A Regional Examination of Foreclosures

By

Russ Kashian and David Welsch

Working Paper 08 - 04

University of Wisconsin – Whitewater
Department of Economics
4th Floor Carlson Hall
800 W. Main Street
Whitewater, WI 53538

Tel: (262) 472 -1361

A Regional Examination of Foreclosures

Russ Kashian
Department of Economics
University of Wisconsin – Whitewater
kashianr@uww.edu

David M. Welsch
Department of Economics
University of Wisconsin – Whitewater
welschd@uww.edu

August 2008

Foreclosures, causes and remedies, are being discussed and fiercely debated across our nation. Although there has been some examination of the causes of foreclosures, the current research has devoted its attention to examining what factors change the probability that an individual will go into foreclosure. By examining Wisconsin counties over eight years this paper makes a major contribution to the literature by taking a regional approach to examining the causes of foreclosures. This regional approach has greater policy applications since policy is often based on regional not individual factors. Several empirical models are estimated and there are consistent results that greater unemployment, a lower median age, larger families in rental units, and a smaller percentage of Asian or Native Americans leads to more foreclosures in a county. There is also evidence that education seems to affect foreclosures in a non-monotonic way; higher percentage of the population with a high school degree vs. non high school graduates increases foreclosures, but there is a negative impact or no significant difference between bachelors degree and no high school degree.

JEL Classification Codes: R100, R330
Key Words: Foreclosures, Regional Economics, Housing, Spatial Econometrics

Contact Author's Information:
Russ Kashian
Department of Economics
University of Wisconsin-Whitewater
Carlson Hall
Whitewater, WI 53190
kashianr@uww.edu

1. Introduction

Foreclosures in general and the causes and remedies of foreclosures in particular are currently being widely discussed. Most of the research to this point has examined the causes of foreclosures at the individual level, examining what affects an individual's probability of going into foreclosure; there are few, if any, papers that examine foreclosures at a regional level. This papers examines an eight year panel of Wisconsin counties. A regional approach to foreclosures expands beyond the current literature; it offers a view to policymakers and analysts regarding those regions in need and how to address the need. Thus this paper takes a different approach, with possibly greater policy applications, of foreclosure analysis than the historic research on mortgage foreclosure that evaluated what causes individuals to go into foreclosure.

As if in concert with the rise in homeownership (Myers, et. al 2003 and Borjas, 2002), the literature on mortgage foreclosures has been expanding over the past forty years. Theoretical models of mortgage default based on options analysis show when the equity in a home hits a certain negative point, the best option for the borrower is to default on that loan (see for example, Kau et. al 1994 and Capozza et. al 1998). Empirical models have been refined in response to insights from option pricing models, and option pricing models have been refined to introduce more realism.

While little of the empirical research analyzes the incidence of foreclosure in a county or on a regional basis, the historic literature provides a guide regarding the selection of variables. Many of the micro variables that have repeatedly been found to be significant in the probability of foreclosure are included in this analysis. One of the earliest papers on mortgage defaults (Jung, 1962) found that there was a relationship between the loan to value ratio and the interest rate. These two factors repeat themselves often in the literature. Much of this earlier literature is

covered in Quercia and Stegman (1992) and Vandell (1995). Foster and Van Order (1985) returns to Jung's original model and demonstrate that interest rates influence the borrower's decision to default. Williams et. al (1974) found that areas with a high unemployment rate also exhibit higher mortgage defaults rates. Campbell and Dietrich (1983) also add the regional unemployment rate to the equation. Miller and Peng (2006) extend this discussion by including MSA economic growth data in their analysis of default volatility. While loan to value appears quite often in the literature, the compounding issue of transaction costs is generally inconclusive (Kau et. al, 1993; Lekkas, et. al, 1993; Quigley and Van Order, 1995). However, notable issues were raised in these paper. Lekkas et. al found that homeowners wait until the values of their houses have dropped by 20 to 30 percent before defaulting. This may identify a lag between the loss of a job or a divorce and the ultimate default. As a result, Quigley and Van Order (1995) contend that the cost of trading a house is an important transaction cost.

Capozza et. al (1997) examine the effects of three mortgage default trigger events: unemployment, moving rates, and divorce. As unemployment increases, borrowers encounter ability-to-pay problems leading to higher default rates, as well as increases in moving rates and divorces. One valuable addition to the literature is their inclusion of a home rental cost divided by home price as a measure of the dividend or asset yield. It can also be considered an opportunity cost of owning. A negative relationship with default was found. Their overall conclusion is that if house prices are low, defaults will be high regardless of whether other events occur or not. This may be a reflection of the availability of rental housing and the cost of that housing.

Default produces two possible avenues: the borrower can cure the default or face foreclosure (Ambrose and Capone, 1998). Their paper reviews the determinants of foreclosure,

given default. These determinants include borrower characteristics, mortgage terms, and economic conditions. Lauria et. al (2004) expand this path by examining the variables that determine the time between default and foreclosure. One significant determinant is that the time between default and foreclosure for homes of borrowers who defaulted due to loss of job was significantly faster. In addition, Ambrose et. al (2001) found that the incidence of divorce influences the speed of mortgage defaults.

These issues are not entirely universal in the literature. Clapp (2001) found that current-loan-to-value ratios (CLTV) and borrower credit scores were the determinants of mortgage defaults. Danis and Pennington-Cross (2008) focused specifically on subprime lending and found that low credit scores and past delinquency rates significantly increased the likelihood of default by subprime borrowers. Pennington-Cross (2003) found that the greater the housing price volatility, the greater the probability of negative home equity and more severe mortgage foreclosure losses.

The large body of empirical mortgage studies repeatedly confirms that most defaults occur on loans with low down payments and in areas where house prices have been flat or fallen (see for example, Capozza et. al. 1997 or Ambrose and Deng 2001). Where low down payments intersect with a falling house price, a substantial number of borrowers may have negative equity and some of these borrowers will default on their mortgage. Mortgage default studies, while accepting the pivotal role of the importance of equity in the default decision, implicitly accept the starting loan to value ratio as determined by the initial down payment. However, little attention has been placed on the regional characteristics of the foreclosure process.

Mortgage defaults are important to the lending industry as well as to borrowers and investors. During the last few decades, research papers have focused increasingly on the pricing

of credit risk in the mortgage market. In order to lower their credit risk, lenders utilize such data-based research devoted exclusively to understanding the causes and consequences of mortgage default risk. While not eliminating the incidence of foreclosure, such research provides an opportunity to reduce the risk.

One early researcher (Von Furtstenberg, 1969; Von Furtstenberg, 1970a; Von Furtstenberg, 1970b; Von Furtstenberg, 1974) approached the examination of risk, quality and delinquency; much of his literature focused on individual microeconomic level data. However, the issue of location did arise in one article (Von Furtstenberg, 1974). In this article, a dummy variable was included to differentiate between properties located in Allegheny County and those outside the county.

In spite of this extensive research, mortgage foreclosures have risen throughout the 21st century in the State of Wisconsin. It is argued that, in the U.S., the large number of so called subprime mortgages utilized for home ownership of single-family housing has recently led to a high frequency of foreclosure, with big losses for borrowers and often also for lenders. The prediction is that this situation will continue to occur in the future. In the United States, data show that quite large regional differences in the risk-of-foreclosure exist for owner-occupied single-family housing. For instance, the number of foreclosures in percent of turnovers (in the period prior to the Subprime era) has been considerably lower in some parts of the United States than in other parts of the country during the whole period 1993-2006. This has occurred in spite of the lenders being aware of the larger risks of lending to some parts of the country. One would expect that a rational lending policy would result in more restrictive lending practices in such regions in order to diminish that region's risk-of foreclosures, such as giving a lower loan-to-value ratio.

Therefore, since there are regional differences in the rate of foreclosures, it would appear they have to be explained by local variables. The aim of this paper is to explain such differences. The current paper uses panel data from Wisconsin counties to examine the determinates of foreclosures. In Wisconsin, quite large differences in the foreclosures for single-family housing exist between counties. The aim of this paper is to explain such differences, using data on foreclosures for 71 Wisconsin Counties over eight years. This paper differs from the general option-based model. These micro based studies look at individual factors where the risk-of-foreclosure is a function of such things as housing prices and incomes, as well as market-wide housing density and housing price volatility. We modify this model by using regional variables in place of the micro data on the individual homes. The basic descriptive statistics indicate that some of the factors of the option-based model explanations of the variation in foreclosure rates are consistent on an aggregate level. Specifically, price level, income, and employment should explain some of the total regional variation. However, when the structural models are estimated some of these variables do not remain consistently significant. This analysis serves the public interest since government action and policy is often based on regional factors, not individual. Individuals suffering from distress are often awarded assistance through regional sources who have obtained this assistance based on the overall problem.

The remainder of the paper is as follows. The following section discusses the data along with a brief description of the overall characteristics. Section 3 discusses the empirical models and estimation procedures. Section 4 presents the results of estimations, and the final section discusses policy implications and offers concluding remarks.

2. Data

Foreclosures are widely discussed but rarely formally defined. This paper uses the traditional definition of foreclosures; a foreclosure is defined as the occurrence of a foreclosure filing. This court filing is a legal procedure in which a mortgagee (or a lien holder) attempts to obtain a court ordered termination of a mortgagor's equitable right of redemption. This redemption would occur as a delinquent borrower attempts to bring their delinquent account current.

We must take this one step further and adjust this foreclosure variable. Foreclosures must be adjusted because it is common that debtors, by the time they have arrived at a state of foreclosure, have acquired more than one mortgage, all of which may have the option or opportunity to foreclose. In addition, they may have delinquent property tax bills leading the government to foreclose. For example in Wisconsin one property was foreclosed on eight times in a given year. While this property may be facing two, three, or in rare cases even more legal actions, it is only one property. By reporting these, without correcting for the repeated foreclosure, the impact of the situation is overstated. In effect, only one property is at risk. Those properties foreclosed on multiple times in a single year have been corrected to reflect only one foreclosure. This leads to the use of what we will refer to (and use as a dependent variable in the rest of the paper) as "adjusted foreclosures".

Data are drawn from 71 counties in the state of Wisconsin over 8 years (2000-2007). Only one county from Wisconsin has been excluded due to their lack of participation in the statewide Circuit Court database. We will examine how the following county characteristics affect the adjusted foreclosure variable discussed above: the unemployment rate in the county, fair market rent (a proxy for home value)[1], the log of the number of housing units, the log of

[1] While rental properties and single family houses are not perfect substitutes, census data for fair market rent is used due to the unavailability of consistent county by county single family home value data throughout Wisconsin.

population density, the median age of the county, average household size of owner-occupied units, average household size of renter-occupied units, per capita income (lagged one period),[2] percentage of the population that is black, Native American, Asian, or other race (percentage white is the reference group for these four variables), percentage of the population that is Hispanic (non Hispanic is the reference group for this variable),[3] percentage of the population that has a high school degree but no four year degree, percentage of the population that has a Bachelor degree or higher (percentage of the population that did not obtain a high school degree is the reference group for the previous two groups), and fraction of the population that lives in an urban location (percentage of the population living in rural areas is the reference group).

The data come from several sources. Adjusted foreclosures come from Wisconsin Circuit Court Documents, unemployment rate from the United States Bureau of Labor Statistics, number of housing units from the Wisconsin Department of Administration, Demographic Servicers Center, Annual Housing Survey for Years following 2000 Census, per capita income from the Wisconsin Department of Workforce Development, and Population Density comes from Maponics.[4] The remaining variables come from the 2000 Census.

Table 1 shows that Wisconsin Counties have great variation in adjusted foreclosures and other county characteristics. The standard deviation of adjusted foreclosures is about twice the mean showing that there is a wide variation in adjusted foreclosures across counties/time. Table 2 reexamines the means and standard deviations of the independent variables, but it also divides

---

[2] We are forced to use per capita income lagged one period since data on income from 2007 was not yet available when we collected the data, but it probably does not change our results since if the models are rerun with the years 2000-2006 with current per capita income as an explanatory variable it does not drastically alter the results. These results are available from the authors.

[3] Note that Hispanic is from census data so the reference group is non-Hispanic. That is in our racial descriptors each of the following sum to 100%, (% black)+(%native American)+(%Asian)+(%Other Race) and (%Hispanic +%Non-Hispanic)

[4] More information on Maponics data collection service can be found on their website: http://www.maponics.com/index.html

the counties into two groups: those that are above the mean number of adjusted foreclosures per housing units and those that are below the mean number of adjusted foreclosures per housing units. These two groups of counties are further divided into counties that are more than 1 standard deviation above the mean number of adjusted foreclosures per housing units and counties that are more than 1 standard deviation below the mean number of adjusted foreclosures per housing units.

Two interesting findings are that in counties with a large number of adjusted foreclosures the fair market rent and the per capita income is higher, showing that a larger number of adjusted foreclosures occur in counties where houses are worth more and the residents earn more money. Another interesting finding is that counties with a large number of foreclosures also have a larger percentage of residents that are blacks or Hispanics. An additional finding related to race is that standard deviation is higher for counties with a large number of foreclosures, indicating that counties with a large number of foreclosures differ more from each other in minority make up than counties with few adjusted foreclosures. Yet one must interpret these results with caution since these results are not from a full structural equation that holds the other characteristics of the counties constant.

3. Empirical Strategies

To examine what types of variables affect foreclosures, we estimate several different models that will have similar interpretations for the coefficients, an OLS and an Random Effects model with 1 + log of adjusted foreclosures as the dependent variable, a Negative Binomial model with total adjusted foreclosures as the dependent variable, an OLS and Random Effects model with adjusted foreclosures in a county as a fraction of total households as the dependent

variable, a lagged dependent variable model that helps control for past county characteristics and policies, and a random effects spatial error model. In the models estimated with both pooled OLS and Random Effects a Breusch-Pagan Lagrange Multiplier test is estimated, the results are found at the bottom of Table 3. The Breusch-Pagan Test overwhelming rejects pooled OLS versus random effects; we include the OLS results to show that the substance of the results do not change even if an OLS estimation is used. Note that a fixed-effects model is not estimated because many of the variables we are interested in do not vary over time in our data (since for many variables we use census data) and others vary very little over time. In reality these variables probably do not vary substantially over time; we do adjust the model for clustering within a county (as discussed below), which corrects for intragroup correlation of the errors. We first discuss the OLS estimate of log of 1+ adjusted foreclosures, followed by a Negative Binomial model, followed by models where adjusted foreclosures are measured as a fraction of the households in the county, then the lagged dependent variable model, and finally the random effects spatial error model; these separate models can be thought of as robustness checks for each other on the significance and insignificance of the variables.

3.1 Base Model

The regression model takes the form

$$F_{it} = C'_{it}\delta + \mu_i + \varepsilon_{it} \qquad (1)$$

where F_{it} is adjusted foreclosures; this will be estimated with two variables, the first will be the natural log of 1 + adjusted foreclosures (the coefficients [times 100] in this regression may be interpreted as the effect of the independent variable on percentage of adjusted foreclosures) and the second will be the adjusted foreclosures as a fraction of housing units in the county , C_{it} is a

vector of the county characteristics discussed in the data section and a constant, where some vary over time but most do not, with estimable coefficients δ, and μ_i is the unobserved effect, it captures the unobserved time constant factors that affect our dependent variable (it is constant across time), which is the individual county heterogeneity; not accounting for this county effect could bias the estimates. In the OLS model μ_i will be set equal to zero; in order for the specifications associated with the random effects model to hold, it must be assumed that μ_i is uncorrelated with each explanatory variable. A Breusch-Pagan Lagrange Multiplier test and results are at the bottom of Table 3, showing an overwhelming rejection pooled of OLS versus random effects. Finally, ε_{it} is the time-varying error or idiosyncratic error; it captures unobserved factors that affect the dependent variable which vary over time.

We do not estimate a fixed effects model since many of the variables of interest do not vary over time. All of our models are estimated with Huber-White standard errors since we have observations that are different sizes and as mentioned above the standard errors are also adjusted for within group correlation of the error terms.[5]

Beyond greater policy applications, examining aggregate data to county level could have econometric benefits as well. It may actually be advantageous to aggregate to the county level; the use of average characteristics and total foreclosures probably has fewer errors in measurement than a model examining individual characteristics and individual probability of

---

[5] This estimator allows errors within each county to be correlated. It is estimated by $Var\left[\hat{\delta} \mid C\right] = \frac{N*T-1}{N*T-k}\frac{N}{N-1}(C'C)^{-1}\left(\sum_{j=1}^{N}\tilde{\varepsilon}_j'\tilde{\varepsilon}_j\right)(C'C)^{-1}$ where $\tilde{\varepsilon}_j = \sum_{i=1}^{N_k}\hat{\varepsilon}_i c_i$, N is the number of clusters (in our model this is the 71 counties), N_j is the number of observations in the jth cluster (in our model this will always be 8 since we have an observation for each county for 8 years), and c_i is a 1:k vector of regressors of the ith observation in the jth cluster.

foreclosures.[6] This aggregation may have one particular disadvantage; this disadvantage is that while (assuming linearity) the estimates of the model are unbiased, they are less precise. Since this study is primarily concerned with the ability to make policy application on the regional level we believe this regional approach leads to a greater ability to apply the results to policy.

3.2 Negative Binomial Model

Since the dependent variable is a count variable, an alternative estimation procedure is to start with an equation similar to (1) but estimate it by maximum likelihood estimation with a Negative Binomial regression. Let F_{it} now be a count variable that takes on values 0,1,2,… of the number of adjusted foreclosures in a county. The density function for the negative binomial model is then given by:

$$f(F_{it} \mid \gamma, \alpha) = \frac{\Gamma(F_{it} + 1/\alpha)}{\Gamma(1/\alpha)\Gamma(F_{it} + 1)} \left(\frac{1/\alpha}{\gamma_{it} + 1/\alpha} \right)^{1/\alpha} \left(\frac{\gamma_{it}}{\gamma_{it} + 1/\alpha} \right)^{F_{it}} \tag{2}$$

where $\Gamma(\cdot)$ is the gamma function, $\gamma_{it} = \exp(\mathrm{C}'_{\mathrm{it}}\delta)$, $\alpha > 0$ is the overdispersion, and the first two moments are:

$$\begin{aligned} E[F_{it} \mid x_{it}] &= \gamma_{it} \\ V[F_{it} \mid x_{it}] &= \gamma_{it} + \alpha(\gamma_{it})^2 \end{aligned} \tag{3}$$

If $\alpha = 0$ there would be no overdispersion (conditional mean equals conditional variance) and this model would reduce to the Poisson model.[7] We run two tests for overdispersion; both types of tests have $\alpha = 0$ as their null hypothesizes (no overdispersion). The first test is a standard Likelihood-ratio test that compares the negative binomial model to the

[6] For more details on why aggregation may have fewer errors in measurement see Hanushek (1979).
[7] Note this model is referred to Negative Binomial 2 (NB2) by Cameron and Trivedi (1998 and 2005); they also refer to an NB1 model and there are many other specifications, but the NB2 model is the most common. Some other possible models for count data are the lognormal and the inverse-Guassian distribution.

Poisson; The result of this test is a value of 1,535.89 which has a p-value less than 0.01. The second test has two versions and was suggested by Cameron and Trivedi (1990 and 2005). Both versions of this test involve regressing (by OLS) $\frac{(F_{it} - \hat{\gamma}_{it})^2 - F_{it}}{\hat{\gamma}_{it}}$ on $\alpha \frac{g(\hat{\gamma}_{it})}{\hat{\gamma}_{it}}$ and an error term with no constant, where $\hat{\gamma}_{it}$ is the exponential of the fitted values of the Poisson model $\left(\hat{\gamma}_{it} = \exp(\mathrm{C}'_{\mathrm{it}}\hat{\delta})\right)$, and examining the t-statistics of the coefficient α. For the first test $g(\hat{\gamma}_{it}) = (\hat{\gamma}_{it})^2$ and the second test $g(\hat{\gamma}_{it}) = \hat{\gamma}_{it}$, the second test just reduces to regressing on a constant; the t-stats from these test are 7.10 and 7.34 respectively which both have p-values less than 0.01. All tests reject the null of no overdispersion which shows strong evidence that there is overdispersion, thus a negative binomial model is preferred to a Poisson. All of the regressions are again adjusted for within group correlation of the error terms.

3.3 Lagged Dependent Variable Model

This model starts with the possibly more realistic assumption that foreclosures are a function of all past county level characteristics (versus just being a function of current characteristics):[8]

$$F_{it} = F_t\left[C_i(t), \mu_i, \varepsilon_{it}\right] \tag{4}$$

where F_{it} is the adjusted foreclosures of county i in year t, $C_i(t)$ is a vector of county characteristics ($C_i(t)$ represents the entire history of county characteristics), μ_i is a variable that represents county time invariant characteristics, and ε_{it} captures measurement error.

[8] The following exposition draws heavily on Sass's (2006) work on the value-added education production function.

If we assume $F_{it}(\cdot)$ does not vary with time (for example suppose event A happened in t and affects foreclosures in t+2, this would have the same impact on foreclosures in t+3 if event A had happened in t+1), and that it is additive separable, we can write foreclosures as:

$$F_{it} = \beta_1 C_{it} + \beta_2 C_{it-1} + \ldots + \beta_t C_{i1} + \mu_i + \varepsilon_{it} \tag{5}$$

Estimating this form of the equation would require having data for both the current county characteristics and all prior county characteristics. The need for all past county characteristic data can be eliminated if we assume that the marginal impact of all past county characteristics decline geometrically at the same rate (i.e. $\lambda\beta_t = \beta_{t+1}, \lambda^2\beta_t = \beta_{t+2} \ldots$). This makes equation (5):

$$F_{it} = \beta_1 C_{it} + \lambda\beta_1 C_{it-1} + \ldots + \lambda^{t-1}\beta_1 C_{i1} + \mu_i + \varepsilon_{it} \tag{6}$$

Now subtract λ times prior adjusted foreclosures from current foreclosures:

$$\begin{aligned} F_{it} - \lambda F_{it-1} = {} & \beta_1 C_{it} + \lambda\beta_1 C_{it-1} + \ldots + \lambda^{t-1}\beta_1 C_{i1} + \mu_i + \varepsilon_{it} \\ & - \lambda\left[\beta_1 C_{it-1} + \lambda\beta_1 C_{it-2} + \ldots + \lambda^{t-2}\beta_1 C_{i1} + \mu_i + \varepsilon_{it-1}\right] \end{aligned} \tag{5}$$

Simplify cancel terms and add λF_{it-1} to both sides:

$$F_{it} = \beta_1 C_{it} + \lambda F_{it-1} + (1-\lambda)\mu_i + \varepsilon_{it} - \lambda\varepsilon_{it-1} \tag{8}$$

Simplifying further gives

$$F_{it} = \beta_1 C_{it} + \lambda F_{it-1} + a_i + u_{it} \tag{9}$$

where $a_i = (1-\lambda)\mu_i$ and $u_{it} = \varepsilon_{it} - \lambda\varepsilon_{it-1}$.[9] In this equation the number of adjusted foreclosures is a function of current county characteristics and lagged adjusted foreclosures. We will estimate this equation using both pooled OLS (assuming $a_i = 0$) and random effects with log of 1+ adjusted foreclosures as the dependent variable, and lagged log of 1+ adjusted foreclosures as an

[9] Note this lagged dependent variable model still estimates foreclosure levels, not foreclosure growth. The following model would estimate foreclosure growth $\Delta F_{it} = \delta_1 C_{it} + \lambda\Delta F_{it-1} + \psi_i + \zeta_{it}$

independent variable. As demonstrated above this specification allows us to account for any inertial effects. The results for the OLS and Random Effects models are virtually identical so we only present the Random Effects model.

3.4 Spatial Model (Random Effects Spatial Error Model)

When observations are geographic in nature, spatial issues are often a concern. In our model spatial autocorrelation could be an issue. The error term from one county may be correlated with the error term in a neighboring county (conditional on the independent variables); that is, the unobserved heterogeneity in one county may affect the unobserved heterogeneity in a neighboring county.

We start with a brief introduction of the (non panel data) spatial error model (Anselin, 1988 and Lesage, 1998) and then extend this to the random effects spatial error model.

$$\begin{aligned} F &= C\delta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \upsilon \\ \upsilon &\sim N\left(0, \sigma^2 I_n\right) \end{aligned} \tag{10}$$

where W is a symmetric spatial weight matrix where $W_{ij} = 1$ for counties that share a border and 0 otherwise (usually this matrix is standardized to have the row sum to one) and λ is the coefficient on the spatially correlated errors.[10] For information on how to estimate this model by maximum likelihood see Anselin (1988) and Lesage (1998).

Following Elhorst (2003) and Baltagi and Lee (2004 and 2006) we estimate an extension of this model to random effects. This starts with an equation that combines the random effects aspect of equation (1) with the spatial error autocorrelation of equation (10):

$$F = C'\delta + \left(\iota_T \otimes I_N\right)\mu + \left(I_T \otimes B^{-1}\right)\varepsilon \tag{11}$$

[10] Note that λ here does not correspond to the λ in the lagged dependent variable model.

where ι_T is a $(T \times 1)$ vector of ones, I_N is a $(N \times N)$ identity matrix, and $B = I_N - \lambda W$; λ is again called the spatial autocorrelation (autoregressive) coefficient. The result for the spatial autocorrelation coefficient is at the bottom of Table 3 and shows that it is highly significant.[11]

Elhorst shows how this can be used to create the following simplified log-likelihood function:

$$\log L = -\frac{NT}{2}\log\left(2\pi\sigma^2\right) - \frac{1}{2}\sum_{i=1}^{N}\log\left[1 + T\theta^2\left(1-\lambda\omega_i\right)^2\right] + T\sum_{i=1}^{N}\log\left(1-\lambda\omega_i\right) - \frac{1}{2\sigma^2}\sum_{t=1}^{T} e_t{}' e_t \qquad (11)$$

Where ω_i are the characteristic roots of W, $e_t = F_t^* - C_t^*\delta$, $F_t^* = P\overline{F} + B\left(F_t - \overline{F}\right)$, $C_t^* = \left(I_N - \lambda W\right)C_t - \left(P - \left(I_N - \lambda W\right)\right)\overline{C}$, and P is such that $P'P = \left[T\theta^2 I_N + \left(B'B\right)^{-1}\right]^{-1}$. For more details on this log likelihood function and how to estimate it see Elhorst (2003).[12]

Note spatial models are often estimated with a neighboring region's dependent variable as an independent variable (a lagged spatial model). Intuitively this model is probably not appropriate for our estimations because foreclosures in one county are most likely not directly dependent on a neighboring county's foreclosure level; it is more likely that the unobserved heterogeneity (unobserved to the researcher) from one county will affect the foreclosure level in a neighboring county. As in most of the other specifications we use log of 1+ adjusted foreclosures as the dependent variable.

4. Results

Since the estimates of all of the models are similar they are robustness checks for each other, thus we discuss them simultaneously. Table 3 displays the results for all of the models. In

[11] The variance covariance matrix is: $\sigma_\mu^2\left(\iota_T\iota_T' \otimes I_N\right) + \sigma_\varepsilon^2\left(I_T \otimes \left(BB'\right)^{-1}\right)$

[12] To do this we use Matlab and a variant of a program first written by J. Paul Elhorst.

the models where log of 1 + adjusted foreclosures are the dependent variable estimate, coefficients (* 100) should be interpreted at the effect of a one unit change of the independent variable on percentage of foreclosures.[13] The interpretation of the size of the coefficients from the negative binomial results are similar to the log dependent variable model since they are approximately what the proportionate change (or percentage change if the coefficient is multiplied by 100) in the dependent variable for a one unit change in the independent variable (if the independent variable is in level not log form).[14,15]

Consistent with expectations, the dummy variables for years in the first five results shows an increasing amount of adjusted foreclosures over time and all the results show that there was an increase in foreclosures in 2006 and 2007; also with an increase in the percentage of housing units we would expect the percentage of adjusted foreclosures to increase. Next the main results of the paper are discussed.

Consistent with individual models of foreclosures, unemployment rate has a positive effect on adjusted foreclosures (higher unemployment leads to more foreclosures); unemployment is highly statistically significant in all seven specifications and is also large in "practical significance". Specifically if a county has a 1% increase in unemployment we would expect foreclosures to increase by approximately 3-9%. Even if we take the conservative estimate of 5% this effect is reasonably large. Suppose there are two counties that are exactly the same except one has an unemployment rate of 5% (approximately the mean) and the other has an unemployment rate that is 6.3% (approximately 1 standard deviation above the mean); since the

[13] The "R-square" reported for the Random Effects Models in Table 2 is in quotes because it is not the typical OLS R^2 and does not have all of the properties of the OLS R^2. Rather it is a correlation square or a R^2 from a second round regression.

[14] Technically it measures how much the difference in logs of the expected counts changes (or the log of the ratio of counts) for a one unit change in the independent variable, which should be approximately the proportion, if the proportion is small.

[15] If the independent variable is entered in log form then the interpretation of the coefficient is the elasticity.

second county's unemployment is 1.3 percentage points higher, this would mean that the second county would have 6% more adjusted foreclosures. These results remain roughly consistent if unemployment in the current period is replaced with unemployment lagged one period.[16]

Also of interest is that as the size of households in renter occupied units increases adjusted foreclosures increase; this variable is significant in all specifications. One possible explanation for this is that landlords that rent to large families have an increased probability of foreclosures due to possibly higher costs and or lower returns associated with renting to larger families. Some other consistent results are the following: counties with a larger percentage of Native Americans or Asians have less adjusted foreclosures (versus percentage of county that is white), and there is consistent evidence that the percentage of foreclosures falls as the median age increases. Median age, percentage Native American, and percentage Hispanic are significant in six, seven, and five out of seven specifications respectively.

When taken together the education variables suggest that education has a non-monotonic effect on foreclosures. Counties with a larger percentage of individuals with high school degrees versus individuals that have not obtained a high school degree have a greater percentage of foreclosures, but the results show that there is either a negative effect or no statistical difference between a county with a larger percentage of college graduates versus no high school degree. This implies more education leads to greater foreclosures up to a point, but when education increases even more foreclosures may begin to decrease. One possible explanation is that people with high school degrees (but not a four year degree) are more likely to have access to loans than those without high school degrees, but are also more likely not to be able to handle homeownership as well as people with bachelor degrees.

[16] The results with unemployment lagged one period are available from the authors.

The results also show no evidence that the following affect adjusted foreclosures: the percentage of a county that is Black or Hispanic, the fraction of a county in an urban area, and the population density of a county (note the previous two results may not be significant because they are likely highly correlated). There are mixed results for fair market rent, which is positive and significant in three specifications but is not significant and of mixed sign in the other specifications; per capita income is significant only in the spatial model.

5. Conclusions

Discovering the factors that lead to a change in foreclosures has important policy implications. This paper contributes to the literature by being the first to examine a full structural model of foreclosures at a regional level. To summarize our key findings: a higher unemployment rate or larger size of households in renter occupied units leads to more foreclosures, counties with larger populations of Native Americans or Asians and higher median age have fewer foreclosures, and education appears to affect foreclosures in a non-monotonic way as percentage of the population with a high school degree versus non high school graduates increases foreclosures, but there is a negative impact or no significant difference between bachelors degree and no high school degree. The above results appear to be robust since they are consistent across a multitude of specifications.

If policy makers want to address the foreclosure issue, evidence from this paper suggests they should address unemployment, create policies to reduce the size of households in rental units, and increase college education. Practical advice for lenders is that they should investigate a strategy of increasing mortgages in areas (assuming a constant interest rate) where the median

age is higher and the percentage of Native Americans or Asians is larger; these areas may present an arbitrage opportunity for lenders.

References

Ambrose, B. W., C.A. Capone, and Y. Deng. 2001. "Optimal Put Exercise: An Empirical Examination of Conditions for Mortgage Foreclosure." *Journal of Real Estate Finance and Economics* 23 No 2: 213-234.

Ambrose, B. and C. Capone. 1998. "Modeling the Conditional Probability of Foreclosure in the Context of Single Family Mortgage Default Resolutions." *Real Estate Economics* 26 No 3: 391-429.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. Dordrecht, the Netherlands: Kluwer.

Baltagi, B. H. and D. Lee 2004. "Prediction in the panel data model with spatial correlation." In *Advances in spatial econometrics: Methodology, tools, and applications,* edited by L. Anselin, R. J. G. M. Florax, and S. J. Rey. Heidelberg: Springer.

Baltagi, B. H. and D. Lee 2006. "Prediction in the Panel Data Model with Spatial Correlation: the Case of Liquor." *Spatial Economic Analysis* 1, No. 2: 175-185.

Borjas, G.J. 2002. Homeownership in the Immigrant Population. *Journal of Urban Economics* 52 No 3: 448-476.

Cameron, A. C. and Trivedi, P. K. 1990. "Regression Based Tests for Overdispersion in the Poisson Model." *Journal of Econometrics* 46: 347-364.

Cameron, A. C. and Trivedi, P. K. 1998. *Regression Analysis for Count Data,* Econometric Society Monograph No. 30, Campbridge, UK, Cambridge University Press.

Cameron, A. C. and Trivedi, P. K. 2005. *Microeconomics: Methods and Applications*. New York: Cambridge.

Campbell T.S. and J.K. Dietrich. 1983. "The Determinants of Default on Insured Conventional Residential Mortgage Loans." *The Journal of Finance* 38, No 5: 459-477.

Capozza, D.R., D. Kazarian, and T. A. Thomson. 1997. "Mortgage Default in Local Markets." *Real Estate Economics* 25 No 4: 631-656.

Capozza, D.R., D. Kazarian, and T. A. Thomson. 1998. "The Conditional Probability of Mortgage Default." *Real Estate Economics* 26 No 3: 359-389.

Clapp, J.M. 2001. "Movers and Shakers: Independent Prepayment Decisions." *Real Estate Economics* 29 No 4: 631-656.

Danis, M.A. and A. Pennington-Cross. 2008. "The Delinquency of Subprime Mortgages." *Journal of Economics and Business* 60 No 1-2: 67-90.

Elhorst, J. P. 2003. "Specification and Estimation of Spatial Panel Data Models." *International Regional Science Review* 26, No.3: 244-268.

Foster, C and R. VanOrder. 1984. "An Option-based Model of Mortgage Default" *Housing Finance Review* 3 No 4: 351-72.

Hanushek, Eric, A. 1979. Conceptual and Empirical Issues in the Estimation of Educational Production Functions. *The Journal of Human Resources.* 14, no. 3: 351-388.

Jung, A.F. 1962. "Terms on Conventional Mortgage Loans on Existing Houses." *Journal of Finance* 17 No 3: 432-443.

Kau, J.B., D. C. Keenan, and T. Kim. 1993. "Transaction Costs, Suboptimal Termination and Default Probabilities." *The Journal of Real Estate Finance and Economics* 19 No 3: 247-263.

Kau, J.B., D. C. Keenan, and T. Kim. 1994. "Default Probabilities for Mortgages." *The Journal Urban Economics* 35 No 3: 278-296.

Lauria, M., V. Baxter, and B. Bordelon. 2004. "An Investigation of the Time between Mortgage Default and Foreclosure." *Housing Studies*, 19 No. 4: 581–600

Lekkas, V.J., J. M. Quigley, and R. Van Order. 1993. Loan Loss Severity and Optimal Mortgage Default." *Journal of the American Real Estate and Urban Economics Association* 21 No. 4: 353-371.

Lesage, J. P. 1998. *Spatial Econometrics*. Unpublished manuscript University of Toledo.

Myers, D., G. Painter, Z Yu, and SH Ryu. 2003. Regional Variation in Homeownership Progress of the Baby Boom Generation." School of Policy, Planning, and Development at the University of Southern California.

Miller, N. and Liang Peng. 2006. "Exploring Metropolitan Housing Price Volatility." *Journal of Real Estate and Financial Economics* 33 No 1: 5-18.

Pennington-Cross, A. 2003. "Credit History and the Performance of Prime and NonPrime Mortgages." *The Journal of Real Estate and Economics* 27 No 3: 279-301.

Quercia. R.G. and M.A. Stegman. 1992. "Residential Mortgage Default: A Review of the Literature." *Journal of Housing Research* 3 No 2: 341-379.

Quigley, J.M. and R. VanOrder. 1995. "Explicit Tests of Contingent Claims Models of Mortgage Default." *The Journal of Real Estate Finance and Economics* 11 No 2: 99-117.

Sass, T. R. 2006. "Charter Schools and Student Achievement in Florida," *Education Finance and Policy* 1: 91-122.

Vandell, K.D. 1995. "How Ruthless is Mortgage Default? A Review and Synthesis of the Evidence." *Journal of Housing Research* 6 No 2: 245-264

Von Furtstenberg, G. 1969. "Default Risk on FHA-Insured Home Mortgages as a Function of the Terms of Financing: A Quantitative Analysis." *The Journal of Finance* 24, No 3: 459-477.

Von Furtstenberg, G. 1970a. "Risk Structures and the Distribution of Benefits within the FHA Home Mortgage Insurance Program." *The Journal of Money Credit and Banking* 2, No 3: 303-322.

Von Furtstenberg, G. 1970b. . "Home Mortgage Delinquencies: A Cohort Analysis." *The Journal of Risk and Insurance* 37, No 3: 437-445.

Von Furtstenberg, G. 1974. "Home Mortgage Delinquencies: A Cohort Analysis." *The Journal of Finance* 29, No 5: 1545-1548.

Williams, A.O., W. Beranek, and J. L. Kenkel. 1974. "Default Risk in Urban Mortgages: A Pittsburgh Prototype Analysis." *American Real Estate and Urban Economics Association Journal* 2 No 2: 101-112.

Table 1: Descriptive statistics

	N	Mean	Standard Deviation	Min	Max
ADJUSTED FORECLOSURE VARIABLES					
Adjusted foreclosures	568	162.99	349.21	0.00	4,815.00
Log of Adjusted foreclosures	567	4.39	1.11	0.69	8.48
Log of 1+ Adjusted foreclosures	568	4.40	1.10	0	8.48
Adjusted foreclosures as a fraction of housing units	568	0.43	0.20	0.00	1.48
INDEPENDENT VARIABLES					
Unemployment Rate	568	5.17	1.31	2.30	12.40
Fair Market Rent	568	527.67	105.75	392	951
log of Number of Housing Units	568	9.92	0.92	7.65	12.93
Log of Population Density	568	4.06	1.19	2.20	8.26
Median Age	568	38.01	3.29	27.70	45.80
Average household size of owner-occupied units	568	2.62	0.14	2.30	3.13
Average household size of renter-occupied units	568	2.15	0.25	1.74	3.99
Per capita median family income (lagged 1 period)	568	26,884	5,300	15,883	56,816
% Black (White is the reference group)	568	1.14	3.20	0.06	24.59
% Native American	568	2.70	10.55	0.11	87.26
% Asian	568	0.78	0.94	0.00	4.54
% Other Race	568	1.55	1.10	0.53	6.50
% Hispanic	568	1.70	1.72	0.33	8.77
high school degree but no 4 year degree [ŧ]	568	66.64	3.64	51.52	72.61
Bachelor degree or higher [ŧ]	568	17.03	6.16	9.97	40.64
% urban (Rural is the reference group)	568	0.38	0.29	0.00	1.00

ŧ - no high school degree is the reference group

Table 2:

	All Counties		Counties above mean Foreclosures per Housing Units		Counties1 standard deviation above mean Foreclosures per Housing Units		Counties below mean Foreclosures per Housing Units		Counties1 standard deviation below mean Foreclosures per Housing Units	
Number of Counties	568		247		81		321		87	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Unemployment Rate	5.17	1.31	5.27	0.93	5.30	0.90	5.09	1.53	4.72	1.81
Fair Market Rent	527.67	105.75	569.62	106.15	619.62	99.83	495.40	93.53	474.79	93.30
log of Number of Housing Units	34,011.77	54,338.90	40,081.26	66,437.83	43,621.25	63,272.77	29,341.48	42,288.03	31,021.82	48,077.58
Log of Population Density	157.41	466.88	221.40	642.82	235.90	607.52	108.17	250.94	92.91	134.99
Median Age	38.01	3.29	37.64	2.72	37.40	2.64	38.30	3.65	38.52	4.13
Average household size of owner-occupied units	2.62	0.14	2.63	0.11	2.64	0.11	2.61	0.16	2.60	0.18
Average household size of renter-occupied units	2.15	0.25	2.16	0.11	2.18	0.11	2.14	0.32	2.18	0.41
Per capita income (lagged 1 period)	24,775.96	51,22.49	25,932.58	3,851.12	27,191.33	3,438.01	23,885.97	5,767.61	22,752.47	6,348.09
% Black (White is the reference group)	1.14	3.20	1.78	4.40	2.25	4.42	0.64	1.63	0.60	1.01
% Native American	2.70	10.55	0.86	1.63	0.75	1.07	4.12	13.80	6.49	18.33
% Asian	0.78	0.94	0.75	0.87	0.72	0.76	0.80	0.98	0.81	1.09
% Other Race	1.55	1.10	1.84	1.40	2.17	1.56	1.32	0.71	1.29	0.70
% Hispanic (non-Hispanic is reference group)	1.70	1.72	2.23	2.20	2.71	2.41	1.29	1.06	1.19	0.89
% No high school degree	16.33	3.68	16.86	3.23	16.79	3.22	15.93	3.95	15.67	4.31
% high school degree but no 4 year degree	66.64	3.64	66.94	2.94	66.76	2.73	66.40	4.09	65.38	5.29
% Bachelor degree or higher	17.03	6.16	16.20	4.57	16.45	4.39	17.67	7.08	18.95	8.72
fraction urban (Rural is the reference)	38.11	28.93	42.29	28.31	45.91	29.83	34.89	29.04	29.42	31.02

There is only one county in one year that is two standard deviations below the mean number of foreclosures, and only 20 that are 2 standard deviations above

Table 3:

	Log of Foreclosures				Negative Binomial		Fraction of Housing Units				Includes lagged Foreclosures (RE)		RE with Spatial Autocorrelation	
	OLS		RE				OLS		RE					
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Lagged Log Adjusted Foreclosures											0.374**	0.164		
Unemployment Rate	0.094***	0.025	0.082***	0.030	0.078***	0.021	0.038***	0.012	0.029**	0.014	0.062***	0.024	0.079***	0.022
Fair Market Rent	8.83E-04**	3.99E-04	-1.70E-04	2.42E-04	8.08E-04***	3.00E-04	3.16E-06**	4.38E-06	-1.37E-04	1.87E-04	5.19E-04	3.50E-04	2.00E-05	3.03E-04
Log of Number of Housing Units	1.050***	0.058	1.095***	0.070	1.112***	0.044	0.042*	0.024	0.079*	0.045	0.664***	0.162	1.082**	0.064
Log of Population Density	0.104	0.078	0.061	0.092	0.031	0.062	0.028	0.031	0.002	0.048	0.073	0.060	0.069	0.079
Median Age	-0.055***	0.019	-0.053**	0.022	-0.049***	0.014	-0.017**	0.007	-0.012	0.008	-0.036*	0.020	-0.051***	0.018
Average household size of owner-occupied units	-0.524	0.431	-0.224	0.517	-0.290	0.299	-0.050	0.159	0.169	0.240	-0.310	0.373	-0.258	0.388
Average household size of renter-occupied units	0.553***	0.203	0.624***	0.206	0.612***	0.167	0.286***	0.084	0.314***	0.098	0.478***	0.138	0.605**	0.244
Per capita income (lagged 1 period)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000*	0.000
% Black (White is the reference)	-0.016	0.010	-0.007	0.012	-0.009	0.008	-0.004	0.004	0.001	0.006	-0.011	0.008	-0.008	0.013
% Native American	-0.023***	0.005	-0.025***	0.005	-0.027***	0.005	-0.011***	0.002	-0.012***	0.003	-0.018***	0.004	-0.025***	0.006
% Asian	-0.067	0.042	-0.093**	0.046	-0.077**	0.032	-0.038**	0.018	-0.056**	0.023	-0.038	0.027	-0.089**	0.037
% Other Race	0.016	0.087	0.004	0.094	0.059	0.068	0.040	0.030	0.025	0.036	0.017	0.060	0.004	0.088
% Hispanic	0.011	0.052	0.032	0.055	-0.010	0.043	-0.011	0.020	0.004	0.022	-0.006	0.037	0.029	0.057
high school deg. but no 4 year deg. [ŧ]	0.022	0.014	0.032**	0.016	0.028***	0.010	0.013**	0.005	0.019**	0.008	0.017**	0.009	0.030**	0.014
Bachelor degree or higher [ŧ]	-0.033**	0.014	-0.018	0.015	-0.025***	0.009	-0.007	0.004	0.003	0.007	-0.020	0.014	-0.020*	0.011
fraction urban (Rural is the reference)	-0.017	0.184	-0.007	0.200	-0.042	0.159	-0.028	0.079	-0.010	0.095	-0.023	0.124	0.020	0.191
Year 2001 (2000 is the reference) [¥]	0.206***	0.043	0.227***	0.047	0.219***	0.036	0.048***	0.016	0.066***	0.018			0.228***	0.051
Year 2002	0.266***	0.075	0.320***	0.079	0.302***	0.059	0.071**	0.030	0.111***	0.032	-0.024	0.050	0.318***	0.065
Year 2003	0.235**	0.107	0.304**	0.120	0.315***	0.068	0.077**	0.032	0.127***	0.034	-0.102***	0.037	0.287***	0.072
Year 2004	0.225**	0.086	0.341***	0.084	0.266***	0.065	0.055*	0.031	0.131***	0.032	-0.114	0.074	0.327***	0.070
Year 2005	0.302***	0.096	0.434***	0.091	0.347***	0.071	0.092***	0.034	0.179***	0.034	-0.028	0.051	0.412***	0.074
Year 2006	0.510***	0.108	0.660***	0.102	0.566***	0.082	0.203***	0.040	0.302***	0.041	0.155**	0.064	0.635***	0.080
Year 2007	0.602***	0.133	0.795***	0.122	0.674***	0.096	0.285***	0.050	0.411***	0.052	0.178**	0.088	0.767***	0.093
Constant	-6.676***	2.509	-8.354***	2.998	-8.362***	1.665	-1.256	0.941	-2.485*	1.438	-4.490***	1.249	-8.082***	2.276
Adj R-square ("R-square")	0.94		(0.94)				0.70		(0.67)		(0.95)		0.99	
n	568		568		568		568		568		568		568	
Breusch-Pagan LM			221.3 (0.00)						254.4 (0.00)		10.9 (0.00)			
Sigma													0.44	
Spatial Autocorrelation Coef.													0.228***	0.075

S.E. is the heteroskedasticity-robust standard error clustered on counties
*,**,***: significant at the 10,5, and 1% level, respectively.
¥ : for the lagged dependent variable specification 2002 is the reference group
ŧ : no high school degree is the reference group