gavin, & Schlagerhauf 2006). Some of the increase can be attributed to the obtainment of subprime loans.

Table 2-1: Homeownership Rates by Ethnic Group from 1994 to 2004 (Garriga et al 2006)

<table>
<thead>
<tr>
<th>Home Ownership Rates by Ethnic Group</th>
<th>Percent Change in Homeownership Rates</th>
<th>Rate in 2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate in 1994</td>
<td>1994 to 2004</td>
<td>Rate in 2004</td>
</tr>
<tr>
<td>United States</td>
<td>64</td>
<td>69</td>
</tr>
<tr>
<td>Non-Hispanic Whites</td>
<td>70</td>
<td>76</td>
</tr>
<tr>
<td>Black</td>
<td>42.3</td>
<td>49.1</td>
</tr>
<tr>
<td>American Indian</td>
<td>51.7</td>
<td>55.6</td>
</tr>
<tr>
<td>Asian or Pacific Islander</td>
<td>51.3</td>
<td>59.8</td>
</tr>
<tr>
<td>Hispanic or Latino</td>
<td>41.2</td>
<td>48.1</td>
</tr>
</tbody>
</table>
2.6 Statistical Methods and HMDA Data in Home Mortgage Studies

2.6.1 Studies Using HDMA Data

Logistic regression has been utilized in many mortgage lending studies over the past 20 years. Multiple variables are used by lending institutions to determine if an applicant is accepted or denied a home mortgage and the same technique is used to help determine if banks are discriminating against low-income, minority populations.

In a 2005 home mortgage discrimination study, Judith Clarke used HMDA data to create binary response models to determine if underwriting practices by financial institutions are discriminate by making the outcome of loan applications either denied (0) and accepted (1) (2005). Variables included race, income, credit history, debt-to-income, insufficient funds to close, etc (Clarke, Courchane, & Nilanjana 2005). In the study, discrimination is determined by testing if the impacts of the race variable are equal (Clarke et al 2005).

Jacob Rugh and Douglas Massey, in a 2010 study covering racial segregation and the foreclosure crisis, used Ordinary Least Squares (OLS) models to assess the effect of segregation on foreclosures in the top 100 metropolitan areas in the United States (Rugh & Massey 2010). This study also utilized HMDA data provided by the FFIEC.

A prime example of regression analysis, with HMDA data, in mortgage lending was undertaken by Stephen Holloway and Elvin Wyly. In the article, “The Color of Money Expanded: Geographically Contingent Mortgage Lending in Atlanta,” Holloway and Wyly described their use of HMDA data to create three denial probability logistic
regression models to map lending discrimination in Atlanta: first to determine denial probability at the individual level (race); second to determine denial at the neighborhood level (redlining); the third included interaction terms between applicant race and census tract race composition (Holloway & Wyly 2001).

2.6.2 Omitted Variable Bias

The validity of home lending discrimination studies using HMDA data is questioned due to the phenomenon of omitted variable bias. Regression analysis is a model utilized by academics in the social sciences to help predict socioeconomic outcomes using data from sources such as the United States Census Bureau and HMDA. Many critics of such studies believe that there are unaccounted for variables that data sets lack, which can explain the occurrence or absence of an action. In the case of home lending studies, critics of regression analysis believe that variables, namely credit score, are missing from data sets which could better fit the model (Yezer 2010).

An example of a study scrutinized for a perceived omitted variable bias is a study of home mortgage discrimination in Boston using HMDA data by the Federal Reserve Bank of Boston, headed by Alicia Munnell. The paper “Mortgage Lending in Boston: Interpreting HMDA Data” explains how Munnell and her group of researchers concluded that Blacks were more likely than Whites to be denied for a loan, all other factors held constant (Munnell et al 1992). Subsequently, Munnell’s study came under fire from other academics in the social science about her chosen methodology. The study claimed to be
controlled to handle omitted variable bias, but many academics rebutted the study with use of the same data and variables collected for the Boston FED study, showing that dummy variables and the use of other independent variables from the study corrected for the perceived discrimination detected in the first study (Yezer 2010). An example is Glennon and Stengle’s (1994) with concluded that they agree with Munnell’s study that there is discrimination detectable in Boston in 1990, but that additional variables or omitted variables could better explain the detected discrimination.

When social scientists and fair housing advocates suggest that credit score and other explanatory variables be included in HMDA data, representatives for the lending industry cry foul and use their legal and lobbying powers to keep such variables off HMDA data sheets. The reasons given are highlighted in a hearing before a House of Representatives Congressional Subcommittee on Oversight and Investigation of the Committee on Financial Services, on July 25, 2007. In the transcript titled “Rooting Out Discrimination in Mortgage Lending: Using HMDA as a Tool for Fair Lending Enforcement” Bill Himpler, Executive Vice President of American Financial Services Association, explained four reasons why credit score is not and should not be included in HMDA data (House Hearing: July 25, 2007):

(1) Identity security
(2) What credit score system would be used?
(3) Lenders would have to divulge their weighting system to competitors
(4) An expansion of HMDA data wouldn’t increase the effectiveness of regression models
Though individual cases are aggregated to the census tract, some believe that it would be possible to attach divulged credit scores to an applicant. This makes applicants susceptible to identification (House Hearing: July 25, 2007).

Industry spokesmen also believe that there would be an issue with the credit system used to show credit worthiness of applicants (House Hearing: July 25, 2007). There is no universal credit scoring system and systems vary from institution to institution. This could be solved by simply reporting the system used and the assigned score of the applicant. This also creates a situation where the credit company would have to publicly display credit system information which puts them at a competitive disadvantage (House Hearing: July 25, 2007), but if all lenders have to divulge it would seem that it would not hinder competition, but act as a catalyst for competition.

The final reason mentioned for leaving credit information off HMDA forms is that it would not increase the effectiveness of regression models used in home lending studies (House Hearing: July 25, 2007). Industry insiders, such as Bill Himpler, believe that there is still a variable which accounts for significance in race and ethnicity that is not included in the study. They believe that the credit score variable will not account for this omitted variable bias.

Bill Himpler is a lobbyist for the American Financial Services Association and has fought legislation calling for more regulation in the financial sectors, namely the credit industry, for years. He spent the last three years fighting the creation of the Consumer Financial Protection Agency (Milbank 2012), but failed as the agency began operations in July of 2011.
2.6.3 Studies Using other Datasets

Another application of statistics in lending studies was conducted by Sharron Van Zandt in 2007. The study examined the outcomes of participation in national homeownership education programs in low income neighborhoods, using survey data from the Home Ownership Pilot Program, and used logistic regression to predict probabilities that respondents to a survey live in crowded conditions, in fair or poor housing, or a live in a neighborhood of a specific level of minority residents (Van Zandt 2007).

Immergluck and Smith simply used 1990 and 2000 census data to describe the changes in home ownership throughout the Chicago area in the 1990s (Immergluck and Smith 2001). Charts and graphs were created to illustrate how homeownership increased throughout the Chicago area, and that high-poverty areas increased in population and in area (Immergluck & Smith 2001).
Chapter 3

Data and Methodology

3.1 Combination of Methods

Two different studies were conducted: the first focused on the spatial patterns associated with the raw HMDA data for both 2006 and 2006; the second focused on the models to determine significant HMDA variables in determining the denial of loan applications. The first half of the study helped identify spatial patterns (namely spatial autocorrelation) within basic home lending characteristics. The binary logistic regression models were used to answer why there is observed spatial patterns in the data. For example, if denial rates show spatial clustering in the urban areas, maybe the models will detect significance for race for the same time period. The models will explain what the spatial autocorrelation maps have detected.

3.2 Home Mortgage Disclosure Act Data

The Home Mortgage Disclosure Act (HMDA) of 1975 requires mortgage lenders to disclose data pertaining to home mortgage loans. This data is available through the
Federal Financial Institutions Examination Council (FFIEC), and allows for transparency and analysis of home lending practices by academics, community organizations, and the general public. Other purposes HMDA data serves are to make sure lending institutions are meeting the housing needs of residents in communities they serve and to serve public officials with a tool to better help attract private investment in areas which need it the most (FFIEC 2011).

HMDA data is aggregated in the Metropolitan Statistical Areas (MSAs) and is available in csv format. Many of the variables in the tables are categorical with few variables being ratio. HMDA data include the following information pertaining to a loan applicant case:

- Respondent Information
- Property Location
- Loan Information
- Applicant Information
- Purchaser and Denial Information
- Other Data
- Census Information

### 3.3 Logistic Regression

The method of analysis for the study is logistic regression. Home Mortgage Disclosure Act (HMDA) data will be used to create two predictive models (2006 and
2009) pertaining to loan denial (dependant variable) based on loan characteristics, applicant characteristics, census data (independent variables).

Multiple logistic regression is a form of statistical analysis in which an action (dependant variable), having only two possible outcomes, is predicted using variables which influence the action (independent variable). Logistic models help determine the significance each variable plays in determining/predicting the dependant variable. The data need to fit the model and variables showing co-linearity should be removed.

A comparison of outputs of the predictive models between 2006 and 2009 was performed. The data are categorical and ready for logistic regression. A code sheet was downloaded which explains each variable and decodes the responses given for each variable. HMDA data are aggregated and are specific to the census tract level, due to the sensitive nature of the subject and to protect the privacy of the applicants for the home loan.

SPSS statistical software was used to perform logistic regression. Logistic regression has been applied to HMDA data in previous studies, such as Clarke, Courchane and Nilanjana’s study on racial discrimination in mortgage lending (Clarke et al 2005). The formula used for multiple logistic regression, as explained by Agresti and Kinlay (1997) in *Statistical Methods for the Social Sciences*, is as follows:

$$\text{logit}[P(y = 1)] = \alpha + \beta_1 x_1 + ... + \beta_k x_k$$

Data for the 2006 and 2009 was modified in order to run the model in SPSS. First, a code sheet was downloaded and used to label fields in the csv files. Next, loan amount
and applicant income fields were changed to reflect values in the thousands. These two variables were then used to create a debt-to-income field using the following formula:

\[
\frac{\text{Loan Amount}}{\text{Applicant Income}} = \text{Debt-to-Income}
\]

A subprime field was created using the rate spread column. If a rate spread value was included for a case, it meant it was subprime. A value of 0 was given to cases with no rate spread value and a 1 for cases with a rate spread value.

All cases with no value for applicant income were eliminated. SPSS only handles variables or fields with proper values. Also, any action type which was not acceptance or denial of the loan was eliminated along with any application that did not pertain to home purchase loans.

A denied field was created using the action field. All cases which were accepted were given a value of zero and those that were denied were given a value of 1. This field was used as the dependent variable in the model.

The race and ethnicity fields were combined. This was done to eliminate any possibility of multicollinearity. If the applicant was White and non-Hispanic, the applicant was considered White. If the applicant was White, but was Hispanic, the applicant was considered Hispanic. If the applicant was Black, regardless of ethnicity, the applicant was considered Black. The same applied to the races of Native Hawaiian or Other Pacific Islander and American Indian. If the applicant was Asian in race and Hispanic in ethnicity, the applicant was considered Asian. If there was no report on race and the applicant was Hispanic, the applicant was considered Hispanic. If no data for either race or ethnicity, the value was considered no data or no value.
Variables included in both the 2006 and 2009 models are as follows:

Table 3-1: List of Variables in the 2006 and 2009 Regression Models

<table>
<thead>
<tr>
<th>Variables included in 2006 and 2009 models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan Type</td>
</tr>
<tr>
<td>Conventional</td>
</tr>
<tr>
<td>FHA-insured (Federal Housing Administration)</td>
</tr>
<tr>
<td>VA-guaranteed (Veterans Administration)</td>
</tr>
<tr>
<td>FSA/RHS (Farm Service Agency or Rural Housing Service)</td>
</tr>
<tr>
<td>Owner-Occupancy</td>
</tr>
<tr>
<td>Owner-occupied as a principal dwelling</td>
</tr>
<tr>
<td>Not owner-occupied</td>
</tr>
<tr>
<td>Not applicable</td>
</tr>
<tr>
<td>Applicant Race and Ethnicity</td>
</tr>
<tr>
<td>White</td>
</tr>
<tr>
<td>Asian</td>
</tr>
<tr>
<td>Black</td>
</tr>
<tr>
<td>Native Hawaiian or Other Pacific Islander</td>
</tr>
<tr>
<td>American Indian or Alaska Native</td>
</tr>
<tr>
<td>Hispanic</td>
</tr>
<tr>
<td>Not applicable or information not provided</td>
</tr>
<tr>
<td>Applicant Sex</td>
</tr>
<tr>
<td>Male</td>
</tr>
<tr>
<td>Female</td>
</tr>
<tr>
<td>Information not provided</td>
</tr>
<tr>
<td>Not applicable</td>
</tr>
<tr>
<td>No co-applicant</td>
</tr>
<tr>
<td>Purchaser Type</td>
</tr>
<tr>
<td>Loan was not originated or was not sold in calendar year covered by register</td>
</tr>
<tr>
<td>Fannie Mae (FNMA)</td>
</tr>
<tr>
<td>Ginnie Mae (GNMA)</td>
</tr>
<tr>
<td>Freddie Mac (FHLMC)</td>
</tr>
<tr>
<td>Farmer Mac (FAMC)</td>
</tr>
<tr>
<td>Private securitization</td>
</tr>
<tr>
<td>Commercial bank, savings bank or savings association</td>
</tr>
<tr>
<td>Life insurance company, credit union, mortgage bank, or finance company</td>
</tr>
<tr>
<td>Affiliated institution</td>
</tr>
<tr>
<td>Other type of purchaser</td>
</tr>
<tr>
<td>Subprime</td>
</tr>
<tr>
<td>Not subprime</td>
</tr>
<tr>
<td>Subprime</td>
</tr>
<tr>
<td>Loan Amount</td>
</tr>
<tr>
<td>Applicant income</td>
</tr>
<tr>
<td>Debt-to-Income</td>
</tr>
<tr>
<td>Population (total population in census tract)</td>
</tr>
<tr>
<td>Minority Population %</td>
</tr>
<tr>
<td>Tract to MSA/MD Median Family Income Percentage</td>
</tr>
<tr>
<td>Number of Owner Occupied Units</td>
</tr>
<tr>
<td>Constant</td>
</tr>
</tbody>
</table>
3.4 Spatial Autocorrelation

Spatial pattern is a phenomenon associated with most socioeconomic data, and most data with a spatial component will display a pattern over a given area. Spatial autocorrelation is the measure of clustering and clusters at the global and local levels, respectively. The most basic and commonly used statistical method for detecting and quantifying spatial autocorrelation is Moran’s I.

There are two forms of Moran’s I: Global and Local. The global version of Moran’s I measures for clustering or spatial pattern in a given dataset, identifying when values and/or locations are closer together than normal (Maguire, Batty, & Goodchild 2005). The formula for Global Moran’s I is as follows:

$$I = \frac{\sum_i \sum_j z_i z_j w_{ij}}{S_0} / \frac{\sum_i z_i^2}{N}$$

- $z_i$: observation on a variable at I in deviations from the mean
- $N$: number of observations
- $S_0$: normalizing factor equal to the sum of the weights
- $w_{ij}$: spatial weights

The local version of Moran’s I is used to identify clusters and outliers where values in an area are more similar than usual (Maguire et al 2005). The formula for Local Moran’s I is as follows:

$$(1/m) z_i \sum_j w_{ij} z_j$$

- $m$: constant scaling factor

2006 and 2009 HMDA data for the Toledo Metropolitan Statistical Area was obtained, cleaned, and aggregated for averages and percents at the census tract level.
Most HMDA data is in the categorical form, but for mapping purposes, all categorical data was converted into a binary format. Continuous data, such as loan amount, applicant income, and rate spread were kept in the original format. A new field was created for both 2006 and 2009: Debt-to- Income. Aggregation of data to the census tract level was done using pivot tables in Microsoft Excel. From there, averages at the census tract level were obtained. The following attributes were created in Excel, using standard fields found in HMDA data:

**Average Rate Spread**
Loans with rate spreads at least 3 percentage points above the Lipper Average at the time of origination
(Mean average was obtained for each census tract using a pivot table)

**Average Debt-to-Income Ratio**
\[
\text{Loan amount} \quad = \quad \text{Average Debt-to-Income Ratio} \\
\text{Applicant income}
\]
(Mean average was obtained for each census tract using a pivot table)

**Percent Denied**
Denied in each census tract * 100 = Percent Denied
Total loans in each tract

**Percent Subprime**
Subprime loans in each tract * 100 = Percent Subprime
Total loans in each tract

The attributes analyzed in this study were chosen because of their impact on the overall health of the housing market. Census tracts with high percentages of subprime loans also have higher rates of foreclosures. Census tracts with higher rates of denial could indicate disinvestment by lending institutions. Census tracts with higher debt-to-income averages could indicate that borrowers may be receiving a larger loan than they
can reasonably afford. Census tracts with high average rate spreads also see higher rates of foreclosures.

Eight tables were created in total, one table for each attribute for both 2006 and 2009. These tables were then joined to a merged shapefile of Fulton, Lucas, Ottawa, and Wood Counties, by FID number (each table was joined to its own merged shapefile, resulting in eight shapefiles) in ArcMap 10. The following census tracts were left out with the join because of lack of data:

<table>
<thead>
<tr>
<th>Table 3-2: Census Tracts with No Data by Year and Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006 Average Rate Spread</td>
</tr>
<tr>
<td>Census Tract With No Data</td>
</tr>
<tr>
<td>2006 Average Rate Spread 13.04, 218</td>
</tr>
<tr>
<td>2009 Average Rate Spread</td>
</tr>
<tr>
<td>2009 Average Rate Spread 8, 9, 12.02, 13.02, 18, 19, 22, 23, 24.02, 27, 28, 29, 30, 31, 34, 35, 38, 40, 41, 42, 43, 48.01, 70.02, 85.02, 217.01, 218, 220</td>
</tr>
<tr>
<td>2006 Average Debt to Income 100.01, 100.02, 101.218</td>
</tr>
<tr>
<td>2009 Average Debt to Income 25, 27, 28, 29, 30, 31, 32, 36, 41, 218</td>
</tr>
<tr>
<td>2006 Percent Denied</td>
</tr>
<tr>
<td>Census Tract With No Data</td>
</tr>
<tr>
<td>2006 Percent Denied 218</td>
</tr>
<tr>
<td>2009 Percent Denied 27, 28, 218</td>
</tr>
<tr>
<td>2009 Percent Subprime</td>
</tr>
<tr>
<td>Census Tract With No Data</td>
</tr>
<tr>
<td>2009 Percent Subprime 27, 28, 218</td>
</tr>
</tbody>
</table>

Spatial autocorrelation (Global Moran’s I), located in the Spatial Statistics toolbox, was performed on each layer. The desired input layer and input field were selected and the following parameters were used:

- Conceptualization of Spatial Relationships: Inverse Distance
- Distance Method: Euclidean Method
- Standardization: Row
- Band Distance: 42,713 ft
Outputs from this procedure came in the form of graphs in HTML format.

Outputs for each layer include (ArcGIS.com):

- Moran’s Index: Values closer to 1 indicate clustering; Values closer to -1 indicate dispersion
- Expected Index: Null hypothesis
- Variance: Distance between high and low values
- Z-Score: Standard Deviation. Depending on the confidence interval, this will determine if the null hypothesis can be rejected
- P-value: Probability that the observed spatial pattern is created by a random process. Smaller P-values mean the null hypothesis can be rejected

A Cluster and Outlier Analysis (Local Anselin Moran’s I), located in the Spatial Statistics toolbox, was performed on each layer. The desired input layer and input field were selected, an output layer was named, and the following parameters were used:

- Conceptualization of Spatial Relationships: Inverse Distance
- Distance Method: Euclidean Method
- Standardization: Row
- Distance Band: 42,713 ft

Outputs from this procedure came in the form of new map layers. The new output layers contain the following fields (ArcGIS.com):

- Local I Index: Values closer to 1 indicate clusters; Values closer to -1 indicate outliers
- Z-scores: Standard Deviation. Depending on the confidence interval, this will determine if the null hypothesis can be rejected, feature by feature.
- P-values: Probability that the observed spatial pattern is created by a random process. Smaller P-values mean the null hypothesis can be rejected, feature by feature.
• Cluster Type: High positive Z-score for features indicates that neighboring features have similar values (high or low). These high clusters are labeled HH for clusters of high values and LL for clusters of low values.

Low negative Z-scores indicate statistically significant outliers. Outliers are labeled HL for high value features surrounded by low value features, LH for low value features surrounded by high value features.
Chapter 4

Patterns in the Raw Data

4.1 Spatial Autocorrelation Map Outputs and Patterns

4.1.1 Global Moran’s I

The results for Global Moran’s I showed clustering for a majority of the variables. Average Rate Spread (Figures 2 & 3) was the only variable for which no significant clustering was identified, with a Moran’s Index of .038456 in 2006 and .005337 in 2009. For 2006 and 2009, this variable displayed random distribution over the study area. For Average Debt-to-Income (Figures 4 & 5), significant clustering was identified for both years, with a Moran’s Index of .381487 in 2006 and .138692 in 2009, with P-values and Z-scores at a 99 percent confidence level. For Percent Denied (Figures 6 & 7), significant clustering, at the 99 percent confidence level, was identified for both 2006 and 2009, with Moran’s Indexes of .353373 and .372498 respectively. For Percent Subprime (Figures 8 & 9), significant clustering, at the 99 percent confidence level, was identified for 2006 (Moran’s Index of .204722), but was found to be randomly distributed in 2009 (Moran’s Index of .019397).
Figure 4-1: 2006 Global Moran’s I Output for Average Rate Spread

<table>
<thead>
<tr>
<th></th>
<th>2006 Global Rate Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moran’s Index</td>
<td>0.038456</td>
</tr>
<tr>
<td>Expected Index</td>
<td>-0.001848</td>
</tr>
<tr>
<td>Variance</td>
<td>0.000588</td>
</tr>
<tr>
<td>Z-score</td>
<td>1.48755</td>
</tr>
<tr>
<td>P-value</td>
<td>0.138355</td>
</tr>
</tbody>
</table>

Figure 4-2: 2009 Global Moran’s I Output for Average Rate Spread

<table>
<thead>
<tr>
<th></th>
<th>2009 Global Rate Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moran’s Index</td>
<td>0.005337</td>
</tr>
<tr>
<td>Expected Index</td>
<td>-0.005757</td>
</tr>
<tr>
<td>Variance</td>
<td>0.001275</td>
</tr>
<tr>
<td>Z-score</td>
<td>0.338975</td>
</tr>
<tr>
<td>P-value</td>
<td>0.734852</td>
</tr>
</tbody>
</table>
Figure 4-3: 2006 Global Moran’s I Output Average Debt to Income

2006 Global Average Debt to Income

| Moran’s Index | 0.381487 |
| Expected Index | -0.005917 |
| Variance | 0.000986 |
| Z-score | 13.06132 |
| P-value | 0 |

Figure 4-4: 2009 Global Moran’s I Output for Average Debt-to-Income

2009 Global Average Debt to Income

| Moran’s Index | 0.138692 |
| Expected Index | -0.006086 |
| Variance | 0.000998 |
| Z-score | 4.582277 |
| P-value | 0.000005 |
Figure 4-5: 2006 Global Moran’s I Output for Percent Denied

Figure 4-6: 2009 Global Moran’s I Output for Percent Denied
Figure 4-7: 2006 Global Moran’s I Output for Percent Subprime

<table>
<thead>
<tr>
<th>2006 Global Percent Subprime</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moran's Index</td>
</tr>
<tr>
<td>Expected Index</td>
</tr>
<tr>
<td>Variance</td>
</tr>
<tr>
<td>Z-score</td>
</tr>
<tr>
<td>P-value</td>
</tr>
</tbody>
</table>

Figure 4-8: 2009 Global Moran’s I Output for Percent Subprime

<table>
<thead>
<tr>
<th>2009 Global Percent Subprime</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moran's Index</td>
</tr>
<tr>
<td>Expected Index</td>
</tr>
<tr>
<td>Variance</td>
</tr>
<tr>
<td>Z-score</td>
</tr>
<tr>
<td>P-value</td>
</tr>
</tbody>
</table>
4.1.2 Local Anselin Moran’s I

The results for Local Anselin Moran’s I shows little clustering, in 2006 and 2009, for Average Rate Spread (Figures 10 & 11). HH clusters are isolated to central city Toledo, with LH outliers around the City of Toledo. There are HL outliers identified within and south of Toledo. One LL cluster is identified, in 2006, in and around the City of Bowling Green.

For Average Debt-to-Income (Figures 12 & 13), in 2006, Anselin Local Moran’s I detected large clusters of HH in western Lucas County, eastern Lucas County, western Ottawa County, and southern Wood County. There was a large cluster of LL in central Toledo for Average Debt-to-Income in the same year. For Average Debt-to-Income, in 2009, clusters of LL were identified in central city Toledo and central Lucas County, with HL outliers throughout Lucas County. There were significantly less HH clusters and more HL clusters in 2009 compared to 2006.

For Percent Denied (Figures 14 & 15), in 2006, a cluster of LL was identified, which stretches from northwest Lucas County and extends to the census tracts just south of Bowling Green in Wood County. An HH cluster occupies a majority of central city Toledo. Around the HH cluster lie sporadic areas of LH. There is a single tract of HL identified in western Lucas County. For Percent Denied, in 2009, the same cluster of LL is identified, with one tract added in the northwest corner of Wood County. The same cluster of HH is identified in is identified in central city Toledo, the outliers of LH located just east of Toledo.
For Percent Subprime (Figures 16 & 17), in 2006, a cluster of LL is identified in western Lucas County, extending into areas of northern Wood County. A HH cluster is identified in central city Toledo and central Lucas County, for the same year. LH outliers are located in and around central city Toledo and Lucas County. For Percent Denied, in 2009, the LL cluster identified in 2006 in western Lucas and northern Wood counties, is not present. The HH cluster, identified in 2006 in central city Toledo and central Lucas County, is much smaller. There are few HL and LH outliers in central Lucas County for 2009.
Figure 4-9: 2006 Anselin Local Moran’s I Output for Average Rate Spread

Figure 4-10: 2009 Anselin Local Moran’s I Output for Average Rate Spread
Figure 4-11: 2006 Anselin Local Moran’s I Output for Average Debt-to-Income

Figure 4-12: 2009 Anselin Local Moran’s I Output for Average Debt-to-Income
Figure 4-13: 2006 Anselin Local Moran’s I Output for Percent Denied

Figure 4-14: 2009 Anselin Local Moran’s I Output for Percent Denied
Figure 4-15: 2006 Anselin Local Moran’s I Output for Percent Subprime

Figure 4-16: 2009 Anselin Local Moran’s I Output for Percent Subprime
The results from the Global and Local Moran’s I show that both the 2006 and 2009 HMDA datasets display clustering and clusters for the chosen variables, with changes over time. The Global Moran’s I detected clustering for all variables except for average rate spread in 2006. This shows that though percent subprime may show clustering in 2006 that the degree of which the loan is subprime is not clustered. The change from clustered to random for percent subprime between 2006 and 2009 displays that the housing collapse had a significant effect on underwriting standards and that subprime lending became significantly less prevalent in 2009.

The clustering detected for percent denied in both 2006 and 2009 shows that percent denial was unaffected by the housing collapse and that percent denied clustered high a higher significance after the housing collapse. This shows that the lending practices of home mortgage originators became more stringent after the housing collapse as banks and lenders began to hoard capital in an attempt to stabilize. Average debt-to-income was clustered in both 2006 and 2009, but with much lower significance in 2009. This shows that banks were beginning to pull back the amount they were willing to lend for a property, in most cases not lending for more than the house was worth after the collapse. Also, this shows that home values were declining and had significantly declined between 2006 and 2009.

The results from the Local Moran’s I show that are spatial patterns associated with the 2006 and 2009 HMDA variables selected. In both 2006 and 2009, average rate spread shows small clustering of high values with high significance within the inner city of Toledo. In 2006, average debt-to-income shows significant clusters which vary over space. High value clusters are located in suburban areas, while low value clusters are
prevalent in urban areas. This changes significantly in 2009 when the high value clusters nearly disappeared completely and the low value clusters in the city of Toledo diminished significantly. This could be explained by the fact that housing values were decreasing, especially in suburban areas. Percent denied displayed clusters in both 2006 and 2009, with very little change between the two years. Applicants looking to purchase in more affluent, White areas were less likely to be denied a loan compared to applicants looking to purchase a home in a poorer, Black inner city Toledo. The changes in spatial patterns for percent subprime were the most significant of the variables. In 2006, high values of percent subprime displayed a spatial fix in inner city Toledo in contrast to the low value clustering observed in the more affluent suburbs in western Lucas County. In 2009, clustering of percent subprime nearly became nonexistent. This shows that after the housing collapse, subprime lending became both less prevalent and less concentrated throughout the Toledo MSA.

Overall, both the Global and Local versions of Moran’s I showed that there are detectable clusters and clustering associated with the 2006 and 2009 HMDA datasets. The results show that there are clear, distinct patterns which may be drawn along economic and racial boundaries throughout the Toledo MSA. The binary logistic regression models may better explain the reasons for the observed spatial autocorrelation within the variables and their changes between 2006 and 2009.
4.2 Discussion of Raw Data Tables

Raw data from the 2006 and 2009 tables give a general idea of lending before and after the housing collapse. Overall, the number of loan applications decreased from 58,047 in 2006 to 31,534 in 2009. This reflects the lending freeze after the collapse of the financial markets in 2008. Around this time, lending institutions essentially stopped all lending to help remain solvent as the markets plummeted day after day. Data pertains to all loan purposes which include home purchase, home improvement, and refinance.

Raw demographic information shows that a majority of loan applicants are White males which made up 65.41 percent of all loan applications in 2006 and 75.96 percent in 2009. This follows the demographic profile for the Toledo MSA as Whites make up a majority of the population. Blacks have the second largest number of loan applications. Between 2006 and 2009, the percentage of Black applicants dropped by 4.99 percent. Hispanics are the third largest loan applicant population in both 2006 and 2009. The percentage of Hispanic applicants dropped by 0.57 percent, between 2006 and 2009. Asians, Native Hawaiians, and American Indian accounted for only about 1 percent of all loan application in 2006, which Asian applicants slightly increasing to 1.04 percent in 2009. No information was the second largest response for applicants in both 2006 and 2009. With 12,704 applicants in 2006 and 5,154 applicants in 2009 giving no race or ethnicity information, the percentage dropped by 5.54 percent. The decrease in Black applicants may be explained by a few different factors: an increased awareness of subprime and predatory lending; stricter underwriting standards established after the housing collapse; or this could also be a symptom of racial discrimination in lending. The
binary logistic regression models with give a better explanation for these observed disparities between applicants.

Sex data shows that male applicants far exceed female applicants in both 2006 and 2009, with a 6.9 percent increase between 2006 and 2009 for males and a decrease in female applicants by 3.49 percent for the same years. Though females outnumber males in the Toledo MSA, making up 51.7 percent of the population in the 2000 Census (census.gov), females made up much less of a percentage of loan applicants in both 2006 and 2009. This shows that a majority of the time men are the primary applicant while the women tend to be the co-applicant.

Table 4-1: Demographic Characteristics Counts and Percentages of 2006 and 2009 HMDA Data

<table>
<thead>
<tr>
<th>Demographics of 2006 and 2009 HMDA Data</th>
<th>2006</th>
<th>2009</th>
<th>2006%</th>
<th>2009%</th>
<th>Percent Difference from 2006 to 2009</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Applicant Race and Ethnicity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: White</td>
<td>57967</td>
<td>23953</td>
<td>65.41</td>
<td>75.96</td>
<td>10.55</td>
</tr>
<tr>
<td>2: Asian</td>
<td>325</td>
<td>329</td>
<td>0.56</td>
<td>1.04</td>
<td>0.48</td>
</tr>
<tr>
<td>4: Native Hawaiian or Other Pacific Islander</td>
<td>83</td>
<td>49</td>
<td>0.14</td>
<td>0.16</td>
<td>0.01</td>
</tr>
<tr>
<td>5: American Indian</td>
<td>201</td>
<td>125</td>
<td>0.35</td>
<td>0.40</td>
<td>0.05</td>
</tr>
<tr>
<td>6: Hispanic</td>
<td>1533</td>
<td>651</td>
<td>2.64</td>
<td>2.07</td>
<td>-0.57</td>
</tr>
<tr>
<td>7: No Information</td>
<td>12704</td>
<td>5154</td>
<td>21.89</td>
<td>16.34</td>
<td>-5.54</td>
</tr>
<tr>
<td><strong>Applicant Sex</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: Male</td>
<td>3233</td>
<td>19849</td>
<td>56.05</td>
<td>62.94</td>
<td>6.90</td>
</tr>
<tr>
<td>2: Female</td>
<td>10210</td>
<td>7707</td>
<td>27.93</td>
<td>24.44</td>
<td>-3.49</td>
</tr>
<tr>
<td>3: Information not provided by applicant in</td>
<td>4173</td>
<td>1626</td>
<td>7.19</td>
<td>5.12</td>
<td>-2.06</td>
</tr>
<tr>
<td>4: Not applicable</td>
<td>5130</td>
<td>2361</td>
<td>8.84</td>
<td>7.49</td>
<td>-1.35</td>
</tr>
<tr>
<td>5: No co-applicant</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Though there were 26,513 fewer applicants in 2009 than in 2006, the percentage of origination increased by 8.73 percent, with loan denial decreasing by 6.19 percent. This can be explained by the increase in refinancing due to declining interest rates. Generally, applicants already in home loans do not have to go through the rigors of the more stringent home mortgage guidelines that took effect after the housing collapse.
The types of loans and their characteristics showed significant changes between 2006 and 2009. Conventional loans applications, those obtained from a savings and loan or a commercial bank, decreased by 26.25 percent from 2006 to 2009, while FHA-insured applications, those secured and insured by the Federal Housing Administration, increased by 23.10 percent. This was due in part to the difficulties of obtaining private mortgage insurance (PMI) by loan applicants. Lenders were hesitant to give out PMI policies unless there was backing from the government, namely in the form of FHA insured loans. PMI is needed when there is a down payment of less than 20 percent of the value of the loan.

The loan purpose made a significant shift between 2006 and 2009. This is due in part that people who were already in a home loan took advantage of record low interest rates and refinanced the loan they were in, as refinancing applications increased 12.47 percent between the two years. Home purchase and home equity loan applications both declined between the years as home quickly lost their value and home equity building became less valuable and counterproductive. Also, fewer applications in home purchase loans in 2009 could be a sign of the financial turmoil and strife created by the economic recession the country found itself in at the time.
Table 4-3: Loan Characteristics Counts and Percentages of 2006 and 2009 HMDA Data

<table>
<thead>
<tr>
<th>Loan Type</th>
<th>2006</th>
<th>2009</th>
<th>2006%</th>
<th>2009%</th>
<th>Percent Difference from 2006 to 2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: Conventional (any loan other than FHA, VA, FSA, RHS)</td>
<td>56369</td>
<td>22345</td>
<td>97.11</td>
<td>70.86</td>
<td>-26.25</td>
</tr>
<tr>
<td>2: FHA-insured (Federal Housing Administration)</td>
<td>1403</td>
<td>8048</td>
<td>2.42</td>
<td>25.52</td>
<td>23.10</td>
</tr>
<tr>
<td>3: VA-guaranteed (Veterans Administration)</td>
<td>257</td>
<td>863</td>
<td>0.44</td>
<td>2.74</td>
<td>2.29</td>
</tr>
<tr>
<td>4: FSA/RHS (Farm Service Agency or Rural Housing)</td>
<td>17</td>
<td>277</td>
<td>0.03</td>
<td>0.88</td>
<td>0.85</td>
</tr>
<tr>
<td><strong>Property Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: One to four-family (other than manufactured home)</td>
<td>57133</td>
<td>31154</td>
<td>98.43</td>
<td>98.75</td>
<td>0.37</td>
</tr>
<tr>
<td>2: Manufactured housing</td>
<td>824</td>
<td>543</td>
<td>1.42</td>
<td>1.09</td>
<td>-0.33</td>
</tr>
<tr>
<td>3: Multifamily</td>
<td>89</td>
<td>34</td>
<td>0.15</td>
<td>0.11</td>
<td>-0.04</td>
</tr>
<tr>
<td><strong>Loan Purpose</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: Home purchase</td>
<td>13333</td>
<td>7916</td>
<td>33.31</td>
<td>25.10</td>
<td>-8.20</td>
</tr>
<tr>
<td>2: Home improvement</td>
<td>5873</td>
<td>1845</td>
<td>10.12</td>
<td>5.85</td>
<td>-4.27</td>
</tr>
<tr>
<td>3: Refinancing</td>
<td>32840</td>
<td>21772</td>
<td>56.57</td>
<td>69.04</td>
<td>12.47</td>
</tr>
<tr>
<td><strong>Occupancy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: Owner-occupied as a principal dwelling</td>
<td>52570</td>
<td>29811</td>
<td>90.56</td>
<td>94.54</td>
<td>3.97</td>
</tr>
<tr>
<td>2: Not owner-occupied</td>
<td>5215</td>
<td>1672</td>
<td>8.98</td>
<td>5.30</td>
<td>-3.68</td>
</tr>
<tr>
<td>3: Not applicable</td>
<td>281</td>
<td>50</td>
<td>0.45</td>
<td>0.16</td>
<td>-0.29</td>
</tr>
</tbody>
</table>

The raw HMDA data is revealing about lending in the Toledo MSA and the changes of application characteristics between 2006 and 2009. The data reveals significant changes in application characteristics such as increase in FHA loans in 2009, an increase in refinancing loans in 2009 due to low interest rates, and an increase in denials between 2006 and 2009. What the tables do not explain is the role and significant these characteristics play in the denial of a home purchase loan. The following logistic regression models will help determine the role and the significance some of the raw variable play in predicating probability of loan denial.
Chapter 5

Logistic Regression Results

5.1  2006 Model Statistical Analysis

The 2006 model was run using SPSS Statistical Analysis software and the following statistics were supplied for each variable present in the model: Exp (β); β; standard error (S.E.); Sig or significance (p value). Exp (β) is the odds ratio a variable plays in determining the outcome of the dependant variable, in this case the denial of a home purchase loan. β is the value of the independent on the prediction of the dependant variable. Standard error is the standard deviation of a statistic. Sig (significance) is the value which at which Null Hypothesis can be disregarded and the variable plays a significant role in determining the dependant outcome at a 99, 95, 90 percent confidence level.

The 2006 model suggests that of the variables chosen for this study, nine are significant in determining the denial of a home purchase loan. Financial variables such as loan amount, debt-to-income, and tract to MSA/MD income, had high significance in the model, all having p-values of 0.00. Loan amount had a standard error of 0 and a β of 0.00. Debt-to-income had a standard error of 0.03 and a β of 0.189. Tract to MSA/MD
income had a standard error of 0.002 and a β of -0.01. Of the three significant financial variables, debt-to-income has the highest Exp (β) with a value of 1.208, meaning that applicants with a higher debt-to-income value are 1.208 more likely to be denied a home purchase loan according to the model.

Race and gender were also significant variables in the model. Race as a whole had a significance of 0.00. The race that was significant in the model and the most significant of all variables in the model was Black, with a significance of 0.00. The standard error for Black was 0.114 and the β was 1.006. Overall, a Black applicant was 2.735 more likely to be denied a home purchase loan compared to a White applicant according to the model.

Females were 1.254 more likely to be denied a home purchase loan compared to males in 2006. Applicant sex as a whole scored a significance of 0.009, while females score a significance of 0.001. The standard error for females was 0.068 and scored a β of 0.226.

Occupancy not applicable, meaning the applicant did not specify whether the property would be owner-occupied or rented out, was the variable with the highest Exp (β) score with a 3.789. With a significance of 0.005, the model suggested that an applicant that selected not applicable for occupancy was 3.789 times more likely to be denied a loan compared to the reference applicant. This suggests that lenders were more wary of applicants who did not disclose their purpose in purchasing a property.

Census data which showed significance in the model were tract population, number of owner-occupied units, and number of 1-to-4 family units. Tract population had a significance score of 0.003 and an Exp (β) of 1. Number of owner-occupied units had a
significance of 0.023 and an \( \text{Exp}(\beta) \) of 1. Number of 1-to-4 family units scored a significance of 0.062 and an \( \text{Exp}(\beta) \).

Variables that showed no significance were kept in the model to act as control variables. Control variables are used to isolate and improve the significance level of desired independent variables. A constant was used in both 2006 and 2009 models which helped to correct for any bias in the models. The two major control variables in both models are purchaser type and subprime.

<table>
<thead>
<tr>
<th>Purchaser Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan was not originated or was not sold in calendar year covered by register</td>
</tr>
<tr>
<td>Fannie Mae (FNMA)</td>
</tr>
<tr>
<td>Ginnie Mae (GNMA)</td>
</tr>
<tr>
<td>Freddie Mac (FHLMC)</td>
</tr>
<tr>
<td>Farmer Mac (FAMC)</td>
</tr>
<tr>
<td>Private securitization</td>
</tr>
<tr>
<td>Commercial bank, savings bank or savings association</td>
</tr>
<tr>
<td>Life insurance company, credit union, mortgage bank, or finance company</td>
</tr>
<tr>
<td>Affiliate institution</td>
</tr>
<tr>
<td>Other type of purchaser</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Subprime</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not subprime</td>
</tr>
<tr>
<td>Subprime</td>
</tr>
</tbody>
</table>

Like previous studies using HMDA data and regression, for example Elvin Wyly’s and Steve Holloway’s “The Color of Money Revisited”, a Black applicant was more likely to be denied a home loan compared to a similar White applicant, all other variables help constant in 2006 (Holloway & Wyly 2001). These findings also match up with Wyly and Hammels findings in “Gentrification, Segregation and Discrimination in the American Urban System”, where Blacks were three times more likely to be denied a home purchase loan compared to similar White applicants (Wyly & Hammel 2004).
The Exp (β) of female applicants being denied a home loan compared to males also fits previous finds. Wyly and Holloway in “American Housing Dilemmas: Race, Gender, and the Challenge of Statistical Citizenship” explain how women of color are more likely to be denied a loan compared to similar male applicants (Wyle & Holloway 2003).

The significance of occupancy, not applicable is eye-catching, but after closer examination of the raw data tables it is clear that the significance of this variable is due to the fact that there are so few cases in which occupancy, not applicable is selected. If only a few of the 33 cases of occupancy, not applicable were denied it would show up as significant in the model.

Table 5-2: SPSS Output for 2006

<table>
<thead>
<tr>
<th>Variable</th>
<th>Exp (β)</th>
<th>β</th>
<th>S.E.</th>
<th>Sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupancy</td>
<td>***3.789</td>
<td>1.332</td>
<td>0.436</td>
<td>0.005</td>
</tr>
<tr>
<td>Not Applicable</td>
<td>***1</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Loan Amount</td>
<td>***1</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Debt-to-Income</td>
<td>***1.208</td>
<td>0.189</td>
<td>0.03</td>
<td>0</td>
</tr>
<tr>
<td>Applicant Ethnicity Race</td>
<td>***2.736</td>
<td>1.006</td>
<td>0.114</td>
<td>0</td>
</tr>
<tr>
<td>Black</td>
<td>***1.254</td>
<td>0.226</td>
<td>0.068</td>
<td>0.001</td>
</tr>
<tr>
<td>Applicant Sex</td>
<td>***1</td>
<td>0</td>
<td>0</td>
<td>0.003</td>
</tr>
<tr>
<td>Female</td>
<td>***1</td>
<td>0</td>
<td>0</td>
<td>0.023</td>
</tr>
<tr>
<td>Population</td>
<td>***1</td>
<td>0</td>
<td>0</td>
<td>0.062</td>
</tr>
<tr>
<td>Tract to MSA/MI Income</td>
<td>***0.99</td>
<td>-0.01</td>
<td>0.002</td>
<td>0</td>
</tr>
<tr>
<td>Number of Owner Occupied Units</td>
<td>**1</td>
<td>0</td>
<td>0</td>
<td>0.062</td>
</tr>
<tr>
<td>Number of 1 to 4 Family Units</td>
<td>*1</td>
<td>0</td>
<td>0</td>
<td>0.023</td>
</tr>
</tbody>
</table>

* .9 confidence level
** .95 confidence level
*** .99 confidence level
5.2 2009 Model Statistical Analysis

The results from the 2009 model suggest that 12 of the selected variables are significant in predicting the denial of a home purchase loan. Financial variables of loan amount, debt-to-income and tract to MSA/MD income are significant variables in the model. Loan amount had a significance score of 0.00 and an Exp (β) score of 1. Debt-to-income had a significance score of 0.00 and an Exp (β) score of 1.208. Tract to MSA/MD income had a significance of 0 and an Exp (β) score of 0.99.

Race was significant in the 2009 model. Scoring a significance score of 0.01 as a whole, Asian and Hispanic both showed significance. Asian scored a significance of 0.063 and an Exp (β) score of 2.101, meaning that an Asian applicant would be 2.101 times more likely to be denied a home purchase loan compared to similar White applicants, according to the model. Hispanic scored a significance of 0.002 with an Exp (β) score of 2.923, meaning that a Hispanic applicant is 2.923 times more likely to be denied a home purchase loan compared to a White applicant.

Occupancy as a whole showed significance of 0.091. Not applicable had a significance of 0.002 and an Exp (β) score of 5.531. Not owner-occupied scored a significance of 0.029 and an Exp (β) score of 1.486.

Minority population was another significant variable with a significance score of 0.034 and an Exp (β) score of 1.011. This meant that an applicant applying for a home purchase loan, the minority makeup of the area mattered.

Loan type was significant in the 2009 model with a significance score of 0.00. FHA-insured, VA-insured, and FSA/RHS types all were significant. FHA-insured loans
had a significance of 0 and an Exp (β) score of 1.919. VA-insured loans had a
significance score of 0.002 and an Exp (β) score of 2.85. FSA/RHS loans had a
significance of 0.099 and an Exp (β) score of 1.697. This shows that the type of loan
matters in the denial of a loan in this model.

The significance of loan type in the 2009, specifically, FHA-insured loans, was
unexpected. Conventional wisdom would have suggested that FHA-insured loans would
have many an applicant less likely to be denied. FHA-insured loans were the preferred
loan type of lending institutions after the housing collapse, as they were fully backed by
the federal government. The significance of VA-guaranteed and FSA/RHS loans can be
explained away by the relatively small amount of cases for each, as there were only 202
VA-guaranteed and 127 FSA/RHS loan application in 2009.

As in the 2006 model, the significance of owner occupancy was an unexpected
outcome. But as in 2006, both not owner-occupied (423 cases) and not applicable (2
cases) can be explained away by the small amount of cases with these variables selected.

The significance of applicant ethnicity race was expected in 2009. In this model,
Hispanic and Asian replaced Black for significance. This was unexpected. The small
amount of Asian applicants in 2009 can explain away its significance (91 cases) and the
same for Hispanic (123 cases).
5.3 Changes between 2006 and 2009

Between 2006 and 2009, the housing market went from being relatively stable and healthy to a complete tailspin. The outcomes of the 2006 were somewhat expected, but the outcomes of the 2009 model shows the instability of the housing market at that time. The significance of loan amount, debt-to-income, and the tract to MSA/MD income in both 2006 and 2009 shows that regardless of the housing collapse, being able to afford the loan an applicant was applying for made a difference, more so in 2009. As
underwriting standards became more stringent after the housing collapse, variables such as debt-to-income and loan amount became more important.

Race was significant in both 2006 and 2009, but the type of race or ethnicity varied between the two years. In 2006, Black was the significant race, whereas Asian and Hispanic were significant in 2009. Though difference races were significant at different times, race was significant in both 2006 and 2009. The significance of minority population in 2009 may display a slight shift back towards place based discrimination as opposed to applicant based discrimination. The sheer drop off in Black applicants between 2006 and 2009 was due in part to the fact that Blacks tend to be economically depressed, especially in economically trying times. More money was needed for a down payment in 2009 compared to 2006 and this would have put an heavier burden on Black applicants. This fact alone shows societal disparities in between races, though this is through the means of obtaining wealth. Before the mid 1990s, redlining was a tool used by lending institutions to systemically keep Blacks out of the home lending arena. In the mid 1990s, lending institutions slowly started to allow Blacks into the market with solid, safe loans. Eventually, subprime lenders decided that more capital could be extracted out of the Black segment of the market with high priced loans. These events display the shift from place based to race based discrimination. The subprime loan was a staple of home lending practices up until 2008 when the market nearly shut down from the mass amount of toxic loans in origination. The 2009 model shows small signs of a shift back to place based discrimination.
The significance of applicant sex, female in 2006 was of no surprise, but the absence of significance of applicant sex, female in 2009 was unforeseen. This could possibly be explained by loan type playing a more significant role in the denial of a loan.

The significance of loan type in 2009 shows that housing collapse ushered in a period in which if you could not secure a conventional loan you had little chance of securing a loan. Also FHA loans had a higher rate of denial in 2009 compared to 2006 because the amount of FHA loans increased from 492 to 2255, making up a 42 percent of all home purchase loans in 2009. The increase in FHA-insured loans could explain the significance of FHA loans in 2009.

Overall, the outcome of the 2006 model fits the outcomes from previous home lending studies in which race, gender, and financial variables are significant in predicting the denial of a home purchase loan. The significance of race, Black in the model was expected as a previous study conducted by Steve Holloway in 1998, where Black applicants were more likely to be denied a loan compared to a similar White applicant, produced similar results (Holloway 1998). The significance of gender, female in the prediction of denial in 2006 was also expected and fits previous studies (Wyly et al 2003).

The outcome of the 2009 model displayed significant changes from the 2006 model. The disappearance of gender significance was unexpected as was the significance of loan type. The 2009 model outcome somewhat reflects the instability of the mortgage markets at the time. Few logistic regression denial studies have been conducted after the crash to compare to the 2009 output.
Chapter 6

Conclusion

The outcome of this research suggests that there were patterns associated with home mortgage lending in the Toledo MSA in 2006 and 2009. The global and local versions of Moran’s I detected spatial autocorrelation for a majority of the attributes analyzed. The global version detected clustering affects for all but average rate spread. Clustering was detected for all attributes except average rate spread in 2006. In 2009, percent subprime changed to random from clustered, showing far less significance in 2009 compared to 2006. Though clustering was detected in both 2006 and 2009, average debt-to-income lost much of its significance between 2006 and 2009. This shows that either lenders were lending less money for homes, home prices were depreciating, or applicants were earning less, therefore purchasing cheaper homes. As for percent denied, the attribute showed clustering affects in both 2006 and 2009, but the significance rose in 2009. This follows a national trend of increased denial rates after the housing collapse.

The changes in the patterns in the local version of Moran’s I for percent subprime and average debt-to-income between 2006 and 2009 reflect drastic changes in the underwriting standards in home mortgage lending after the collapse of the housing market. Subprime loans became less prevalent throughout the study area, with some
pockets of high spatial correlation in inner city Toledo. The severity of the subprime loan, the average rate spread, showed minimal autocorrelation and minimal changes in and between 2006 and 2009. There was slight bias towards originating more severe subprime loans to applicant looking to purchase in inner city locals. This followed a documented trend of inner cities being ground zero for the subprime boom in the mid 2000s.

Average debt-to-income displayed significant changes between 2006 and 2009 throughout the MSA. Borrowers looking to purchase homes closer to inner city Toledo were borrowing much less compared to those in suburban locals, such as Waterville, Sylvania, Holland, and Oregon. Borrowers in suburban areas were borrowing much more for their desired homes in 2006, but in 2009 lenders were much more hesitant to originate loans for more than the home was worth. The properties within the city of Toledo have less value and were less likely to increase in value with upfront repairs compared to homes in suburban communities, so little change was noticed within the city between 2006 and 2009.

The persistence of percent denied in both 2006 and 2009 shows that spatial disparities in the denial of home purchase mortgages were unaffected by the collapse. Though fewer home loans were originated, the denial rates for 2009 show an inner city fix. Suburban areas show spatial autocorrelation of lower percentages of denials, showing that there may be a slight denial bias towards applicants looking to purchase a home in inner city Toledo.

The logistic regression models show that certain variables show more significance in the models compared to others. The significant variables change from 2006 to 2009 along with the level of significance. Categorical variables which showed significance in
2006 were occupancy, applicant ethnicity and race, and applicant sex. Ratio variable which showed significance in 2006 were loan amount, debt-to-income, tract population, tract to MSA/MD income, number of owner-occupied units, and number of 1-to-4 family units. The most significant of variables in 2006 were occupancy-not applicable and applicant ethnicity and race-Black. If owner-occupied or not owner-occupied were not selected during the application process, the applicant was 3.789 time more likely to be denied than the reference. If the applicant was Black, the applicant was 2.735 more likely to be denied compared to the reference. All values which were significant, except number of owner-occupied units and number of 1-to-4 family units, where significant at the .99 confidence level.

In 2009, the significant variables changed to include loan type and minority population. Loan type-FHA insured, VA-guaranteed, and FSA/RHS were significant variables. Minority population was significant at the .95 confidence level. The variables applicant sex, tract population, and number of 1-to-4 family units were not significant. Occupancy remained significant with both not owner-occupied and not applicable showing significance. Applicant race-Asian (.9 confidence level) and Hispanic (.99 confidence level) both showed significance. Loan amount and debt-to-income remained similarly significant from 2006 and 2009, showing that financial variables played a significant role in the denial of loans in both years.

Ethnicity and race seemed to play a significant role in denial in both 2006 and 2009. Though different races were affected, race clearly was a determinate in the denial of a loan in both 2006 and 2009. The sheer drop off in Black applicants between 2006 and 2009 was due in part to the fact that Blacks tend to be worst off financially,
especially in economically trying times. More money was needed for a down payment in 2009 compared to 2006 and Black populations would have less of the means to provide a 20 percent down payment and the eligible credit score to meet financial requirements for a loan.

Overall, the 2006 logistic regression model fell in line with previous home mortgage studies, with similarities in variable significance and the level of significance. On the other hand, the 2009 model showed outcomes that reflect the instability of the time period, with the significance of unexpected variables and significance levels.
References


