Bridging the Gap Between Censuses: Using the Longitudinal Tract Data Base to Analyze Foreclosures in Dane County, Wisconsin

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Abstract

The extension of mortgage loans to non-prime borrowers peaked in the mid 2000s as nontraditional mortgage products and lax lending standards became more prevalent. Using the concentration of "high-cost loans" tabulated by the Home Mortgage Disclosure Act (HMDA) as a proxy for lending to non-prime borrowers over the 2004-2006 period, 10.8 percent of borrowers located in Dane County entered mortgage loan contracts with high interest rates. Spatial analysis techniques at the Census tract level reveal that this proxy accounts for a notable amount of variation in Dane County foreclosure sales observed in 2011 and 2012.

Key Words: Foreclosures, Census, MAUP, Spatial Autocorrelation, Spatial Regression Analysis

The purpose of this study is multifaceted and takes an interdisciplinary approach regarding foreclosure studies. While economists have consistently identified the market structures lending themselves to higher numbers of foreclosures, geographers have tended to focus on the spatial distribution of the foreclosures as they pertain the unfair lending practices regarding minorities in large urban areas like Chicago, Detroit, and Minneapolis (Allen 2011; Chan et al. 2010; LI 2011). Though the availability of data regarding foreclosures is limited, specific data regarding individual foreclosures are available from third party agencies at significant costs. While high levels of funding are available to some, newly developed geospatial techniques along with publically available data, can allow for thoughtful research regarding spatial patterns of foreclosures at no cost to the researcher.

Based the availability of free data from the U.S. Census, U.S. Department of Housing and Urban Development, and the Dane County Sherriff's Office, a spatial analysis of foreclosures was conducted at no monetary cost to the researchers. Through the analysis of these data, two main questions emerge: 1) Do spatial patterns of high costs loan equate to higher levels of foreclosures? 2) Can the Longitudinal Tract Database conversion allow for temporal analysis of tracts across censuses?

Existing Literature

Existing foreclosure studies, particularly those focused on the most recent decade, suggest a need to account for mortgage lending patterns. Schloemer et al. (2006), for example, point to the relatively high rate of foreclosure among borrowers with subprime loans within the first five years of origination (13 percent), which is rooted in the fact that mortgage loans in this category commonly include features that increase the risk of default and, therefore, foreclosure; these features include, but are not limited to, adjustable interest rates, balloon payments, and prepayment penalties. The 2004-2006 period, in particular, is characterized by a surge in non-prime lending, with subprime originations, specifically, reaching a peak of approximately 20 percent of all mortgage originations in the U.S. in 2005, up from a share of just 6 percent in 2000 (Furlong and Krainer 2007; Inside Mortgage Finance 2007). Furthermore, mortgage underwriting standards grew increasingly lax as subprime lending surged and loan quality deteriorated, contributing to higher delinquency rates for loans originated in the mid 2000s (Demyanyk and Van Hemert, 2011; Wilcox, 2009).

Information about mortgage lending trends from the years leading up to the housing market downturn is important to consider even when focusing on foreclosures occurring in 2011 and 2012. This importance stems from mortgage lending practices and events that now stand out as being unusual by historical standards, including the aforementioned spike in the volume of subprime mortgage loans originated during the 2004-2006 period. The fact that there is no official definition of what constitutes a subprime loan does present a challenge, but the Home Mortgage Disclosure Act (HMDA) does offer a proxy for subprime lending; a "high cost loan" is a mortgage loan characterized by an interest-rate that exceeds the prevailing Treasury rate by at least three percentage points for first-lien loans. Based on this measure, the U.S. Department of

Housing and Urban Development (HUD) estimates that the share of subprime lending increased from 14.5 percent of mortgage originations in 2004 to 29.4 percent in 2006 (U.S. Housing Market Conditions, 2008).

In addition to the surge in subprime lending, loans originated in the period leading up to the collapse of the U.S. housing market in 2007 and 2008 continue to perform poorly. Demyanyk and Van Hemert (2011), after adjusting for differences in loan and borrower characteristics, show that both the delinquency and foreclosure rates are notably higher for subprime loans originated in 2004-2007 as compared to subprime loans originated earlier in the decade. Furthermore, there is evidence to suggest that most borrowers with subprime loans intended for the situation to be temporary with refinancing the loan as the intended next step; unfortunately for borrowers taking out subprime loans closer to the start of the crisis, house prices were no longer increasing at the same rate, and many borrowers were presented with little, if any, opportunity to refinance as house prices began to decrease (Demyanyk, 2009; Krainer and Laderman, 2011). The result is a widespread issue with delinquency, default, and foreclosure among borrowers with any type of subprime loan originated in the years leading up to the downturn in the housing market (Demyanyk and Van Hemert, 2011). Krainer and Laderman (2011) identify loan vintage, or the year of origination, as a factor that remains important for explaining delinquencies and defaults in more recent periods, with nearly 20 percent of mortgages originated in 2006 delinquent as of the first quarter of 2010.

Outside of housing market downturns, existing studies point to the role of socioeconomic factors related to foreclosure activity. Calem, Gillen, and Wachter (2004), for example, find that subprime lending is more prevalent among lower income and black borrowers based on individual- and census tract-level data for Chicago and Philadelphia. With a focus on Hennepin and Ramsey Counties in Minnesota, Crump (2007) discusses the concentration of foreclosures in communities characterized by a large minority population; this correlation is consistent with the myriad of findings that identify a minority borrower as being more likely to receive a high-cost, or subprime, loan, regardless of income. In a comparison of high and low foreclosure rate census tracts within Contra Costa County, California, Perkins (2009), through difference in means tests, identifies census tracts with high rates of foreclosure as also having a significantly higher incidence of subprime lending; statistical results also indicate that census tracts with higher foreclosure rates also have relatively larger proportions of black and Latino residents.

The concentration of subprime lending in such neighborhoods is tied to economic and social factors including, but not limited to, the potential borrowers' understanding of loan products and willingness to actively seek out the best loan terms (Immergluck and Smith, 2005). Furthermore, traditional lenders have expanded operations in higher income neighborhoods characterized by a larger proportion of white residents, leaving the lower income and predominantly minority neighborhoods to be targeted by nontraditional lenders, including subprime lenders (Avery et al., 1997; Immergluck and Smith, 2005).

Given the documented relationship between patterns in mortgage lending and borrowers' likelihood of default and foreclosure, the importance of considering credit risk for the purposes of explaining spatial differences in foreclosure rates is the focus of Grover, Smith, and Todd (2008). Despite controlling for the share of the population deemed to be "very risky" in terms of credit, the multivariate analysis suggests that the change in the minority share of the population has a positive, significant relationship with the foreclosure rate at the census tract level. These empirical results motivate the need to control for the change in the minority share of the population *and* credit risk. Unfortunately, incorporating information about credit scores is a challenge since this data is, generally speaking, proprietary. Grover, Smith, and Todd (2008) highlight the use of HMDA data to construct a proxy as an alternative approach to account for the share of borrowers with risky credit; subprime lending often targets borrowers with risky credit profiles, so the "high cost loan" measure from HMDA data proposed earlier will also reflect information related to credit risk. The use of a proxy is common when facing limited data availability but this alternative approach does have its downsides. Consistent with the findings presented by Grover, Smith, and Todd (2008), it is expected that the use of the proxy exaggerates the estimated impact of the change in the minority share of the population on the rate of foreclosure; this issue is revisited in conjunction with the regression results.

Dane County as a Study Area

Though Dane County does not fit the model of previously cited geographical studies regarding foreclosures as it pertains to race (it is nearly 85%) white, it does provide for a sound economic analysis of foreclosures in an area of the Wisconsin that saw significant population growth between 2000 and 2010. According to the 2010 figures from the U.S. Census Bureau, Dane County's population is 87.7 percent urban with nearly 47.7 percent of the county's population residing in the city of Madison. With Madison as the focal point of economic activity for the county, many of the surrounding cities, towns, and villages provide a commuter outlet illustrated with an average commute of 19.51 minutes. Census tracts are the scale of analysis for this study due to the availability of subprime lending data at the tract level and for the process of tract conversions explained later in this study. Figure 1 shows the 2010 census tracts and the location of cities, towns, and villages throughout Dane County. The largest suburban areas surrounding Madison include Sun Prairie, Fitchburg, and Waunakee.

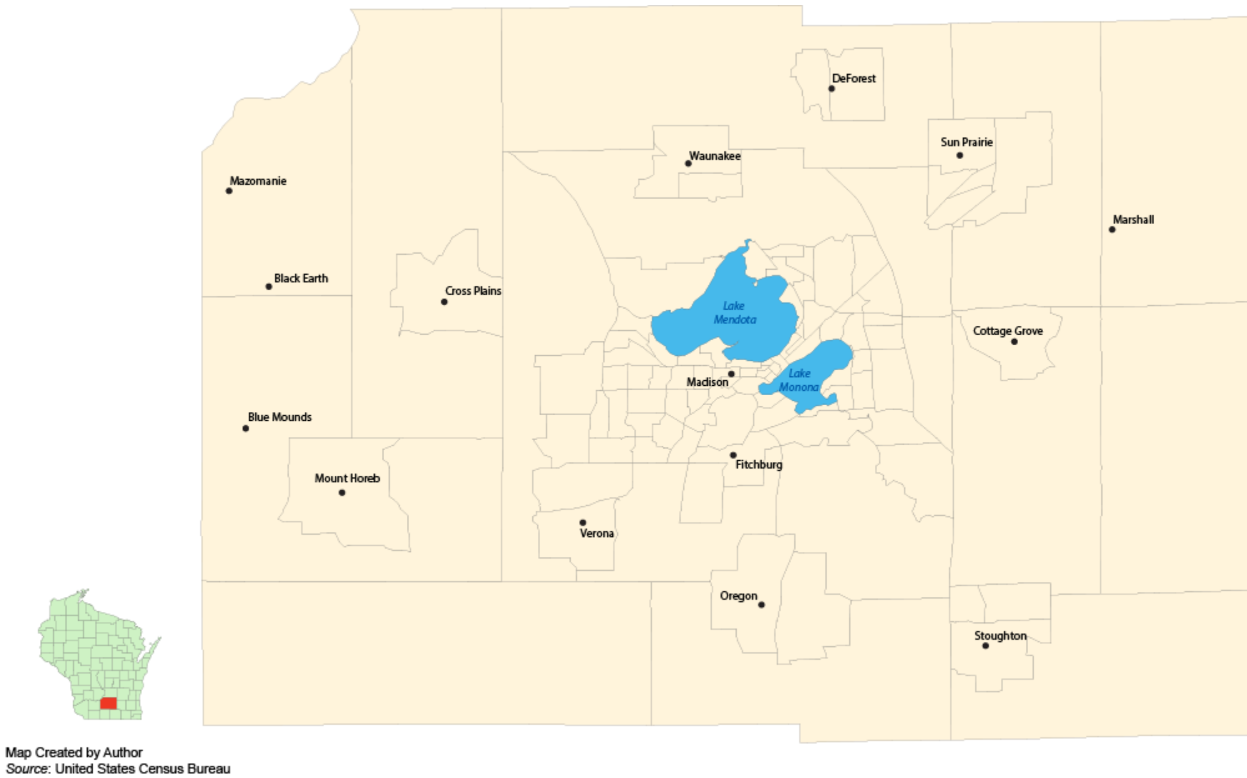


Figure 1 *Map showing study area: 2010 Census Tracts and Metropolitan Areas*

Experiencing the third largest rate of growth in the state of Wisconsin during the most recent decade, the population of Dane Country grew by 14.4 percent by 2010. While white populations saw the largest absolute increase in total population during this period, non-white populations saw an increase of over four percentage points from 11 percent in 2000 to 15.3 percent in 2010. Of the non-white population, the largest growth was found among Latino population. Driven by increases in service industries, manufacturing, and agricultural activities, Hispanic populations in Dane County increased from 12,999 in 2000 to 28,925 in 2010. Figure 2 shows the change of non-white populations in Dane County over the past decade. Non-white populations saw the largest increases in the tracts surrounding the central areas of the county. The few tracts with decreasing non-white populations tend to be focused in the downtown area, particularly in areas characterized by low numbers of owner occupied units located near the state capital and the University of Wisconsin-Madison.

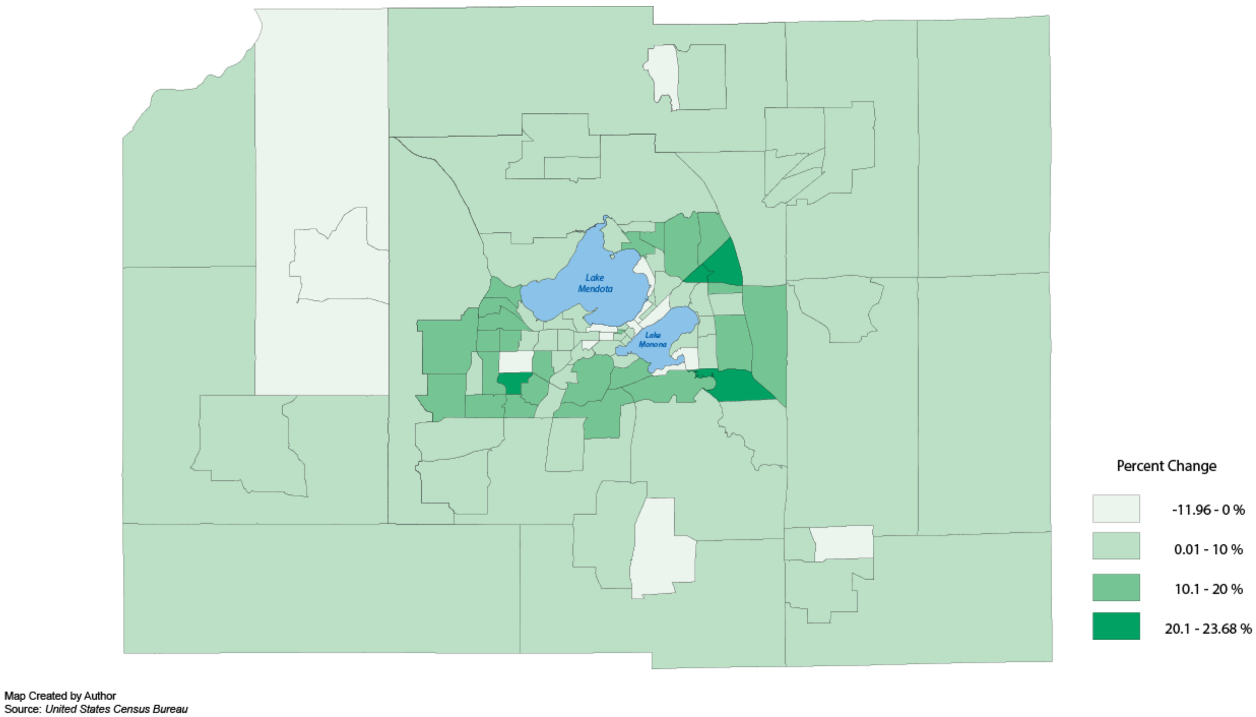


Figure 2 *Map showing percent change of non-white populations from 2000 to 2010. Non-white percentages for 2000 recalculated using the LTBD spatial transformations conforming to 2010 tracts.*

The role of declining house prices and, in particular, the potential for falling prices to leave mortgaged households "underwater" (that is, with a mortgage loan balance greater than the market value of the house) is frequently cited as a reason for rising foreclosures (Capozza and Van Order, 2011; Gerardi, Shapiro, and Willen, 2009). Residents of Dane County continue to endure an environment of depressed home values. After reaching a peak in 2007, the median sale price of homes in Dane County declined by 7.9 percent over the next two years. The median sale price recovered slightly in 2010 before declining again between 2011 and 2012; overall, Dane County experienced a 5.3 percent decline in the median sale price over the 2007-2011 period and an 8 percent decline over the 2007-2012 period (Wisconsin Realtors Association, 2013).

A homeowner's decision to default on the mortgage doesn't depend on equity position alone; a disruption to the homeowner's cash flow, due to unemployment, for example, is also an important issue (Foote, Gerardi, and Willen, 2008). Mayer, Pence, and Sherlund (2009), for example, point to the role of high unemployment alongside falling house prices in explaining the recent rise in mortgage defaults in Midwestern states, in particular. The unemployment rate in Dane County increased by 3.6 percentage points following the start of the recent recession and, as of 2012, remains elevated relative to pre-recession conditions (U.S. Bureau of Labor Statistics, 2013).

	Change in unemployment rate, recent peak vs. pre-recession	**Decline in median sale price, 2007-11**	**Decline in median sale price, 2007-12**
Dane County	3.6 percentage points	5.3%	8%
Milwaukee County	5.6 percentage points	37%	38%
Waukesha County	5.8 percentage points	12.4%	10.04%

Sources: Wisconsin Realtors Association; U.S. Bureau of Labor Statistics

Table 1 *Recent conditions for labor and housing markets*

The recent rise in unemployment and decline in house prices observed in Dane County, however, are muted relative to fluctuations experienced in other parts of Wisconsin (see Table 1). Furthermore, the homeownership rate in Dane County is nearly eight percentage points lower than the state average (61.2 percent and 69.1 percent, respectively), and median household income, at $61,913 in 2010, is notably higher than the state level of $52,374 (U.S. Census Bureau, 2010); therefore, it is somewhat surprising that Dane County experienced the most dramatic increase in foreclosure filings out of Wisconsin's most populous counties, and an explanation of the elevated foreclosure activity in Dane County likely extends beyond the usual focus on dramatic house price depreciation and high unemployment.

Foreclosure filings for homes in Dane County, Wisconsin, increased by nearly 50 percent between 2007 and 2008, the period immediately following the collapse of the U.S. housing market. In the state of Wisconsin, annual foreclosure filings peaked in 2009, but filings in Dane County, in particular, continued to rise, reaching a peak of 1,645 unique filings in 2010 (University of Wisconsin Cooperative Extension, 2012). At this peak, foreclosure filings are 483 percent higher compared to the number of filings recorded in Dane County in the year 2000 (see Table 2). A slow decline in filings has since been recorded, but foreclosure activity in Dane County remains elevated with the number of 2011 foreclosure filings at a level nearly 4.5 times higher than levels observed in 2000. Dane County is Wisconsin's second largest county with respect to population and the number of housing units with a mortgage, but the increase in the number of foreclosure filings, from 2000 to the recent peak, was more dramatic in Dane County compared with either Milwaukee or Waukesha counties; together these three counties make up 4.6 percent of Wisconsin's total area but account for nearly one-third of the state's population and owner-occupied housing units with a mortgage (U.S. Census Bureau, 2010).

	Ratio of Foreclosure Filings in 2011 to 2000	Ratio of Foreclosure Filings at Peak to 2000	Number of housing units with a mortgage
Dane County	*4.49*	*5.83 (Peak = 2010)*	*92,902*
Milwaukee County	*2.96*	*3.68 (Peak = 2009)*	*141,949*
Waukesha County	*4.46*	*4.89 (Peak = 2010)*	*85,879*

Sources: University of Wisconsin Cooperative Extension; U.S. Census Bureau

Table 2 *Foreclosure filings for Wisconsin's largest counties*

A disproportionate number of Dane County foreclosures are located in census tracts located just east of downtown Madison, near Sun Prairie, and lower concentrations of foreclosures are observed in the city center and tracts to the west. This study will investigate the spatial patterns of foreclosures at the census tract level. In addition to documenting the spatial distribution of foreclosures taking place in Dane County in 2011 and 2012, this case study aims to offer some explanation regarding related economic and demographic factors.

As a result, Dane County tracts that are characterized by a disproportionate share of subprime lending, particularly during the mid 2000s, are expected to have relatively high rates of foreclosure in subsequent years. The desire to account for subprime lending patterns from the 2004-2006 period as a possible explanatory factor for foreclosures observed in 2011 and 2012 gives rise to a major issue based on the changing shape of areal units over time. While the vast majority of data related to individual foreclosures and high cost loans is difficult, at best, to obtain and data that is available from private companies extremely expensive, combining free sources of high cost loan data and foreclosures allows a greater audience to employ a variety of methods across various geographic areas. Though missing in the literature concerning foreclosure studies is a direct method for extraction of spatial data related to foreclosures over time accounting for the above mentioned temporal lag. More specifically, in order to carry out the desired regression analysis, point-based data is first aggregated into Census-derived spatial units (tracts) between 2000 and 2010, and comparing tract information between 2000 tract boundaries and 2010 tract boundaries yields inconsistent results.

The Modifiable Areal Unit Problem (MAUP), a term devised by Openshaw and Taylor (1979), states that results are dependent on the bias of the spatial units; furthermore, Dark and Bram (2007) indicate the changing shape of areal units results in complications in both the scale and methods used. Due to the fact this study's data covers Census tracts that change shape between 2000 and 2010, mitigation of this problem will utilize spatial transformations calculated by the Longitudinal Tract Data Base (LTDB). The LTDB uses a process that combines population with area weighting creating a high degree of accuracy as a means to overcome the problem of longitudinal boundary change that has long hampered temporal analysis of Census-derived data (Logan, Xu, and Stults, 2012). Due to the fact that our data covers a number of years between 2007 and 2012, the LTDB process successfully integrates data over this time span using solely 2010 tract polygons. Therefore, the methods explained in this paper provide readers a variety of techniques to utilize readily available and cost efficient data to explore spatial and temporal patterning of foreclosures at the tract level.

Patterns and Statistical Analysis

MAUP and the Longitudinal Tract Data Base

The premise of this study is to understand the relationships between varying spatial scales and aggregations. The decision to aggregate foreclosure sales at the census tract level was dictated by the availability of tract-level data pertaining to housing and socioeconomic characteristics, obtained from the U.S. Census Bureau, and high-cost lending activity from 2004 – 2006, obtained from the U.S. Department of Housing and Urban Development. Concerning MAUP, comparing tract information between 2000 tract boundaries and 2010 tract boundaries would yield inconsistent results. Dane County saw an increase of 61,547 people from 2000 to 2010. This large increase in population resulted in the restructuring of tract boundaries. For example, as indicated by Figure 3, tracts 16.04 and 16.03 (2010 Census) composed tract 16.01 from the 2000 Census. Therefore, given this data as is, spatial-temporal comparisons are not possible.

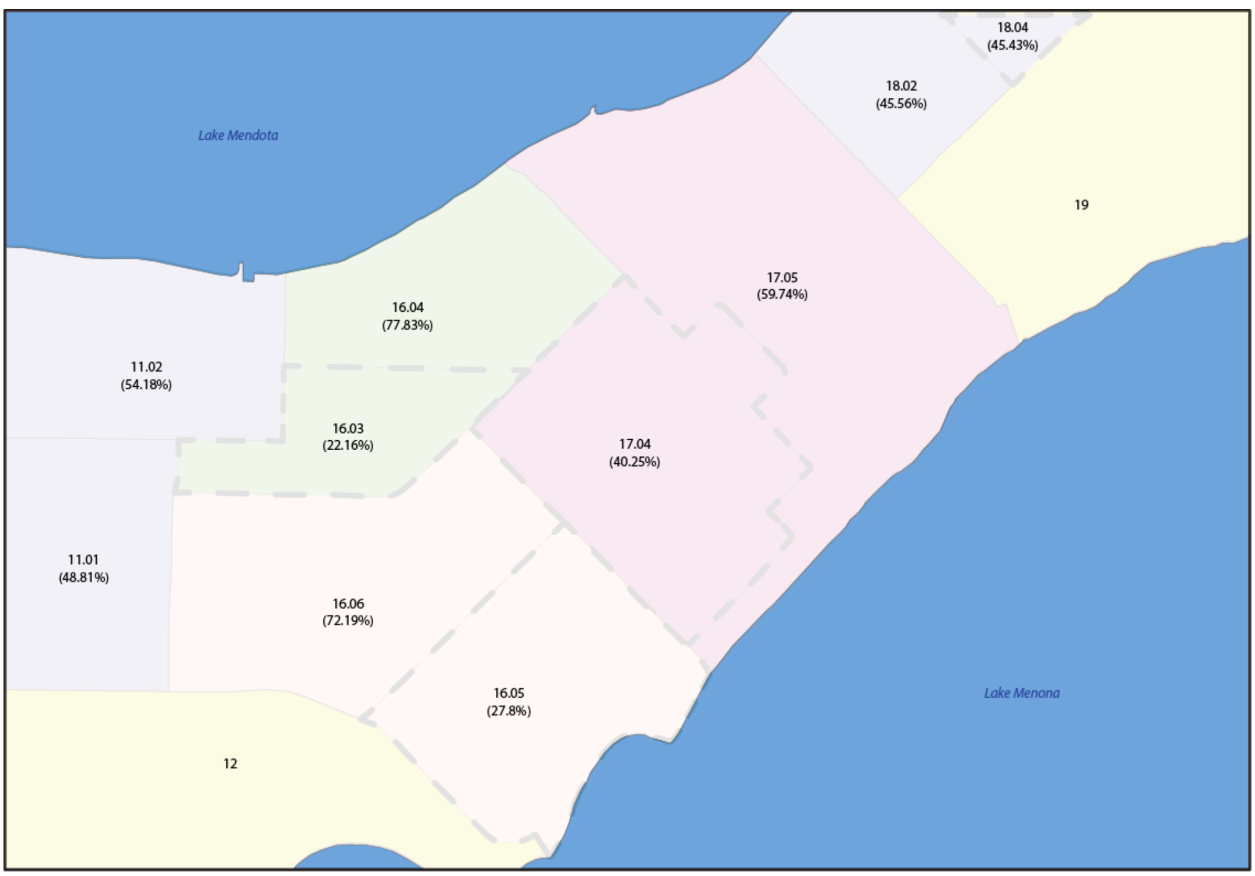


Figure 3 *2010 Census tracts with LTDB spatial weights for selected tracts focused downtown Madison in central Dane County.*

The Longitudinal Tract Data Base (LTDB) was created to provide an alternative spatial analysis in sidestepping the MAUP problem. This process combines population with area weighting with a high degree of accuracy. Research successfully using tract conversions ranges from segregation, to labor markets, to immigration, and housing to name a few (Lee, Iceland, and Sharp, 2012; Bean et al., 2013; Holzer and Hlavac, 2012; Reardon and Bischoff, 2011; Rosenbaum 2012). Figure 3, above, identifies a handful of census tracts near downtown Madison that changed shape between 2000 and 2010. For example tracts 16.05 and 16.06 comprised tract 16.02 from 2000. The percentages below the tract ID show the corresponding spatial weight (created by the LTDB) given to the new tracts in 2010. In 2000 tract 16.02 had a total population of 7,772 people. Multiplying the total population by with spatial weights for 16.05 and 16.06 creates new numbers allowing for temporal comparisons using the 2010 tract boundaries. This process isn't without potential error. The LTBD indicates:

> *One problem is that blocks in 2000 are sometimes split into different portions that are assigned to different 2010 tracts. We allocate the block population to 2010 tracts in proportion to the area of these block fragments. Since blocks are usually small and have few residents, this aspect of the estimation is unlikely to cause much error.*
>
> *A second source of error is probably more important, and it is found in both the LTDB and NCDB. When part of a tract in 2000 is reallocated into a new tract in 2010, we assume that the kinds of people living in that fragment are the same as in the fragment that is reallocated into another new tract. Census tracts are somewhat homogeneous, and on average the people living anywhere in a tract tend to be more like one another than like people in other tracts. But there remains the possibility that in some cases the composition of different tract fragments is quite dissimilar. A reliable check on this problem would require access to the original census data (Logan, Xu, and Stults, 2012).*

While error cannot be discounted, the success of other studies in using the LTBD provides the necessary adjustments to correspond U.S. Department of Housing and Urban Development (HUD) data to 2010 Census data and 2011 and 2012 foreclosure sales data for Dane County.

Geocoding Dane County Foreclosures for 2011 and 2012

Geocoding is a geospatial process in which any data with a Cartesian coordinate can be mapped. We found obtaining foreclosure addresses varies from municipality to municipality. Dane County offered an easily obtainable and complete listing of addresses, on the web, compared to many other areas across the country of similar size. For the purposes of this study, addresses of foreclosed properties listed as sales are obtained from the Dane County Sherriff's Department (DSCO) and were geocoded using a GIS. Addresses with incomplete information from the website were not included in the analysis. The resulting process yielded 1,219 properties in foreclosure in 2011 increasing to 1,316 in 2012. Once the properties were geocoded, the individual points were spatially joined with the 2010 census tracts to provide the number of foreclosures in each census tract. The counts for each tract were then divided by the number of owner-occupied homes with a mortgaged as of the 2010 Census to obtain a normalized measure suited for comparison across census tracts. Figures 4 and 5 are the normalized maps of foreclosures for each of the years. As both maps illustrate, foreclosures are highest in the tracts east of Madison and lowest in the downtown areas of the city.

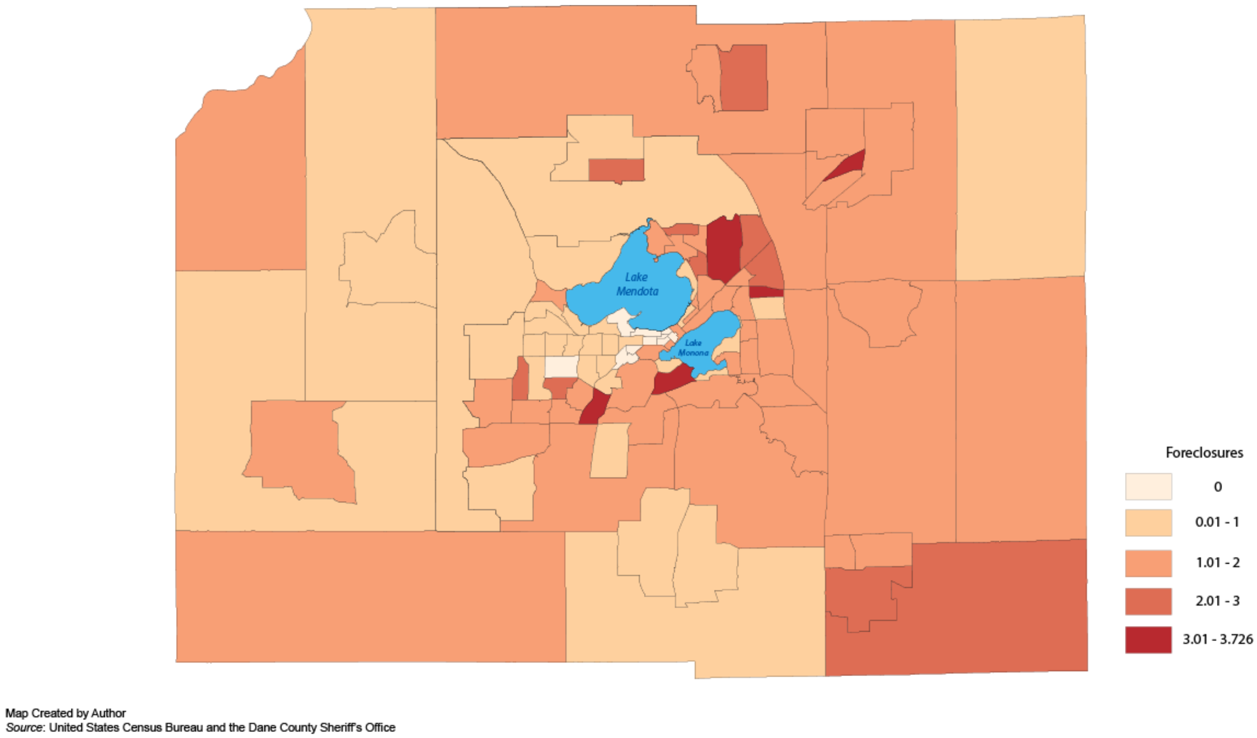


Figure 4 *2011 map of the number of foreclosures per 100 mortgaged homes for 2010 Dane County Census Tracts. N = 1,219*

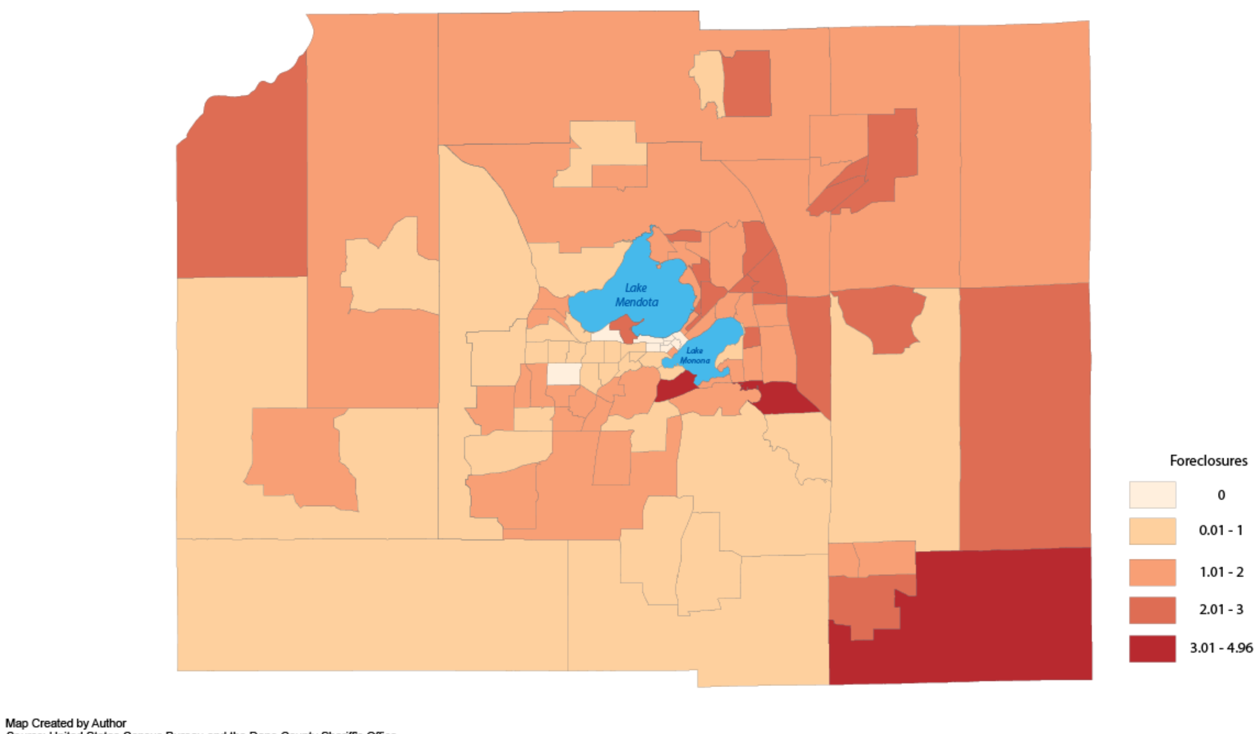


Figure 5 *2012 map of the number of foreclosures per 100 mortgaged homes for 2010 Dane County Census Tracts. N = 1,316*

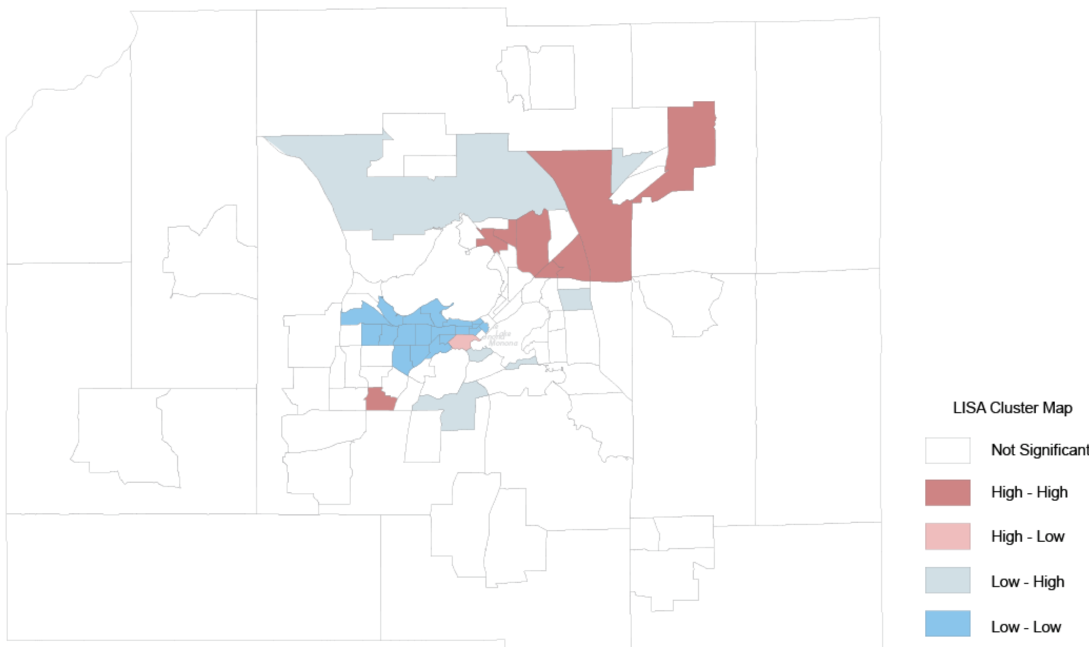
Spatial Autocorrelation Dane County Foreclosures for 2011 and 2012

As Figures 4 and 5 indicate, a distinct spatial pattern of foreclosures exists in Dane County. Rogers and Winter (2009) state, "foreclosures tend to be spatially clustered" (458). Further studies have discovered similar results (Schintler and Istrate, 2011; Can, 1998; Vesselinov and Beveridge, 2008; Clauretie and Daneshavary, 2009; Schintler et al., 2010). A common measure to identify patterns of "spatial" clustering is spatial autocorrelation. Developed by Cliff and Ord (1969), Getis (2007) stated that Getis and Ord believed "the special case of correlation in space, when there is a relationship between nearby spatial units of the same variable, needed to be identified if research questions were to be answered accurately" (492). While a number of statistical procedures exist to test for spatial autocorrelation (i.e. Moran's I, Geary's C, and Ripley's K), this study will use the Moran's *I*. Moran's *I* is a weighted correlation coefficient used to detect departures from spatial randomness. Departures from randomness indicate spatial patterns, such as clusters. Moran's *I* tests for global spatial autocorrelation in group-level data. Positive spatial autocorrelation means that nearby areas have similar rates, indicating spatial clustering, suggesting their populations and exposures are alike. When rates in nearby areas are similar, Moran's *I* will be large and positive. When rates are dissimilar, Moran's *I* will be negative (Moran 1950, 17-19).

Localized Indicators of Spatial Autocorrelation (LISA) provide a spatial output of Moran's I. Developed by Luc Anselin, the choropleth output is classified by four distinct colors: bright red for a high-high association, bright blue for a low-low, light blue for a low-high, and light red for a high-low. The high-high areas suggest clustering of similar high values, low-low clustering of areas with low values, with low-high and high-low depicting spatial outliers

(Anselin, 2005). GeoDa, a freeware statistical package, used TIGER-generated shapefiles from ArcGIS to complete all Moran's *I* and LISA outputs**.**

The resulting measures of spatial autocorrelation for the normalized foreclosure variable produce a Moran's *I* of 0.28 for 2011 with a slight increase to 0.29 in 2012, indicating a moderate level of spatial clustering. Figures 6 and 7 illustrate distinct clustering patterns of normalized foreclosures with higher rates occurring in the eastern tracts of Dane County and lower levels of occurring throughout downtown and the tracts immediately to the west.



Map Created by Author
Source: United States Census Bureau and the Dane County Sheriff's Office

Figure 6 *2011 LISA map of the number of foreclosures per 100 mortgaged homes for 2010 Dane County Census Tracts. Moran's I = 0.28*

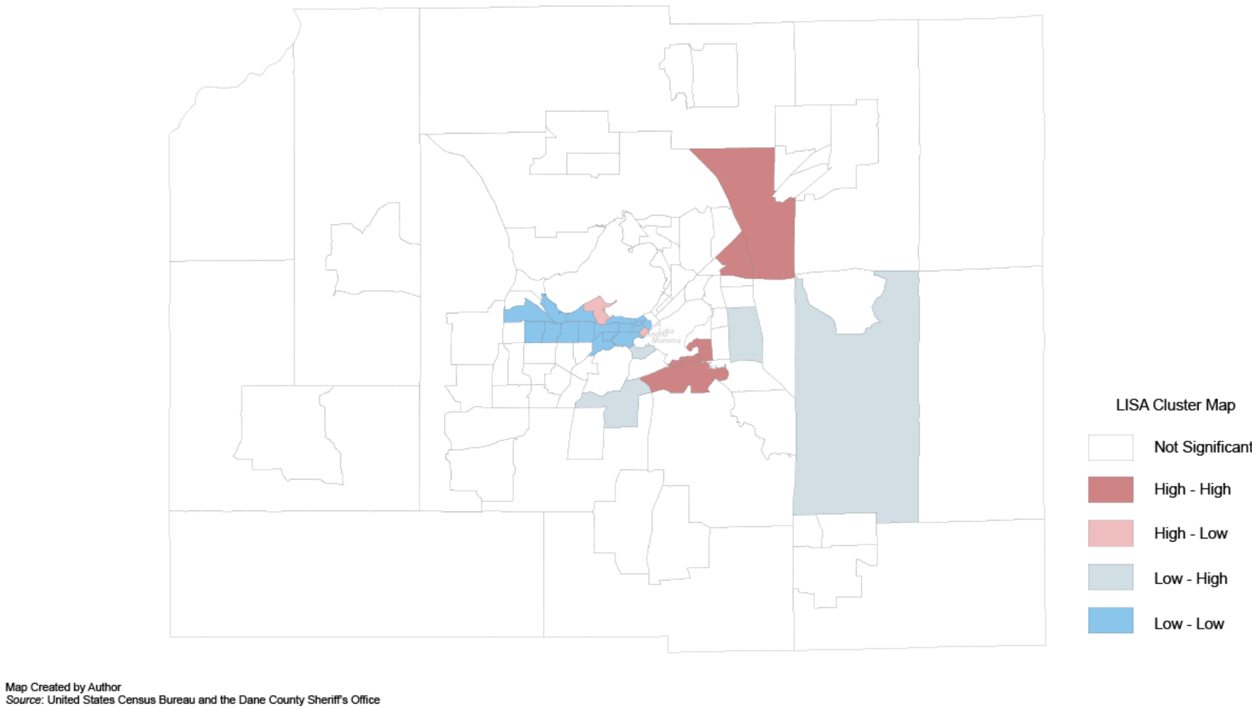


Figure 7 *2012 LISA map of the number of foreclosures per 100 mortgaged homes for 2010 Dane County Census Tracts. Moran's I = 0.29*

The numerous figures provided in the study indicate a general pattern of low rates of foreclosures and high cost loans around downtown Madison and areas of higher foreclosures and high cost loans stretching from the eastern shores of Lake Mendota toward Sun Prairie. To provide some context of these patterns Table 3 differentiates the characteristics of these two distinct areas of Dane County. The area around downtown Madison is predominantly high density student housing, government buildings, and the UW campus, while the eastern section represents newer areas of development trending to suburban development towards the northeast. In all facets, the characteristics of the eastern areas relate to newer and more expensive homes with higher levels of foreclosure, numbers of high cost loans, housing values, and rates of unemployment. While these figures and tables show distinct spatial patterns of foreclosures and lending practices throughout the county, further analysis is needed to identify whether high-cost lending patterns from the 2004-06 period aids in our effort to explain observed clustering of foreclosures in 2011 and 2012 after controlling for other factors likely correlated with foreclosure.

High Foreclosure Areas - East Dane County	
High Cost Loans	11.5
Percent Mortgaged	75.88
Norm Foreclosures 2011	1.8
Norm Foreclosures 2012	1.9
Avg. Median House Value	$205,273
Percent Distressed	26.133
Percent Built 2000 - 2010	15.6
Avg. Commuter Time (mins.)	20.68
Percent Unemployment 2010	4.6
Low Foreclosure Area - Central Dane County	
High Cost Loans	2.5
Percent Mortgaged	58.91
Norm Foreclosures 2011	0.476
Norm Foreclosures 2012	0.489
Avg. Median House Value	$148,733
Percent Distressed	24.66
Percent Built 2000 - 2010	10.66
Avg. Commuter Time (mins.)	17.51
Percent Unemployment 2010	3.5

Table 3 *General characteristics of tracts with high and low numbers of foreclosures and high cost loans in Dane County*

Spatial Regression Analysis of Contributing Factors of Dane County Foreclosures

Traditional regression analysis provides evidence for the influence of independent variables on a dependent variable. The validity of statistical hypothesis tests is contingent on the premise that data are from a random and sampling errors are based on a normal distribution. Due to the spatial clustering of foreclosure data as identified above in Figures 6 and 7, results are neither random nor fit a normal distribution. Explaining this, Waldo Tobler created the “First

Law of Geography," which states, "Everything is related to everything else, but near things are more related than distant things" (Tobler 1970, 236). Cliff and Ord (1969) believed that "the special case of correlation in space, when there is a relationship between nearby spatial units of the same variable, needed to be identified if research questions were to be answered accurately" (Getis 2007, 492). Cliff and Ord realized this could be a problem in the analysis of data that are spatially autocorrelated. Getis explains, "They recognized what is known as the misspecification problem in spatial analysis, that is, models that required traditional statistics for their evaluation were misspecified if spatial autocorrelation was not taken into account when data were georeferenced. To this day, many economists are unaware that for an OLS model to be properly specified, residuals must be spatially independent in the mapped region of study" (Getis 2007, 493). Simply, OLS models that use spatially autocorrelated data tend to overestimate the impacts of explanatory variables on the dependent variables (Ward and Gleditsch 2008).

As indicated in the above section, Moran's I was used as a measurement of spatial autocorrelation. Due the moderate level of spatial autocorrelation detected by the Moran's I for foreclosures and high cost loans in 2011 and 2012, a spatial regression can be run to avoid the situation explained by Getis (2007). In this study, the Moran's I indicates that statistically, foreclosures rates per census tract are affected by foreclosure rates of nearby census tracts. Therefore traditional OLS cannot differentiate spatial autocorrelation of the residuals, but a spatial regression model should account for the spatial dependencies making the residuals of the spatial regression models not autocorrelated (Brusilovskiy 2014).

For this report the spatial regression model used in called the Maximum Likelihood Spatial Lag Model. The Spatial Lag model provides a spatial weight to the dependent variable that can be used to "clean up" the results of the OLS analysis. A spatial lag of a specified variable is computed by taking the weighted average of surrounding polygons. For example: a census tract with three neighboring tracts that had ten, fifteen, and twenty percent blacks would have a spatial lag of fifteen percent. This creates a row-standardized spatial weights matrix that represents the average rate of each neighboring tract. Specifically, a 1st order rook continuity weight was selected for this analysis. Rook contiguity selects weights for polygons only with common borders to define adjacency. Rook continuity accounts for all neighbors (Anselin 2005).

A multivariate spatial regression (spatial lag) framework provides an opportunity to estimate foreclosure sales, measured per 100 mortgaged homes, across Dane County census tracts while accounting for the impact of various factors. Due to the presence of spatial autocorrelation, the spatial lag approach will be contrasted with an ordinary least squares (OLS) approach. The subtle difference between the two equations is the presence of a spatial weight ($W\beta_0$). These methods will then be employed to estimate the rate of foreclosure sales across Dane County census tracts for 2011 and 2012 (separately) using two different equation specifications. As baseline models, Equations 1 and 2, reflect key factors of foreclosures, including financial hardship and the change in non-white populations.

$$\begin{matrix} OLS \\ Foreclosures_i \end{matrix} = \beta_0 + \beta_1 Distress_i + \beta_2 Unemp_i + \beta_3 NWPop_i + \beta_4 Commute_i + \varepsilon_i \quad (1)$$

$$\begin{matrix} Spatial\ Lag \\ Foreclosures_i \end{matrix} = W\beta_0 + \beta_0 + \beta_1 Distress_i + \beta_2 Unemp_i + \beta_3 NWPop_i + \beta_4 Commute_i + \varepsilon_i \quad (2)$$

As highlighted in Been et al. (2011), unemployment may lead to difficulty making monthly mortgage payments, increasing the risk of default; therefore, higher rates of foreclosure in 2011 and 2012 are expected in census tracts with a relatively high unemployment rate as of 2010 (*Unemp*). Because unemployment isn't the only source of hardship, a broader measure of financial distress, defined as the fraction of mortgaged households with monthly housing costs exceeding 35 percent of monthly income (*Distress*), is also accounted for at the census tract level. A desire for affordable housing and a search for cheaper land lead some residents to relocate further away from the city center, contributing to increased suburbanization and commute times (Glaeser and Kahn 2001). The increase in Dane County's population observed over the past decade has been bolstered by growth in the suburban areas, and as populations spread outside of the central city, which, in the case of Madison, includes state government and a major research university, commute times for many surrounding census tracts now exceed nineteen minutes (Census Bureau). Therefore, suburban areas with higher values of *Commute*, measured in minutes, are expected to have relatively higher rates of foreclosure with the commute time acting as a proxy for suburbanization.

The second specification, Equations 3 and 4, includes the same list of explanatory variables with the addition of *High Cost* as a proxy for subprime lending activity (measured per 100 mortgaged homes), motivated by the relatively high incidence of default and foreclosure among subprime borrowers, especially for loans originated during the height of the recent housing boom.

$$\underset{Foreclosures_i}{OLS} = \beta_0 + \beta_1 Distress_i + \beta_2 Unemp_i + \beta_3 NWPop_i$$

$$+\beta_4 Commute_i + \beta_5 HighCost_i + \varepsilon_i \qquad (3)$$

$$\underset{Foreclosures_i}{Spatial\ Lag} = W\beta_0 + \beta_0 + \beta_1 Distress_i + \beta_2 Unemp_i + \beta_3 NWPop_i$$

$$+\beta_4 Commute_i + \beta_5 HighCost_i + \varepsilon_i \quad (4)$$

Home Mortgage Disclosure Act (HMDA) standards determine which loans originated during the 2004-2006 period are deemed “high cost” mortgage loans, and the intention of identifying a mortgage loan as “high cost” is to identify loans that are likely to be subprime (Federal Financial Institutions Examination Council 2005). A higher interest rate is charged on loans when the perceived risk of repayment is higher, and as a result, an area that has a relatively higher share of high cost loans is expected to experience a higher number of foreclosures. It is anticipated that the addition of this variable will also improve the statistical fit of the estimated regression and, given the disproportionate share of subprime lending directed at minority borrowers, alter the estimated slope coefficient of the variable measuring the change in the minority share of population (*NWPop*).

Foreclosures Results

Table 3 displays the estimation results for Equations 1 - 4 for each of the two years included in this study. For the baseline specification, Equation 1, the signs of the estimated slope coefficients conform to expectations, and three of the four explanatory variables are statistically significant at conventional levels for the purposes of explaining both the 2011 and 2012 foreclosure rates for the Dane County census tracts. The foreclosure process itself is lengthy, especially when foreclosures are processed through the judicial system, as they are in Wisconsin; according to the Dane County Housing Authority, the foreclosure process is estimated to take between 11 and 18 months from the time of the initial foreclosure filing.

As Figure 4 and 5 indicate a moderate level of spatial autocorrelation for foreclosures in 2011 and 2012, the spatial lag model will test the impacts of spatial autocorrelation on these variables. As Ward and Gleditsch (2008) indicated, explanatory variables in OLS models tend to be overestimated when spatial autocorrelation is present. This is the case for both 2011 and 2012 models indicated in Table 4. In all cases there were slight decreases in the B values of the significant variables. For example the percent change in nonwhite population in 2011 decreased to 0.047 in the Equation 2 from 0.053 in OLS model in Equation 1. Simply put, Equation 2 shows that the statistically significant variables co-vary with changes in foreclosure sales among its geographical neighbors.

Further interpretation of the results in Table 4 indicate that the Spatial Lag model has slightly improved the output. While R-squared values are imperative in OLS models, in spatial models, due the spatial nature of the date, the validity of the R-square produced cannot be tested. Conversely, the R-squared is not a true test of spatial regression robustness (Anselin 2005). Therefore the R-square equivalent in a spatial lag model is called a pseudo R-squared. Anselin (2005) indicates the proper measures of fit in the spatial lag model are the Log-Likelihood, the Akaike Information Criterion, and the Schwarz Criterion. Anselin continues, "These three measures are based on the assumption of multivariate normality and the corresponding likelihood function for the standard regression model. The higher the log-likelihood, the better the fit. For the information criteria, the direction is opposite, and the lower the measure, the better the fit" (2005, 175).

As Table 4 illustrates the pseudo R-squared value has increased from the R-squared value of the OLS model for Equations 1 and 2. Beyond improvements in the R^2, increases in the log likelihood and decreases in the Akaike and Schwarz Criterion all indicate improvements and the robustness of a spatial lag model compared to the OLS model. The log likelihood increased -

115.064 to -110.97, the Akaike Criterion decreased from 240.128 to 233.94, and the Schwarz Criterion decreased from 253.398 to 249.864.

	2011 Foreclosures Sales (per 100 mortgage homes)			
	Equation 1		**Equation 2**	
	B	Std Error	B	Std Error
(Constant)	*-1.259*	*0.557*	*-1.26*	*0.52*
(Spatial Weight)			*0.324*	*0.118*
Distress	*0.014*	*0.006*	*0.014*	*0.006*
Unemp	-0.044	0.036	-0.061	0.04
NWPop	***0.053***	***0.011***	***0.047***	***0.11***
Commute	***0.09***	***0.025***	***0.07***	***0.024***
R^2	0.278		0.346	
df	100		99	
Log Likelihood	-115.064		-110.97	
Akaike Cri.	240.128		233.94	
Schwarz Cri.	253.398		249.864	

	2012 Foreclosures Sales (per 100 mortgage homes)

	Equation 1		Equation 2	
	B	Std Error	B	Std Error
(Constant)	-1..06	0.59	*-1.142*	*0.551*
(Spatial Weight)			***0.337***	***0.117***
Distress	*0.015*	*0.007*	*0.015*	*0.006*
Unemp	0.042	0.04	0.016	0.036
NWPop	***0.036***	***0.012***	***0.032***	***0.011***
Commute	***0.09***	***0.027***	***0.073***	***0.006***
R^2	0.24		0.318	
df	100		99	
Log Likelihood	-121.973		-117.611	
Akaike Cri.	253.945		247.222	
Schwarz Cri.	267.215		263.146	

	2011 Foreclosure Sales (per 100 mortgaged homes)			
	Equation 3		**Equation 4**	
	B	Std Error	B	Std Error
(Constant)	-0.31	0.467	-0.327	0.458
(Spatial Weight)			0.033	0.119
Distress	0.004	0.005	0.004	0.005

Unemp	-0.062	0.029	-0.06	0.028
NWPop	***0.028***	***0.009***	***0.028***	***0.009***
Commute	0.025	0.02	0.025	0.022
HighCost	***0.119***	***0.016***	***0.116***	***0.017***
R^2	0.536		0.537	
df	99		98	
Log Likelihood	-91.789		-91.744	
Akaike Cri.	195.579		197.488	
Schwarz Ch.	211.502		216.066	

	2012 Foreclosure Sales (per 100 mortgaged homes)			
	Equation 3		**Equation 4**	
	B	Std Error	B	Std Error
(Constant)	-0.23	0.54	-0.304	0.53
(Spatial Weight)			0.076	0.125
Distress	0.006	.006	0.007	0.006
Unemp	0.027	0.034	0.022	0.033
NWPop	0.015	0.011	0.015	0.011
Commute	0.029	0.027	0.029	0.026
HighCost	***0.104***	***0.02***	***0.097***	***0.02***
R^2	0.423		0.43	

df	99	98
Log Likelihood	-107.572	-107.383
Akaike Cri.	227.143	228.765
Schwarz Ch.	243.067	247.343

Note: Italicized coefficients are significant at the 5 percent level; coefficients in bold and italics are significant at the 1 percent level.

Table 4 *Regression Results*

The baseline specification explains just over one-fourth of the variation in foreclosure sales in 2011 (27.8 percent), but the overall fit improves to over 53 percent once the high-cost loan variable is introduced. Qualitatively speaking, the impact is similar for 2012 foreclosure sales; Equation 3 provides a better statistical fit relative to Equation 4 with an R^2 of 0.423 vs. 0.24. Furthermore, the share of high-cost lending has a positive and statistically significant relationship with the dependent variable even after controlling for the fraction of households in financial distress, local economic conditions, and the change in the minority share of the population – a result that is consistent with expectations and supports the inclusion of this proxy variable for the purpose of explaining the observed variation in foreclosure rates across census tracts.

The importance of accounting for mortgage lending patterns is further reinforced by comparing the spatial patterns of high cost lending with foreclosures. With a Moran's *I* of 0.52, Figure 8 illustrates the spatial clustering of high cost loans throughout the study area. Similar to the patterns seen with foreclosures in Figures 4 and 5 there is a greater clustering of high cost lending in the tracts east of downtown Madison and lower to the west.

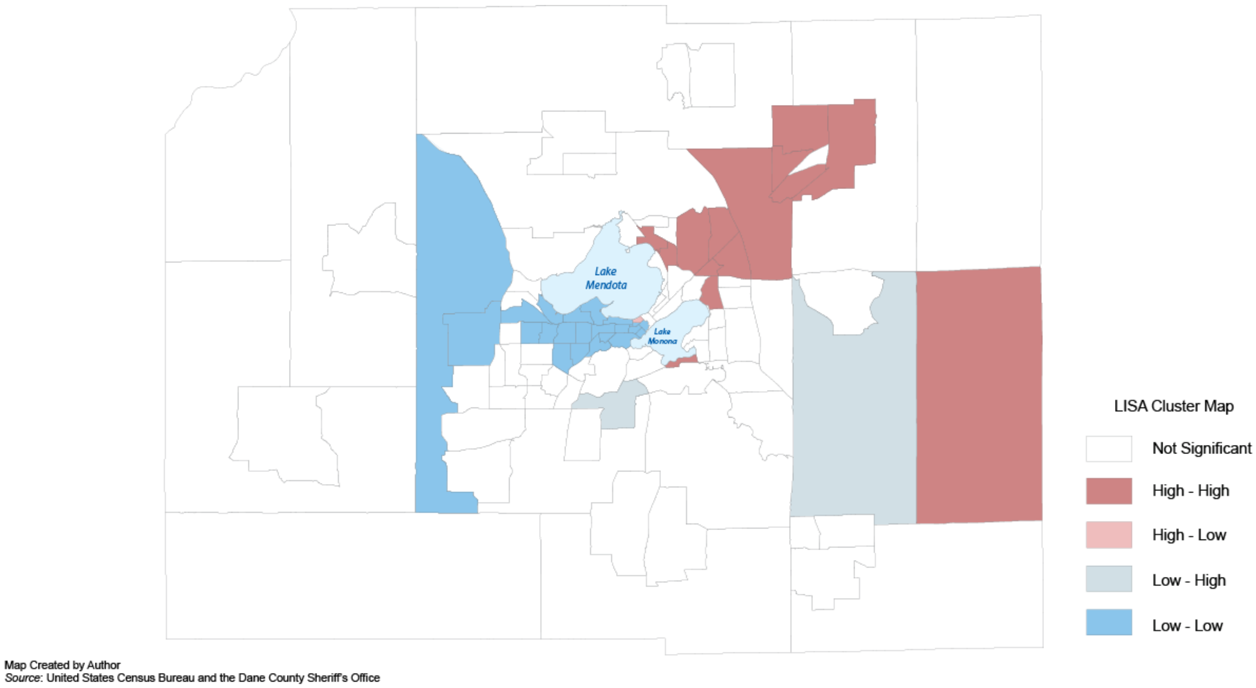


Figure 8 *LISA map of the number of High Cost Loans per 100 mortgaged homes for 2010 Dane County Census Tracts. Moran's I = 0.52*

Bivariate spatial autocorrelation assesses ". . . the extent to which the value at a location for the x-variable is correlated with the weighted average of another variable, with the average computed over the neighboring locations" (Anselin 2005, 157). Calculating a bivariate Moran's *I* between high cost loans and foreclosures yields a value of 0.398 for 2011 and 0.419 in 2012. Figures 9 and 10 are the LISA outputs indicating the areas of eastern Dane County having high levels of both foreclosures and high cost loans, while the areas around downtown and to the west have lower levels of both. Together the spatial statistics and regression results support the notion that areas throughout Dane County with elevated numbers of high cost loans corresponds to higher rates of foreclosure.

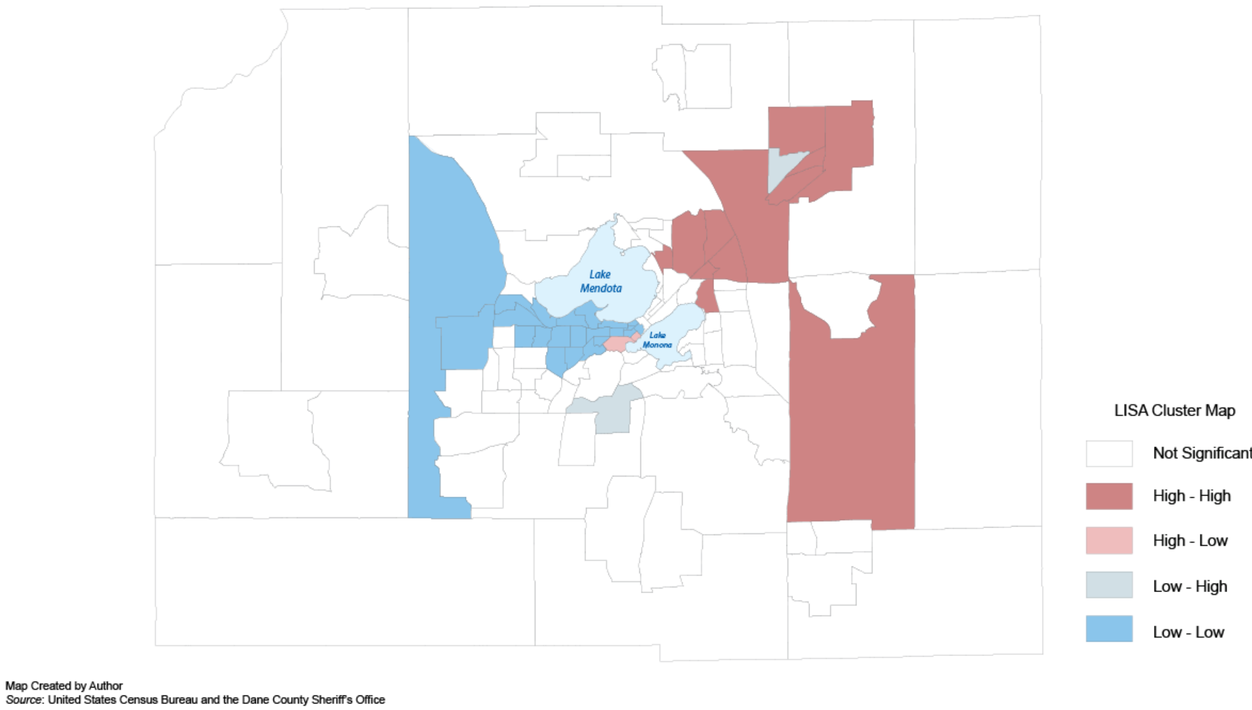


Figure 9 *2011 Bivariate LISA map of the number of High Cost Loans per 100 mortgaged homes and the Foreclosures per 100 mortgaged homes for 2010 Dane County Census Tracts. Moran's I = 0.398*

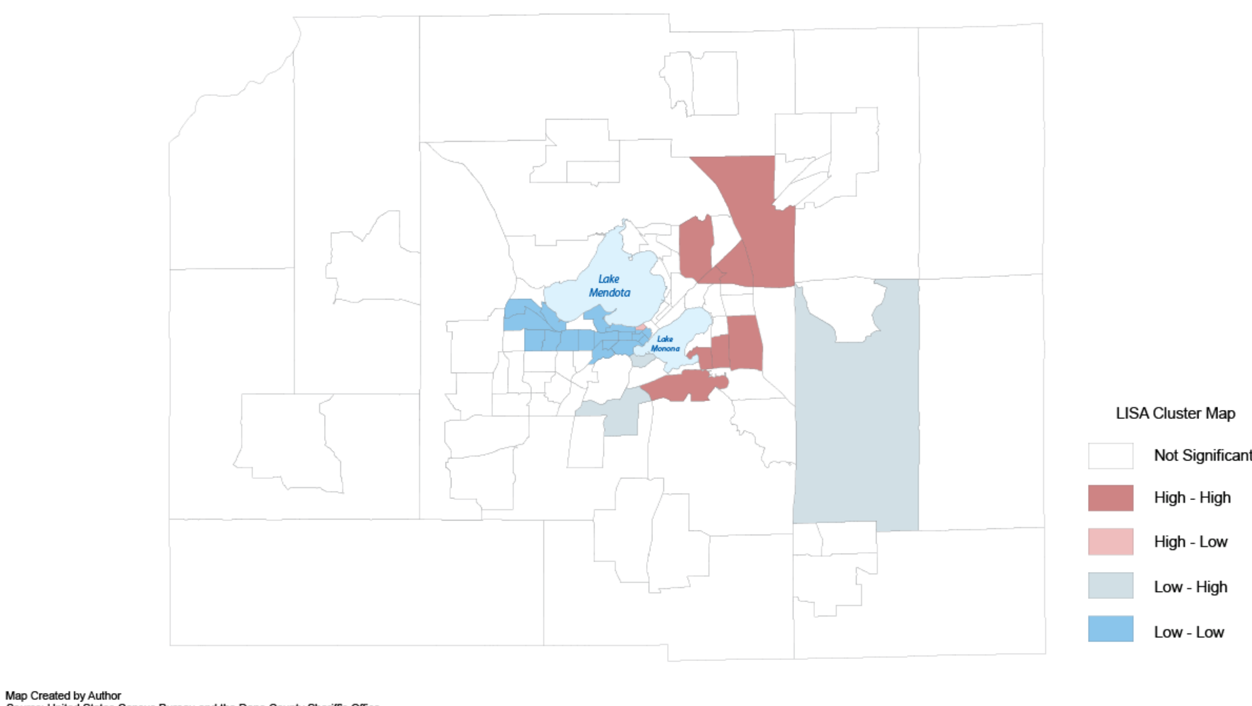


Figure 10 *2012 Bivariate LISA map of the number of High Cost Loans per 100 mortgaged homes and the Foreclosures per 100 mortgaged homes for 2010 Dane County Census Tracts. Moran's I = 0.419*

Some collinearity among the independent variables is expected when real world data is used. The multicollinearity condition numbers for the regressions with and without the *HighCost* variable, 25.80 and 21.20, respectively, suggest that severe multicollinearity is not likely to be an issue since the values are less than 30. Sample correlation coefficients indicate positive correlations between the *HighCost* variable and each of the remaining explanatory factors, consistent with expectations. The sample correlations, ranging from 0.28 for *HighCost* with *Distress* to 0.41 with *Unemp*, help to explain why the introduction of *HighCost* in Equations 3 and 4 affects the statistical significance of *Distress*, for example, for explaining variation in 2012 foreclosure sales. Also, the estimated impact of a one-unit change in *NWPop* on the foreclosure rate is reduced when the proxy for subprime lending is included in all regression equations, an outcome consistent with existing studies. Immergluck and Smith (2005), for example, observe a decrease in the magnitude and statistical significance of the estimated coefficients on a number of demographic variables after controlling for the volume and type of lending. Similar to findings from Kaplan and Sommers (2009), the results do indicate a positive relationship between foreclosure rates observed in 2011 and a measure of non-white populations, even after accounting for variation in high cost lending across census tracts; however, Grover, Smith, and Todd (2008) demonstrate that the use of a proxy for credit risk, when it is an imperfect substitute for actual credit score information, will exaggerate the estimated relationship between foreclosure risk and the minority share of the population.

Analytical Challenges

Spatial and multivariate analyses of Dane County foreclosure sales occurring in 2011 and 2012 both indicate the importance of accounting for mortgage lending patterns during the height of the recent housing boom. More specifically, Dane County census tracts exhibiting elevated foreclosure activity in recent years also, generally speaking, tend to be the recipients of a disproportionate share of risky, high cost mortgage loans during the 2004-2006 period; furthermore, the inclusion of a proxy for subprime lending activity explains a significant amount of variation in foreclosure sales observed across tracts even after accounting for other socioeconomic factors. This is clear in spatial patterning between the eastern tracts of the county and central areas around downtown Madison.

The spatial patterning of foreclosures and the regression results obtained from this study are consistent with other empirical studies of foreclosure conducted for other geographies. More specifically, empirical evidence in support of the hypothesis that a greater occurrence of high cost lending is associated with higher foreclosure rates is also presented for census tracts in the Tenth Federal Reserve District, census block group level in Southern Florida, and counties in Indiana and Ohio (Edmiston, 2009; Li 2011; Yilmazer, Babiarz, and Kiss, 2012). The results for Dane County, Wisconsin, presented in this study are an important addition to this list because the empirical results suggest that mortgage lending practices from the previous decade, 2004-2006, still influence trends in foreclosure rates observed years later, in 2011 and 2012. Both Edmiston (2009) and Yilmazer, Babiarz, and Kiss (2012) discuss the importance of accounting for high cost, or subprime, lending from the years leading up to the crisis but this is in the context of foreclosures that occurred in 2008. The analysis presented by Li (2011) focuses on foreclosures from the 1997-2004 period; as a result, the data does span two census periods, 1990 and 2000, but the area of study was not subject to any boundary changes and the MAUP issue is averted.

The inclusion of the proxy for subprime lending is motivated by findings from existing empirical studies of mortgage default and foreclosure following the recent crisis; however, the desire to include this particular variable in this study of 2011 and 2012 foreclosures leads to a major issue resulting from the changing shape of areal units over time. The LTDB provides an opportunity to consider the high cost loan information, originally matched to the 2000 tract boundaries, alongside other variables that correspond to 2010 tract boundaries. The lagging nature of foreclosures and availability of free data motivated this study. Furthermore, the spatial clustering of foreclosure activities, as indicated by the Moran's I, was better understood and improved upon through the use of a spatial regression model. Therefore the methods included in this analysis and the empirical results suggest that the practical benefits of the LTDB process are significant and offer a means to overcome the problem of longitudinal boundary change that has long hampered temporal analysis of Census-derived data.

References

Allen, R. (2011). Who experiences foreclosures? The characteristics of households experiencing a foreclosure in Minneapolis, Minnesota. *Housing Studies,* 26(6), 845-66.

Anselin, L. (2005). *Exploring Spatial Data with GeoDa: A Workbook*. Urbana-Champaign: Spatial Analysis Laboratory, Department of Geography, University of Illinois.

Avery, R. B., Bostic, R. W., Calem, P.S., & Canner, G. B. (1997). Changes in the distribution of banking offices. *Federal Reserve Bulletin,* 83, 707-25.

Baxter, V., & Lauria, M. (2000). Residential mortgage foreclosure and neighborhood change. *Housing Policy Debate,* 11(3), 675-99.

Bean, Frank D., Bachmeir, James D., Brown, Susan K., & Van Hook , Jennifer, and Leach, Mark A. (2013.) Unauthorized Mexican Migration and the Socicoeconomic Integration of Mexican Americans. In J.R. Logan (Ed.), *Changing Times: American in a New Century.* New York: Russell Sage Foundation, *forthcoming*.

Been, V., Chan, S., Ellen, I. G., & Madar, J. R.. (2011). Decoding the foreclosure crisis: Causes, responses, and consequences. *Journal of Policy Analysis and Management,* 30(2), 388-96.

Brusilovskiy, Eugene. (2014). Spatial Regression: A Brief Introduction. Retrieved January 4, 2014, from http://www.bisolutions.us/A-Brief-Introduction-to-Spatial-Regression.php.

Calem, P. S., Gillen , K., & Wachter,S. (2004). Neighborhood distribution of subprime mortgage lending. *Journal of Real Estate Finance and Economics,* 29(4), 393-410.

Can, A. (1998). GIS and spatial analysis of housing and mortgage markets. *Journal of Housing Research,* 9(1), 61-86.

Chan, S., Gedal, M., Been, V., & Haugwout, A. (2010). The Role of Neighborhood Characteristics in Mortgage Default Risk: Evidence from New York City. Working Paper, NYU Wagner Schools and Furman Center for Real Estate and Urban Policy.

Clauretie, T. M. (1987). The impact of interstate foreclosure cost differences and the value of mortgages on default rates. *AREUEA Journal,* 15(3), 152-67.

Clauretie, T. M., & Daneshvary, N. (2009). Estimating the house foreclosure discount corrected for spatial price interdependence and endogeneity of marketing time. *Real Estate Economics,* 37(1), 43-67.

Cliff, A. D., & Ord, J. K. (1969). The problem of spatial autocorrelation. In A.J. Scott (Ed.), *Papers in Regional Science*, *Studies in Regional Science* (pp. 22-55). London: Pion.

Crump, J. 2007. Subprime lending and foreclosure in Hennepin and Ramsey Counties. *CURA Reporter* 37(2): 14-18.

Dane County Housing Authority (2008). Foreclosure Timeline for Wisconsin (Homestead Property). Retrieved July 8, 2013, from http://www.dcha.net/housingcenter/docs/foreclosure-timeline.pdf.

Dane County Sheriff's Office (DSCO). (2013). Foreclosure *Sales.* Retrieved January 31, 2013, from http://www.danesheriff.com/foreclosure_sales_search.aspx.

Dark, S. J., & Bram, D. (2007). The Modifiable Areal Unit Problem (MAUP) in Physical Geography. *Progress in Physical Geography,* 31(5), 471-79.

Davis, M. W. (2012). *The Modifiable Areal Unit Problem (MAUP) Via Cluster Analysis Methodologies: A Look at Scale, Zoning, and Instances of Foreclosure in Los Angeles County* (Master's thesis). Retrieved from University of Southern California Digital Library.

Demyanyk, Y. (2009). Quick exits of subprime mortgages. Federal Reserve Bank of St. Louis *Review,* 91(2), 79-93.

Demyanyk, Y., & Van Hemert, O. (2011). Understanding the subprime mortgage crisis. *The Review of Financial Studies,* 24(6), 1848-80.

Edmiston, K. (2009). Characteristics of high-foreclosure neighborhoods in the Tenth District. *Economic Review,* Second Quarter, 51-75

Federal Financial Institutions Examination Council (2005). Frequently asked questions about the new HMDA data: The new price data. Retrieved February 29, 2013, from, http://www.federalreserve.gov/boarddocs/press/bcreg/2005/20050331/attachment.pdf

Foote, C. L., Gerardi, K., & Willen, P. S. (2008). Negative equity and foreclosure: Theory and evidence. *Journal of Urban Economics,* 64(2), 234-45.

Furlong, F., & Krainer, J. (2007). The subprime mortgage market: National and Twelfth District developments. *Annual Report*, Federal Reserve Bank of San Francisco, 6-17.

Gabriel, S. A., & Painter, G. (2008). Mobility, residential location, and the American dream: The intrametropolitan geography of minority homeownership. *Real Estate Economics,* 36(3), 499-531.

Gerardi, K., Shapiro, A. H., & Willen, P. S. (2009). *Decomposing the foreclosure crisis: House price depreciation versus bad underwriting* (Federal Reserve Bank of Atlanta Working Paper. Working Paper No. 2009-25). Retrieved May 4, 2013, from http://www.frbatlanta.org/filelegacydocs/wp0925.pdf.

Glaeser, E. L., & Kahn, M. E. (2001). Decentralized employment and the transformation of the American city. *Brookings-Wharton Papers on Urban Affairs*, 1-63.

Getis, A. (2007). Reflections on spatial autocorrelation. *Regional Science and Urban Economics,* 37(4), 491-96.

Grover, M., Smith, L., & Todd, R. M. (2008). Targeting foreclosure interventions: An analysis of neighborhood characteristics associated with high foreclosure rates in two Minnesota counties. *Journal of Economics and Business,* 60, 91-109.

Hiller, A. (2005). Searching for red lines: Spatial analysis of lending patterns in Philadelphia, 1940-1960. *Pennsylvania History,* 72(1), 25-47.

Holzer, H. J., & Hlavac, M. (2012). A very uneven road: U.S. labor markets in the past 30 years. In J.R. Logan (Ed.), *Changing Times: American in a New Century.* New York: Russell Sage Foundation, *forthcoming*.

Immergluck, D., & Smith, G. (2005). Measuring the effect of subprime lending on neighborhood foreclosures: Evidence from Chicago. *Urban Affairs Review,* 40(3), 362-89.

Inside Mortgage Finance. (2007). Mortgage Market Statistical Annual. Bethesda, MD: Inside Mortgage Finance Publications.

Kaplan, D. H., & Sommers, G. G. (2009). An analysis of the relationship between housing foreclosures, lending practices, and neighborhood ecology: Evidence from a distressed county. *The Professional Geographer,* 61(1), 101-20.

Kashian, R. & D. M. Welsch. (2010). A regional examination of foreclosures in Wisconsin. *The Industrial Geographer,* 7(1), 19-38.

Krainer, J., & Laderman, E. (2011). *Prepayment and delinquency in the mortgage crisis period*. (Federal Reserve Bank of San Francisco Working Paper. Working Paper No. 2011-2025). Federal Reserve Bank of San Francisco. Retrieved May 8, 2013, from http://www.frbsf.org/economic-research/files/wp11-25bk.pdf.

Lentz, J. (2009). *Global Statistics – Gettis-Ord General G*. Retrieved May 21, 2013, from http://www.sce.lsu.edu/cego/Documents/Reviews/Geospatial/Spatial_Autocorrelation.pdf.

Li, Y. (2011). Geography of opportunity and residential mortgage foreclosure: A spatial analysis of a U.S. housing market. *Journal of Urban and Regional Analysis,* 3(2), 195-214.

Lee, B. A., Iceland, J., & Sharp, G. (2012). Racial and ethnic diversity goes local: Charting change in American communities over three decades. *U.S. 2010 Project*, *Census Brief*. New York: Russell Sage Foundation. Retrieved June 11, 2013, from http://www.s4.brown.edu/us2010/Data/Report/report08292012.pdf.

Logan, J. R., Xu, Z., & Stults, B. (2012). Interpolating U.S. Decennial Census tract data from as early as 1970 to 2010: A longitudinal tract database. Professional Geographer, forthcoming.

Massey, D. S., & Denton, N. A. (1988). Suburbanization and segregation in U.S. metropolitan areas. *American Journal of Sociology,* 94(3), 592-626.

Mayer, C., & Pence, K. (2009). Subprime mortgages: what, where, and to whom? In E. Glaeser & J. Quigley (Eds.), *Housing Markets and the Economy: Risk, Regulation, and Policy: Essays in Honor of Karl E. Case,* (pp. 149 – 196). Cambridge, MA: Lincoln Institute of Land Policy.

Mayer, C., Pence, K., & Sherlund, S. M. (2009). The rise in mortgage defaults. *Journal of Economic Perspectives,* 23(1), 27-50.

Min, N. (2012). *The Effect of Foreclosure on Vacancy at the Neighborhood Level* (Master's thesis). Retrieved from Georgia Institute of Technology.

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, 37, 17-33.

Openshaw, S. (1984). The modifiable areal unit problem. *Concepts and Techniques in Modern Geography,* 38, 1-40.

Openshaw S., & Taylor, P. 1979. A million or so correlation coefficients: Three experiments on the modifiable area unit problem. In N. Wrigley (Ed.), *Statistical Applications in the Spatial Sciences*, (pp. 127 – 144). London: Pion.

Perkins, K. L. (2009). The geography of foreclosure in Contra Costa County, California. (Community Development Investment Center, Federal Reserve Bank of San Francisco Working Paper. Working Paper No. 2009-2003). Federal Reserve Bank of San Francisco. Retrieved May 10, 2013, from http://www.frbsf.org/publications/community/wpapers/2009/wp2009-03.pdf.

Reardon, S. F., & Bishchoff, K. (2013). Growth in the residential segregation of families by income, 1970-2009. *U.S. 2010 Project*, *Census Brief.* New York: Russell Sage Foundation. Retrieved May 22, 2013, from http://www.s4.brown.edu/us2010/Data/Report/report111111.pdf.

Rogers, W. H., & Winter, W. (2009). The impact of foreclosures on neighboring housing sales. *Journal of Real Estate Research* 31(4), 455-79.

Rosenbaum, E. (2012). Home ownership's wild ride, 2001-2011. *U.S. 2010 Project*, *Census Brief.* New York: Russell Sage Foundation. Retrieved March 18, 2013, from http://www.s4.brown.edu/us2010/Data/Report/report03212012.pdf.

Schafran, A., & Wegmann, J. (2012). Restructuring, race, and real estate: Changing home values and the new California metropolis, 1989-2010. *Urban Geography,* 33(5), 630-54.

Schinter, L., & Istrate, E. (2011). Tracking the housing bubble across metropolitan areas – A spatio-temporal comparison of house price indices. *Cityscape,* 13(1), 165-82.

Schintler, L., Istrate, E., Pelletiere, D., and Kulkarni, R. (2010). The spatial aspects of the foreclosure crisis: A look at the New England region. GMU School of Public Policy Research Paper No. 2010-28.

Schloemer, E., Li, W., Ernst, K., & Keest, K. (2006). *Losing ground: Foreclosures in the subprime market and their cost to homeowners*. Durham, NC: Center for Responsible Lending.

Tobler, Waldo. R. (1970). "A computer movie simulating urban growth in the Detroit region". *Economic Geography*. 46 no. 2 (1970): 234 – 240.

University of Wisconsin Cooperative Extension. (2012). *Wisconsin Housing and Foreclosure Data: 2000-2011 Annual Foreclosure Data by County*. Retrieved February 26, 2013, from http://fyi.uwex.edu/housing/2012/05/02/2000-2011-annual-foreclosure-data-by-county/.

U.S. Bureau of Labor Statistics. (2013). *Local Area Unemployment Statistics: Counties and equivalents.* Retrieved March 5, 2013, from http://bls.gov/data/#unemployment.

U.S. Census Bureau. (2000). *Census 2000, Summary File 1 (Census Tracts): QT-PC. Race and Hispanic or Latino*. Retrieved February 26, 2013, from http://factfinder2.census.gov.

U.S. Census Bureau. (2010). *Census 2010, Summary File 1 (Census Tracts): QT-P3. Hispanic or Latino by Type*. Retrieved February 26, 2013, from http://factfinder2.census.gov.

U.S. Census Bureau. (2010). *Census 2010, ACS 5 Year Estimates (Census Tracts): DP03. Selected Economic Characteristics*. Retrieved February 26, 2013, from http://factfinder2.census.gov.

U.S. Census Bureau. (2010). *Census 2010, ACS 5 Year Estimates (Census Tracts): DP04. Selected Housing Characteristics*. Retrieved February 26, 2013, from http://factfinder2.census.gov.

U.S. Department of Housing and Urban Development. (2008). U.S. Housing Market Conditions, 2nd quarter, 1-13.

U.S. Department of Housing and Urban Development. (2008). *Neighborhood Stabilization Data, NSP1: Neighborhood Level Foreclosure Data: Wisconsin.* Retrieved February 29, 2013 from http://www.huduser.org/portal/datasets/nsp/nsp_fc_u-z.html.

Vesselinov, E., & Beveridge, A. (2008). Avenue to wealth and road to financial ruin? Homeownership and the racial distribution of mortgage foreclosures. In C. Niedt and M. Silver (Eds.), *Forging a New Housing Policy: Opportunity in the Wake of Crisis* (pp. 45-55). Hempstead, NY: National Center of Suburban Studies.

Ward, Micahel D. and Kristian Skrede Gleditsch. (2008). Spatial *Regression Models.* Los Angeles: Sage Publications.

Wilcox, J. A. (2009). Underwriting, mortgage lending, and house prices: 1996-2008. *Business Economics*, 44,189-200.

Wisconsin Realtors' Association. (2013). *Wisconsin Housing Statistics.* Retrieved February 7, 2013, from https://www.wra.org/Resources/Property/Wisconsin_Housing_Statistics/.

Yilmazer, T., Babiarz, P., & Kiss, D. E. (2012). The role of lending practices on the foreclosure crisis: Evidence from Indiana and Ohio. *Family and Consumer Sciences Research Journal* 40(4), 398-416.