“The Contagion Effect of Neighboring Foreclosures on Own Foreclosures”

Charles Towe* and Chad Lawley†

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* Assistant Professor, Department of Agricultural and Resource Economics and the National Center for Smart Growth, University of Maryland, College Park, MD (contact author ctowe@arec.umd.edu)
† Assistant Professor, Department of Agribusiness and Agricultural Economics, University of Manitoba, Winnipeg, MB, Canada

Introduction

There is no question that the US has endured a dramatic period of foreclosure activity unlike any period in recent decades. National foreclosure starts increased from 1.5 million in 2007 to 2.8 million in 2009, and the share of mortgage loans that were seriously delinquent reached 5.2% by the third quarter of 2008, compared to the 1979-2006 average of 1.7% and the previous high of 2.7% in 2002 (Mayer, Pence, and Sherlund 2009). This period of increased foreclosure activity has introduced new phrases to the public lexicon, most notably for this work, the notion of "strategic default," which occurs when those who can afford to pay make the strategic choice to walk away from their mortgage. Strategic defaults are estimated to make up as much as one-quarter of all foreclosures (Guiso, Sapienza, and Zingales 2009) and anecdotal evidence suggests that strategic defaults are becoming more common and more socially acceptable.[1]

Recent academic research has established the price effect of neighboring foreclosures as a significant and highly localized feedback effect. Harding, Rosenblatt, and Yao (2009) find a peak contagion effect of nearby foreclosures on house prices of approximately 1%. Campbell, Giglio, and Pathak (2009) find that each foreclosure within a quarter of a mile radius reduces house prices by between 1 and 2% and foreclosures within one tenth of a mile reduce prices by approximately 9%. This line of research suggests that local foreclosures impact local house prices, but it does not establish a link between neighboring foreclosures and own foreclosures.

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[1] See, for example, Lowenstein, Roger. 2010 "Walk Away from Your Mortgage," New York Times Magazine, January 7, 2010 (http://www.nytimes.com/2010/01/10/magazine/10FOB-wwln-t.html); Streitfeld, David. 2010. "Biggest Defaulters on Mortgages Are the Rich," New York Times, July 8, 2010 (http://www.nytimes.com/2010/07/09/business/economy/09rich.html); 60 Minutes, May 9, 2010, "Strategic Default: Walking Away from Mortgages" (http://www.cbsnews.com/stories/2010/05/06/60minutes/main6466484.shtml).

What differentiates this foreclosure period from the recent past is the potential for non-price effects, which is supported by Guiso, Sapienza, and Zingales (2009). Using survey data, they examine the potential importance of social interactions on the propensity to foreclose. They find evidence that an individual who knows someone in foreclosure is more likely to default, and that homeowners experiencing a steep equity decline feel less of a moral obligation to repay their lender. These results suggest that foreclosures in concentrated areas is an outcome of a contagion effect driven by a reduction in the moral and social constraints on foreclosure, rather than the result of a clustering of households more prone to default.

In this paper, we examine a highly localized contagion effect of foreclosures and find strong evidence that social interactions influence the decision to foreclose. We utilize a hazard model and a unique spatially explicit dataset documenting parcel level residential foreclosures in Maryland for the years 2006 through 2009. We combine these data with tax and assessment data, loan data, Census, and unemployment data. These data allow us to control for important factors influencing the likelihood of foreclosure within a given community, including the prevalence of subprime loans and the distribution of socioeconomic characteristics. Additionally, we use the tax data to construct variables describing individual homes, surrounding homes, and community. These variables include structural characteristics of houses, their price history, and length of ownership.

We overcome a number of identification issues common to empirical analyses of social interactions. First, our framework is based on the social interactions hazard model proposed by Sirakaya (2006). We identify the role of social interactions using time varying measures of the mean number of neighboring foreclosures and the mean time to foreclosure (since the beginning of the study period) among those neighbors that do foreclose.[2] We expect that observing neighbors that foreclose influences the perception of foreclosure, potentially reducing the stigma associated with foreclosure. Similarly, the mean time to foreclosure among those that have foreclosed captures the likely strength of the social interaction. We expect the strength of social interaction to fall over time. Thus, more recent waves of foreclosure reduce the likelihood of foreclosure. if foreclosures in a neighborhood occur early in the sample period and an individual household survives, the household is less likely to foreclose. At a given point in time, greater mean time to foreclosure among neighbors that do foreclose should increase the likelihood of foreclosure. As in Sirakaya (2006), measuring social interaction variables in this manner ensures that group and individual determinants of household behavior are nonlinearly related.

Second, we take advantage of the panel nature of our data, allowing us to avoid issues of simultaneity that often hinder identification of social interactions in empirical studies (Manski 2000). Specifically, as outlined in Manski (2000) and Brock and Durlauf (2000), using lagged values of the social interaction variables overcomes the reflection problem typically encountered in social interaction models.

Third, a general concern in social interaction models is choice of group size. The previous literature examining the price spillover effects of neighboring foreclosures have used spatial buffers to define reference group membership. This method of defining group size in urban areas of differing densities is problematic for identification and may simply be picking up spurious correlation. Consistent with the social interactions work of Iaonnides (2002), our definition of neighbour is the nearest thirteen neighbors by distance. This measure is sufficiently small that spurious correlation among loosely related neighbors is not an issue.

[2] The social interaction variables in Sirakaya (2006) are not time varyng.

We identify a contagion effect consistent with the view that negative equity is a necessary condition for default. We control for house price expectations using a local repeat sales price index, as well as including a variable that measures the extent to which the sales index has fallen relative to its peak value. In addition to house price depreciation, increased originations of subprime loans coincide with an increase in foreclosures (Meyer, Pence, and Sherlund 2009). We find strong evidence that greater prevalence of subprime loans increases the likelihood of observing household foreclosures. We also find that older, higher quality houses, with longer ownership tenures and homes in established communities with fewer rentals are less likely to foreclose.

Most significantly, we find strong evidence that endogenous interactions influence foreclosure decisions. Using our highly localized neighborhood measure we find that a one unit increase in neighboring foreclosures increases the hazard of foreclosure by as much as 4% and an increase in the mean time to foreclosure increases the hazard rate of foreclosure by less than 1%. Both results are statistically significant, suggesting that foreclosures influence the likelihood of future foreclosures in their immediate neighborhoods. This feedback goes beyond a temporary reduction in local house prices and implies a negative social multiplier effect as the societal norm toward foreclosure changes and a chain of spillovers potentially ensues.

The remainder of the paper proceeds as follows. The next section outlines social interactions as they relate to residential foreclosures. Section 2 presents the duration models used in the analysis, followed by a discussion of the variables chosen for the analysis. Results are presented in section 4. The last section provides concluding remarks.

Social Interactions and Foreclosures

There is a well defined literature on social interactions pioneered by Manski (1995). Social interactions arise from three sources – endogenous interactions, contextual interactions, and correlated effects – which are explained in the context of foreclosures in the following paragraphs. Endogenous interactions are of most interest in this study because their presence implies homeowners alter behavior in response to the observed behavior of their neighbors.

Contextual interactions occur when the behavior of an individual group member varies with exogenous events or exogenous characteristics of other group members. Foreclosures may cluster into certain neighborhoods due to job losses initiated by a single employer or a specific employment sector. These workers (and potential neighbors) may have very different socio-economic characteristics, yet have a common employer. In this case, we might observe foreclosures clustering in particular neighborhoods – observationally consistent with contagion due to an endogenous interaction – but the clustering is due to common job losses. An example that is particularly relevant in the current foreclosure episode is a common decrease in local house prices, which is independent of the impact of neighboring foreclosures on prices. A uniform decrease in local house prices may cause foreclosures to cluster into neighborhoods, having the appearance of an endogenous interaction.

Correlated effects occur when individuals with similar preferences, individual characteristics, or institutional environments act in a similar manner. The composition of neighborhoods is the outcome of a sorting process, wherein households with similar socioeconomic characteristics sort into neighborhoods according to variation in the suite of amenities offered by different neighborhoods (Ioannidies and Zabel 2002). In this case, spatial clustering of foreclosures occurs because households with higher inherent propensity to foreclose have sorted into neighborhoods. In the period leading up to the current foreclosure crisis low income households were more likely to have subprime loans, which are more sensitive to price decreases and foreclosure (Gerardi, Shapiro, and Willen 2009).

We are interested in identifying endogenous interactions in residential foreclosure decisions. Endogenous interaction effects occur when the actions of others cause members of a group to act in a similar manner. Manski (2000) identifies three economic processes within endogenous interactions: preference, expectations, and constraints interactions. Constraint interactions arise when the actions of one agent influence the feasible set of options available to another agent; congestion or publicly available knowledge from research and development are examples. Expectations interactions are generated by observational learning, wherein agents form expectations based on observed actions and choices of others. Finally, social interactions may occur when an agents preferences are influenced by the actions or choices made by members of the individuals reference group. Preference interactions might result from conformism, stigma, or other social influences.

In the context of residential foreclosures, much of the research effort to date has focussed on the price depressing effect of neighboring foreclosures – a constraint interaction. Foreclosures increase the supply of houses on the market and decreased upkeep of the foreclosed house deteriorates the visual appeal of the neighborhood to potential buyers. This reduces the value of surrounding houses, therefore altering the equity position of surrounding households. Previous research indicates that the price depressing effect of local foreclosures is small, but the research has not investigated the overall impact of foreclosure on the likelihood of neighboring foreclosures.

We directly examine the endogenous interaction effect of neighborhood foreclosures. Within endogenous interactions, we are primarily concerned with the non-price *preference* interactions of neighboring foreclosures.[3] Without question, strong moral and social constraints on foreclosure have the effect of preventing households from entering into default when it is in their financial interest to do so. Households' willingness to default is influenced by the possibility of social stigma and moral norms that suggest foreclosure is to be avoided, even at significant financial cost. Guiso, Sapienza, and Zingales (2009) present evidence that the social and moral constraints loosen as the number of foreclosures in a households' neighborhood increases. The extent to which endogenous preference interactions influence foreclosure is dependent on the extent to which each homeowner considers foreclosure an option. As suggested by the preliminary work of Guiso, Sapienza, and Zingales (2009), observing others in foreclosure is an important driver when considering the option yourself. In other words, the influence of endogenous preference interactions is likely to be highest in situations of strategic default.

The Model

Following Sirakaya (2006) and Brock and Durlauf (2001), we model social interactions as affecting the likelihood of transition from one state to another. In our case, social interactions influence the probability of an individual household defaulting on its mortgage and going into foreclosure. Let T denote the year the foreclosure occurs, or equivalently, the duration from $t = 0$ that the household does not foreclose. Observations (spells) are realizations of an underlying random process that can be characterized by the probability density function (*pdf*)

$$f(t) = \Pr(t \leq T < t + \delta t) \qquad (1)$$

and the corresponding cumulative density,

[3] Although the price spillover effects are important considerations when evaluating a neighbor's foreclosure position, at a 1-2% decline per neighboring foreclosure it seems implausible that this marginal, and likely temporary, change in equity would lead to a discrete behavioral change like mortgage default.

(2) $$F(t) = \int_0^t f(s)ds = \Pr(T \le t),\ t \ge 0$$

where $T \ge 0$ denotes the duration until failure and *t* denotes a particular value of T. The survival function, *S(t)=1-F(t)*, is the complement of the cumulative distribution function (*cdf*) and is the mathematical representation of the likelihood of surviving until time *t*. Thus $S(t) = \Pr(T > t)$. The survival function serves as the contribution to the likelihood function for observations that do not fail during the time under study.

Finally, the hazard function is the instantaneous probability of failure in the interval δt assuming survival up to time *t*. The probability at time t that a foreclosure occurs by δt, conditional on foreclosure not occurring prior to t, is given by:

(3) $$\lambda(t) = \Pr(t \le T < t + \delta t \mid T \ge t) = \frac{f(t)}{S(t)}$$

The discrete analog to (3) is

(4) $$\lambda(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \le T < t + \Delta t \mid T \ge t)}{\Delta t}.$$

To facilitate estimation, it is necessary to incorporate covariates. This is typically accomplished by specifying the individual foreclosure hazard function for household h at time t with covariate vector z_h as

(5) $$\lambda(t, \mathrm{z}_h) = \lambda_0(t)\exp(\theta' \mathrm{z}_h),$$

where $\lambda_0(t)$ is the baseline hazard and θ is a vector of unknown parameters. The most common approach to estimation is maximum likelihood. Observations are divided into two groups: observed failures and censored observations. As observed failures enter the hazard via their probability density functions and censored observations enter through their survival functions, the general form of the log likelihood function for *N* observations is written as

(6) $$\ln L = \sum_{h=1}^{N} d_i \ln[f(t_i, z_h)] + (1-d_i)\ln[S(t_i, z_h)]$$

Where z_h is observation h's vector of observed covariates and d_{i} is an indicator variable equal to 1 if the h^{th} observation fails during the study period and 0 if the observation is right-censored. From equation (6), it is easy to see how hazard models utilize information from censored observations via the likelihood contribution of the survival function. Equation (6) ignores the possibility of time varying covariates. Including them amounts to adding 'spells' to the data, where a 'spell' is defined as an interval of time and the associated quantities relevant to each observation during that interval. That is, an observation will contribute multiple spells of data, one for each time interval over which covariates remain constant.

There are important explicit assumptions involved in estimating a traditional hazard model, most noticeably the choice of baseline hazard specification. Since there is no *a priori* reason to suspect any shape of the baseline hazard based on institutional knowledge or past experience it is probably most appropriate to utilize either a semi-parametric proportional hazard specification which allows the baseline hazard to take any shape without restriction or a Cox proportional hazard model where the baseline hazard function is not specified.

We estimate a series of piecewise exponential hazard models and Cox proportional hazard models. The piece-wise exponential baseline is

(7) $$\lambda_0(t) = \sum_{g=1}^{G} \lambda_g \gamma(t)$$

where G is the number of intervals over which the baseline is allowed to vary in the sample, $\gamma(t) = 1$ if $t = g$, and $\gamma(t) = 0$ otherwise. We present piecewise exponential models with two and four intervals, as well as a Gamma Frailty model. We present Cox models illustrating random effects, fixed effects, as well as stratified by county to address correlation issues by county. Random and fixed effects models function as in traditional panel models while the stratification allows one to recover a baseline hazard by county.

Social Interactions Model

The neighborhood of each household is denoted n. Ioannides establishes the importance of endogenous interactions in residential neighborhoods, demonstrating that homeowners valuations of their own homes depend on the valuations of their immediate neighbors (Ioannides 2003) and that maintenance decisions depend on the level of maintenance taken on by immediate neighbors (Ioannides 2002).[4] In this paper, each household's immediate neighborhood is comprised of its nearest thirteen neighbors.

The probability of foreclosure for household h depends on household characteristics, x_h; characteristics of the households community, y_c; and the foreclosure behavior of neighborhood households, $m_{n(h)} = \left(\upsilon_{n(h)}, \omega_{n(h)}\right)'$, where $\upsilon_{n(h)}$ denotes the proportion of neighborhood households that foreclose by time τ and $\omega_{n(h)}$ denotes the mean time to foreclose among households that experience a foreclosure. Given these elements of the covariate vector z_h, the hazard model can be rewritten as

(8) $$\lambda\left(t, x_h, y_c, m_{n(h)}\right) = \lambda_0\left(t\right)\exp\left(\alpha' x_h + \beta' y_c + \varphi' m_{n(h)}\right)$$

where $\alpha, \beta,$ and φ are vectors of unknown parameters. Sirakaya (2006) examines the role of social interaction effects in recidivism rates among probationers. In the Sirakaya framework probationers needed to form expectations on the recidivism activity of other probationers in the neighbourhood. The actors in our model directly observe evidence of a neighbors foreclosure

[4] In Ioannides (2002; 2003), the immediate neighborhood includes the nearest ten neighbors.

decision through a number of potential channels, including deferred maintenance to the house and grounds, or personal knowledge of the neighbor or the neighbors situation.

We construct variables measuring the actual percentage of foreclosures among the nearest thirteen neighbors and the conditional mean time to foreclosure as a quarterly adjusted time varying covariate in the model. It is well documented that identification is an issue in interactions models because the group versus individual influences are likely correlated (Brock and Durlauf, 2001). However, as noted from Sirakaya's framework it is not an issue in this model because group and individual determinants are nonlinearly related via the construction of variables defining $m_{n(h)}$. Further, use of a hazard model overcomes the reflection problem discussed by Manski (2000); the data are collected in a panel, permitting specification of the likelihood of foreclosure as a function of neighboring foreclosures occurring recently.

Study Area and Background

Maryland provides a unique opportunity to study the endogenous interaction effects of residential foreclosures. Consistent with the national experience, Maryland experienced a sharp increase in foreclosures starting in 2007. Our study area includes the contiguous block of counties in Maryland from the suburbs of Washington, DC to the suburbs of Baltimore as shown in Figure 1. These counties, including Prince George's County, Montgomery County, Baltimore City, Frederick County, Anne Arundel County, and Baltimore County, accounted for the majority of foreclosure activity in Maryland. Within these six jurisdictions the majority of foreclosures occurred in Price George's County and Montgomery County, and foreclosures in these counties clustered spatially (DHCD 2009). Figures 2, 3, and 4 present the location foreclosures in Maryland over the course of the study period.

One of the primary drivers of any traditional foreclosure decision is job loss, and Maryland, with its proximity to DC, the Federal government and Federal contractor workforce acts as a firewall that protects the region from the full brunt of an economic downturn. For example, as of the middle of 2009 the Bureau of Labor Statistics reports that the unemployment rate in Maryland is 15th lowest and the year over year increase in the unemployment rate is 7th lowest in the nation. The counties in our study area all rank in the bottom third in unemployment rate, between 5.4 and 7.69 (). However, over the same time interval Maryland ranks 12th in the nation in foreclosure rate according to Realty Trac (DHCD 2009). In short, Maryland is at or near the lowest quartile in unemployment statistics while being near the highest quintile in foreclosure activity.

This relates directly to our social interactions research because we do not directly observe job loss at a household level. However, we assume the spatial distribution of job loss is random within a census tract. One would not expect highly localized spatial pockets of job loss as one might expect in a less diverse or more vulnerable labor market such as Las Vegas, Phoenix, Florida, or areas of California where foreclosures have been highest. In other words, a mass layoff event at one factory or in one highly specialized sector will not affect one suburban block of homes disproportionately more than any other suburban block of homes in the same census tract.[5]

Nationally, foreclosures tended to be driven by the dramatic fall in house prices due to bursting of the house price bubble. Although variation in the boom was highly spatially varied, Glaeser, Gottlieb, and Gyourko (2010) estimate the extent of the increase is potentially as high as 46% in real terms between 2001 and 2005. The national fall in house prices from their peak in July 2006 was at least one-third by April of 2009 and remained above one-quarter through

[5] The suburban block is a reasonable description of the 13 nearest neighbors for a vast majority of our data set.

August 2010 (S&P/Case-Shiller Home Price Indices). The experience in the DC-Washington metropolitan area was consistent with the national decline in house prices. As of December of 2009, the Case-Shiller house price index decreased by 29% as compared to the peak of house prices in Washington DC in March 2006. The Maryland study area therefore experienced an average house price decline, as compared to the nation. This implies our results are not driven by a localized collapse in house prices as was experienced in the high foreclosure states of Nevada, Arizona, Florida, and California.

If foreclosures are not driven by job loss, and the extent of the price decline is near the national average, then strategic defaults motivated by reduced moral and social constraints on default is left as a primary driver of foreclosures in Maryland. Overall, strategic defaults likely play a significant role in the relatively high foreclosure rates in Maryland. Since strategic defaults are influenced by moral and social constraints on foreclosure (Guiso, Sapienza, and Zingales 2009), this aids our identification of the role of endogenous interactions, in particular preference interactions, on neighborhood foreclosures.

Data and variable selection

We include variables controlling for contextual interactions and correlated effects in an attempt to isolate the influence of endogenous interactions on foreclosures. The variables listed in Table 1 are classified by household characteristics, neighborhood and community characteristics, loan attributes, house prices, unemployment, as well as the endogenous social interaction terms discussed above. Summary statistics are provided in Table 2.

Endogenous interactions

Households reference the actions of other households in their immediate neighborhood, defined in this study as the nearest thirteen households in terms of distance. The endogenous interaction variables are constructed based on the percentage of neighbors that have foreclosed and the mean time to foreclosure since the beginning of the sample period (January 2006), both adjusted monthly through the sample period of 2006 through 2009.

Household characteristics

We include a number of household-level characteristics representing correlated effects. Measures of the quality of house construction broken down into four categories, low, average, good, and very good (where average is omitted from the model) are used as a proxy for the value of the house, which should be correlated with the income and wealth of the household. One third of the houses in our sample are considered low quality, half average quality, and approximately 15% are rated as good or very good quality.

We control for owner-occupancy with a dummy variable equal to one if the household is an owner-occupier. Gerardi and Willen (2009) find that owner-occupied houses are less likely to go into foreclosure. Since the costs of foreclosure are higher for owner-occupied houses due to relocation costs and sentimental attachment to community, we expect owner-occupied houses are less likely to go into foreclosure. The age of the house is included to control for the vintage of construction as well as to control for the equity position of the homeowner. We expect newly constructed houses to have larger outstanding mortgages and as a consequence, owners of newly constructed homes are more likely to be in negative equity positions due to recent price depreciation. The length of the current ownership tenure is expected to be positively correlated with attachment to community and potential stigma due to default. Longer current tenure is therefore expected to reduce the likelihood of foreclosure.[6] [7]

Finally, we observe whether or not the property is a multi-family home. Previous studies have shown that condos and multi-family properties are more likely to foreclose (Gerardi, Shapiro, and Willen 2009; Foote, Gerardi, and Willen 2008). We do not have strong a priori expectations for multi-family properties in Maryland as the unfolding of this crisis does not have a peer in recent memory.

Neighbourhood and community characteristics

We control for a significant number of potential contextual interactions using socio-demographic indicators at the Census tract and block-group levels. Median rent, percent college educated, percent below poverty line, the percent of state median income of loan applicant, and the percent minority population are included as Census tract-level controls. We also include population density at the block level as a control for the extent of urbanization in the community. As a control for the stability of the neighborhood, we include average turnover in properties over the last five years (measured at the Census block level).

As required for empirical identification, a number of variables are measured at the 'neighborhood' level as opposed to the household level, once again controlling for contextual interactions that may drive common behavior within neighborhoods. We construct a number of neighborhood-level variables within a 500m buffer of each house. Figures 5 and 6 show the size of the 500m buffer relative to the thirteen nearest neighbors and illustrate how this definition of the neighborhood varies with the density of the area.

[6] The current ownership tenure may also be correlated with lower outstanding mortgages. We cannot say for sure – there may be large second mortgages out on houses with relatively long ownership tenures.
[7] Foote et al. (2008) model the baseline hazard as a third order polynomial in the age of ownership experience. The first order impact of age of ownership experience on the likelihood of foreclosure is positive.

We construct the ratio of multi-family to total buildings, as well as the ratio of commercial/industrial buildings to total buildings. Both variables capture potential sorting of individuals into different types of neighborhoods. We include the percentage of owner-occupied houses in the neighbourhood – previous research indicates that owner-occupied properties are less likely to foreclose. Neighborhoods with shorter tenure are more likely to have been recently developed and are also more likely to have weaker social connections among residents. Houses in these neighborhoods are therefore more likely to foreclose. We include the 25^{th} percentile, 50^{th} percentile, and 75^{th} percentile tenure values. We also include the median age of the home. Older homes likely carry lower mortgage balances and are less likely to be in negative equity positions. Also, unless these houses have been refinanced, house price depreciation should not have as large an influence on the likelihood of foreclosure.

Loans

Gerardi, Shapiro, and Willen (2009) find that household's with subprime loans are more likely to enter into foreclosure. To the extent that subprime loans went to low income households, the prevalence of subprime loans in a community can be thought of as a correlated effect – communities with more subprime loans are more likely to experience higher foreclosure rates because the types of households with subprime loans are correlated. Indeed, as discussed in Gerardi and Willen (2009), borrowers that use the subprime market tend to have poorer credit histories, higher initial loan-to-value ratios, and high debt-to-income ratios. The percentage of the 2006 loan portfolio deemed as subprime classification is defined as loans where the rate spread is greater than 3 percentage points on the first lien and 5 on subordinate liens.

We include a number of additional variables characterizing loan activity at the Census tract level. The ratio of refinance loans is included to capture the extent to which households have extracted equity from their houses. We expect refinance activity to be positively correlated with the likelihood of foreclosure. A higher ratio of conventional and home improvement loans increases the likelihood that households intend to remain in their current home. We expect a high ratio of non-owner occupied loans to total loans is positively correlated with foreclosures because these houses tend to be used as rental properties and the owners do not incur the relocation costs associated with foreclosure.

House prices and unemployment

Depreciation in house prices increases the likelihood of foreclosure (Bajari, Chu, and Park 2010). Foote, Gerardi, and Willen (2008) use a town-level house price index to measure the equity position of households – they present evidence that negative equity, brought about by house price depreciation, increases the likelihood of foreclosure. Gerardi, Shapiro, and Willen (2009) show that foreclosures tend to be driven by house price depreciation as opposed to insufficiently cautious underwriting. We include an annual repeat sales house price index at the sub-county level as well as the percent off peak values of the house price index.[8] House price index variables control for contextual interactions due to variation in house price expectations at the sub-county level. The peak year values range from 2005 to 2008 with 35% of the sample experiencing peak prices in 2006 and another 58% in 2007.

We include a measure of the average unemployment rate at the city or county level over the previous twelve months. There is mixed evidence regarding the importance of changes in unemployment in explaining foreclosure activity. Gerardi, Shapiro, and Willen (2009) find that changes in town-level cumulative unemployment rates have no impact on foreclosures. Foote, Gerardi, and Willen (2008) find that the unemployment rate has a positive impact on foreclosure.

[8] The price index is constructed by the authors based on Maryland Property View. Details are available upon request.

Bajari, Chu, and Park (2008) find that the monthly county-level unemployment rate has a negative impact on the likelihood of foreclosure. We include measures of mean unemployment and the standard deviation in unemployment as a control for the exogenous influence of shocks to employment that are common within communities.

Results

The results for the Cox proportional and the piece-wise exponential models are reported in Table 3 and Table 4, respectively. The results are expressed as hazard ratios, implying that values greater than one indicate that the independent variable increases the hazard of foreclosure, whereas values less than one indicate the independent variable reduces the hazard of foreclosure.

Endogenous interactions

Overall, we find strong evidence that endogenous interactions influence foreclosure decisions. The estimated hazard ratios on the endogenous interaction variables are significant in all of the models, and statistically significant at least at the 1% level in six of the seven. Further, the estimated hazard ratios are stable across models. In the Cox proportional models, a one unit increase in neighboring foreclosures increases the hazard of foreclosure by as much as 3%. The mean time to foreclosure among those neighbors that do foreclose, increases the hazard rate of foreclosure by less than 1%. In the piecewise exponential models, a one unit increase in the number of neighboring foreclosures increases the hazard rate of foreclosure by between 2 and 4%. A one unit increase in the mean time to foreclose among those neighbors that do foreclose, increases the hazard rate of foreclosure by less than 1%. Results for the endogenous interaction variables are therefore robust to a number of alternative specifications.

Household characteristics

As with the endogenous interaction variables, results for the household characteristics are robust to alternative model specifications and are generally consistent with expectations. We find that houses of lower quality construction are more likely to foreclose as compared to houses of average quality construction. In fact, the effect of quality is quite large – a low quality house is approximately 50% more likely to foreclose than an average or an above average quality house. We expect that quality of housing controls for household income, and if this is the case, that low income households are more likely to foreclose. This is consistent with the notion that low income households are less able to withstand income shocks and house price depreciation, and are therefore more likely to foreclose.

Owner occupied houses are far less likely to foreclose when compared to rental properties. An owner occupied house reduces the hazard rate of foreclosure by almost 50%. This is likely due to the fact that an owner occupier must bear relocation costs in the event of a foreclosure, whereas a rental property owner does not. The age of the house has a statistically significant, although small, impact on foreclosure. We find that households in older homes are more likely to foreclose but the effect is small; a one year increase in the age of the house increases the hazard of foreclosure by less than one percent. Households that have longer tenure periods are less likely to foreclose. A one year increase in ownership tenure reduces the hazard rate of foreclosure by approximately 6%. This is consistent with the fact that households with longer tenure are more likely to have stronger ties to their current communities and are therefore less willing to choose foreclosure. Perhaps more important than ties to the community, households with longer tenures likely have lower loan to value ratios, both because they have had more time to pay down principle and because they were less likely to purchase during the house price boom. Whereas previous research indicates that condo ownership is positively correlated with the likelihood of foreclosure (Gerardi, Shapiro, and Willen 2009), we find that multi-family dwelling are less likely to foreclose than single family properties.

Neighborhood and community characteristics

Neighborhood and community characteristic are included in the hazard models as controls for the correlated effects that might otherwise cause neighbors to have a similar propensity to foreclose. We find that neighborhood and community characteristics are statistically significant in the majority of cases. The greater the percent of the population below the poverty line in a given Census tract, the less likely a household within that Census tract is to foreclose. Greater population density tends to increase the likelihood of foreclosure, whereas households in Census tracts with higher median incomes tend to be less likely to foreclose. Households in Census tracts with higher percentage minority population are more likely to foreclose, consistent with results of previous research showing that minority borrowers are more likely to have subprime loans.

Hazard ratio estimates for the neighborhood characteristics are stable across all model specifications. An increase in the percent of owner-occupied units in the neighborhood has a positive impact on the hazard rate of foreclosure. An increase in neighbors' tenure in the 25th percentile reduces the likelihood of foreclosure by as much as 8%, whereas an increase in neighbors' tenure in the 75th percentile has little, if any, impact on the hazard rate of foreclosure. These results suggest that the tenure of a household's newest neighbors can have a significant impact on foreclosures. An increase in the median age of structures in the neighborhood decreases the hazard rate of foreclosure by less than 1%. The neighborhood level ratio of multi-family units to total units reduced the likelihood of foreclosure, whereas the ratio of commercial to total units increased the likelihood of foreclosure. Finally, households in Census block groups with a higher average property turnover rate tended to be more likely to foreclose – a one unit increase in the average turnover rate increases the hazard rate of foreclosure by 6% to 7% in all of the hazard model specifications. This result is consistent with the notion that households have fewer ties in less stable communities, as measured by turnover in properties.

Loan characteristics

Households in Census tracts with a greater percentage of subprime loans, as a share of all residential loans, are more likely to foreclose. Being in a Census tract with more than 53% subprime loans increases the hazard rate of foreclosure by more than 100%, compared to being in a Census tract with less than 13% in subprime loans. These results are consistent with previous research indicating that subprime loans go to riskier borrowers and are more sensitive to depreciation in house values (Geradri, Shapiro, and Willen 2009). The extent of refinance, conventional, home improvement, and non-occupancy loans at the Census tract level appears to have little impact on the hazard rate of foreclosure.

Prices and unemployment

A higher price index tends to increase the likelihood of foreclosure, albeit very slightly. Similarly, an increases in the percent prices are below their peak values tends to increase the hazard rate in the majority of the models (in four of the seven) and decreases the hazard rate in two of the seven models. This suggests that a fall in house prices from their peak influences the likelihood of foreclosure, but the magnitude of the impact may be quite small.

A higher average unemployment rate (over the previous twelve months) reduces the likelihood of foreclosure. This is somewhat surprising considering the fact that job loss is typically a factor that increases the likelihood of foreclosure. Further, previous empirical research demonstrates a positive relationship between unemployment and the hazard of foreclosure. Our results may reflect the fact that job loss was not an important factor in Maryland foreclosures. The variability in foreclosure, measured by the standard deviation of foreclosure (over the previous twelve months), has a positive impact on the hazard of foreclosure indicating the appropriate measure of the unemployment might be something other than the mean as is commonly used.

Conclusions

Using a unique and highly disaggregate data set with an appropriate measure of neighborhood we reveal the existence of an important but overlooked behavioral aspect of this foreclosure crisis. This period of foreclosures most assuredly will demonstrate price spillovers as shown many times in the previous literature but it also has the potential of lowering the barriers to exit from the repayment obligation to homeowners mortgage lenders. When a neighbor's foreclosure impacts the likelihood of you repaying your loan the conditions are present for the negative effects implied by the social multiplier suggested by Manski. If my peer group no longer stigmatizes foreclosure and it is in my short term best interest, I may "walk away" from my debt obligation which, in turn, impacts a new set of neighbors and so on. Policy implications from this research suggest that foreclosure prevention is of utmost importance but future work should focus on the tradeoffs between the pace of foreclosure to resell compared to the upfront cost of prevention of the original foreclosure.

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Table 1: Data description

Variable	Description
Social Interaction Variables	
percentFC	percentage of neighboring foreclosures
meanTimeToFC	among the FC neighbors the mean time to foreclosure in months
Household Characteristics	
ownQualityLow	construction quality low
ownQualityGood	construction quality good
ownQualityVGood	construction quality very good
ownerOccupied	owner occupied house
ageHome	age of structure
ownerTenure	length of time owner owns house
condo	condomium indicator
Neighborhood and Community Characteristics	
medianRent	median rent by tract
percentCollege	percent college educated by tract
percentPoverty	percent below poverty by tract
popDensity	population density by block
medianIncome	percent of state median income by tract
percentMinority	percent minority by tract
nOwnerOccupied	percent of owner occupied units in 500 meter buffer
nTenure_25thPtile	25th percentile of neighbors tenure in 500 meter buffer
nTenure_50thPtile	50th percentile of neighbors tenure in 500 meter buffer
nTenure_75thPtile	75th percentile of neighbors tenure in 500 meter buffer
nMedianAge	median age of structures in 500 meter buffer
ratioMultiFamily	ratio of multifamily units to total units in 500 meter buffer
ratioComm	ratio of commercial units to total units in 500 meter buffer
averageChurn	the average turnover rate for properties by blockgroup from 2000-05
Loan Characteristics	
subPrime53-100	percentage of 2006 loans that are subprime by tract
subPrime36-53	percentage of 2006 loans that are subprime by tract
subPrime25-36	percentage of 2006 loans that are subprime by tract
subPrime13-25	percentage of 2006 loans that are subprime by tract
refinanceRatio	ratio of refinance loans to total loans by tract
conventionalRatio	ratio of conventional loans to total loans by tract
homeImpRatio	ratio of home improvement loans to total loans by tract
nonOccupantLoanRatio	ratio of non occupant loans to total loans by tract
Price and Unemployment	
priceIndex	base 2000 repeat sales price index by tract (XX tract merged for data reasons)
percentOffPeak	percent below peak index value by tract
unempMean	previous 12 month average unemployment
unempSD	standard deviation in previous 12 unemployment

Table 2: Summary Statistics

Variable	Mean	Std.Dev.	Range	
Social Interaction Variables				
percentFC	1.89	4.56	0.00	69.23
meanTimeToFC	3.40	10.65	0.00	51.88
Household Characteristics				
ownQualityLow	0.34	0.47	0.00	1.00
ownQualityGood	0.12	0.32	0.00	1.00
ownQualityVGood	0.03	0.18	0.00	1.00
ownerOccupied	0.80	0.40	0.00	1.00
ageHome	32.11	23.69	0.00	307.00
ownerTenure	8.41	9.58	0.00	95.00
condo	0.16	0.37	0.00	1.00
Neighborhood and Community Characteristics				
medianRent	711.34	189.59	0.00	1001.00
percentCollege	59.64	18.26	0.00	100.00
percentPoverty	4.19	3.98	0.00	96.00
popDensity	22.39	36.97	0.00	2486.43
medianIncome	115.12	35.93	0.00	279.00
percentMinority	39.77	28.01	1.00	99.00
nOwnerOccupied	57.27	35.32	0.00	100.00
nTenure_25thPtile	2.20	1.91	0.00	55.00
nTenure_50thPtile	5.42	3.99	0.00	66.00
nTenure_75thPtile	11.41	7.96	0.00	67.00
nMedianAge	24.77	20.85	1.00	283.00
ratioMultiFamily	12.07	24.28	0.00	99.84
ratioComm	4.44	6.84	0.00	100.00
averageChurn	5.37	2.65	0.00	33.33
Loan Characteristics				
subPrime53-100	0.05	0.21	0.00	1.00
subPrime36-53	0.21	0.40	0.00	1.00
subPrime25-36	0.19	0.40	0.00	1.00
subPrime13-25	0.28	0.45	0.00	1.00
refinanceRatio	0.79	0.29	0.00	3.50
conventionalRatio	0.74	0.29	0.00	3.73
homeImpRatio	0.56	0.32	0.00	2.56
nonOccupantLoanRatio	0.68	0.28	0.00	2.67
Price and Unemployment				
priceIndex	75.74	12.49	27.94	182.85
percentOffPeak	3.93	7.65	0.00	65.26
unempMean	4.22	1.46	2.52	10.16
unempSD	0.14	0.13	0.04	0.91

Table 3: Piecewise Exponential Results

	2 intervals			4 Intervals			Gamma Frailty		
	Haz Ratio	Std Err		Haz Ratio	Std Err		Haz Ratio	Std Err	
Social Interaction Variables									
percentFC	1.02	0.00	*	1.04	0.00	*	1.02	0.00	*
meanTimeToFC	1.00	0.00	*	1.00	0.00	*	1.00	0.00	***
Household Characteristics									
ownQualityLow	1.48	0.02	*	1.45	0.02	*	1.55	0.02	*
ownQualityGood	1.01	0.02		0.95	0.02		1.11	0.03	*
ownQualityVGood	1.02	0.05		1.05	0.05		1.31	0.07	*
ownerOccupied	0.52	0.01	*	0.60	0.01	*	0.52	0.01	*
ageHome	1.01	0.00	*	1.00	0.00	*	1.01	0.00	*
ownerTenure	0.94	0.00	*	0.95	0.00	*	0.94	0.00	*
condo	0.79	0.02	*	0.83	0.02	*	0.85	0.02	*
Neighborhood and Community Characteristics									
medianRent	1.00	0.00	**	1.00	0.00	**	1.00	0.00	*
percentCollege	1.00	0.00	*	0.99	0.00	*	1.01	0.00	*
percentPoverty	0.99	0.00	*	0.96	0.00	*	0.98	0.00	*
popDensity	1.00	0.00	*	1.00	0.00		1.00	0.00	*
medianIncome	1.00	0.00	*	1.00	0.00	*	0.99	0.00	*
percentMinority	1.01	0.00	*	1.02	0.00	*	1.01	0.00	*
nOwnerOccupied	1.02	0.00	*	1.02	0.00	*	1.02	0.00	*
nTenure_25thPtile	0.93	0.01	*	0.92	0.01	*	0.92	0.01	*
nTenure_50thPtile	0.96	0.00	*	0.97	0.00	*	0.99	0.01	**
nTenure_75thPtile	1.01	0.00	*	1.02	0.00	*	1.00	0.00	
nMedianAge	1.00	0.00	*	0.99	0.00	*	1.00	0.00	*
ratioMultiFamily	1.00	0.00	*	1.00	0.00		1.00	0.00	
ratioComm	1.02	0.00	*	1.02	0.00	*	1.01	0.00	*
averageChurn	1.07	0.00	*	1.06	0.00	*	1.07	0.00	*
Loan Characteristics									
subPrime53-100	2.04	0.06	*	2.00	0.06	*	3.17	0.41	*
subPrime36-53	2.10	0.05	*	1.89	0.05	*	2.98	0.29	*
subPrime25-36	1.72	0.04	*	1.66	0.04	*	1.87	0.16	*
subPrime13-25	1.59	0.03	*	1.63	0.04	*	1.39	0.10	*
refinanceRatio	0.93	0.06		0.71	0.05	*	1.69	0.42	**
conventionalRatio	0.96	0.06		1.39	0.09	*	1.11	0.25	
homeImpRatio	1.10	0.02	*	0.94	0.02	*	1.13	0.09	
nonOccupantLoanRatio	0.99	0.04		0.81	0.03	*	0.74	0.08	*
Price and Unemployment									
priceIndex	1.00	0.00	*	1.02	0.00	*	0.97	0.00	*
percentOffPeak	0.89	0.00	*	1.08	0.00	*	0.89	0.00	*
unempMean	0.56	0.01	*	0.45	0.01	*	0.48	0.01	*
unempSD	3.08	0.18	*	32195	2100.15	*	24.34	1.52	*
County Fixed Effects	Yes			Yes			Yes		

* <.01, ** <.05, *** <.10

Table 4: Cox Model Results

	Cox			RE Cox (Gamma)			FE Cox			Cox Stratified		
Variable	HR	Std Err		HR	Std Err		HR	Std Err		HR	Std Err	
Social Interaction Variables												
percentFC	1.03	0.00	*	1.03	0.00	*	1.03	0.00	*	1.02	0.00	*
meanTimeToFC	1.00	0.00	*	1.00	0.00	*	1.00	0.00	*	1.00	0.00	*
Household Characteristics												
ownQualityLow	1.53	0.10	*	1.49	0.02	*	1.49	0.02	*	1.49	0.02	*
ownQualityGood	1.02	0.23		1.02	0.02		1.02	0.02		1.02	0.02	
ownQualityVGood	1.05	0.14		1.05	0.05		1.05	0.05		1.05	0.05	
ownerOccupied	0.54	0.05	*	0.52	0.01	*	0.52	0.01	*	0.52	0.01	*
ageHome	1.01	0.00	*	1.01	0.00	*	1.01	0.00	*	1.01	0.00	*
ownerTenure	0.94	0.00	*	0.94	0.00	*	0.94	0.00	*	0.94	0.00	*
condo	0.82	0.08	**	0.80	0.02	*	0.80	0.02	*	0.80	0.02	*
Neighborhood and Community Characteristics												
medianRent	1.00	0.00		1.00	0.00	**	1.00	0.00	**	1.00	0.00	**
percentCollege	1.00	0.00		1.00	0.00	*	1.00	0.00	*	1.00	0.00	*
percentPoverty	0.99	0.01	**	0.99	0.00	*	0.99	0.00	*	0.99	0.00	*
popDensity	1.00	0.00	*	1.00	0.00	*	1.00	0.00	*	1.00	0.00	*
medianIncome	1.00	0.00		1.00	0.00	*	1.00	0.00	**	1.00	0.00	**
percentMinority	1.01	0.00	*	1.01	0.00	*	1.01	0.00	*	1.01	0.00	*
nOwnerOccupied	1.01	0.00	*	1.02	0.00	*	1.02	0.00	*	1.02	0.00	*
nTenure_25thPtile	0.91	0.01	*	0.93	0.01	*	0.93	0.01	*	0.93	0.01	*
nTenure_50thPtile	0.98	0.02		0.97	0.00		0.97	0.00		0.97	0.00	*
nTenure_75thPtile	1.01	0.01		1.01	0.00		1.01	0.00		1.01	0.00	*
nMedianAge	0.99	0.00	*	0.99	0.00	*	0.99	0.00	*	0.99	0.00	*
ratioMultiFamily	1.00	0.00	*	1.00	0.00	*	1.00	0.00	*	1.00	0.00	*
ratioComm	1.01	0.00	*	1.02	0.00	*	1.02	0.00	*	1.02	0.00	*
averageChurn	1.06	0.02	*	1.07	0.00	*	1.07	0.00	*	1.07	0.00	*
Loan Characteristics												
subPrime53-100	2.41	0.51	*	2.23	0.06	*	2.23	0.06	*	2.23	0.06	*
subPrime36-53	2.40	0.37	*	2.25	0.05	*	2.25	0.05	*	2.25	0.05	*
subPrime25-36	2.00	0.31	*	1.94	0.04	*	1.94	0.04	*	1.94	0.04	*
subPrime13-25	1.63	0.22	*	1.68	0.04	*	1.68	0.04	*	1.67	0.04	*
refinanceRatio	1.18	0.31		1.03	0.07		1.03	0.07		1.03	0.07	
conventionalRatio	0.83	0.15		0.86	0.05		0.86	0.05		0.87	0.05	
homeImpRatio	1.01	0.04		1.02	0.02		1.02	0.02		1.02	0.02	
nonOccLoanRatio	1.08	0.13		1.06	0.04		1.06	0.04		1.05	0.04	
Price and Unemployment												
priceIndex	1.01	0.00	***	1.01	0.00	*	1.01	0.00	*	1.00	0.00	*
percentOffPeak	1.01	0.01		1.01	0.00	**	1.01	0.00	**	1.02	0.00	*
unempMean	1.20	0.06	*	0.98	0.02		0.98	0.02		0.96	0.02	**
unempSD	0.36	0.19	***	0.70	0.08	*	0.70	0.08	*	0.78	0.12	**
County Dummies	No			No			Yes					

* <.01, ** <.05, *** <.10

Marginal Effects from Cox models

Variable	Cox Marg Effect	Std Err		RE Cox Marg Effect	Std Err		FE Cox Marg Effect	Std Err		Stratified Cox Marg Effect	Std Err	
Social Interaction Variables												
percentFC	0.246	0.16		0.094	0.012	*	0.164	0.021	**	0.081	0.010	*
meanTimeToFC	0.022	0.01	**	0.008	0.003	*	0.014	0.005	*	0.007	0.002	*

* <.01, ** <.05, *** <.10

Figure 1: Map of Study Area

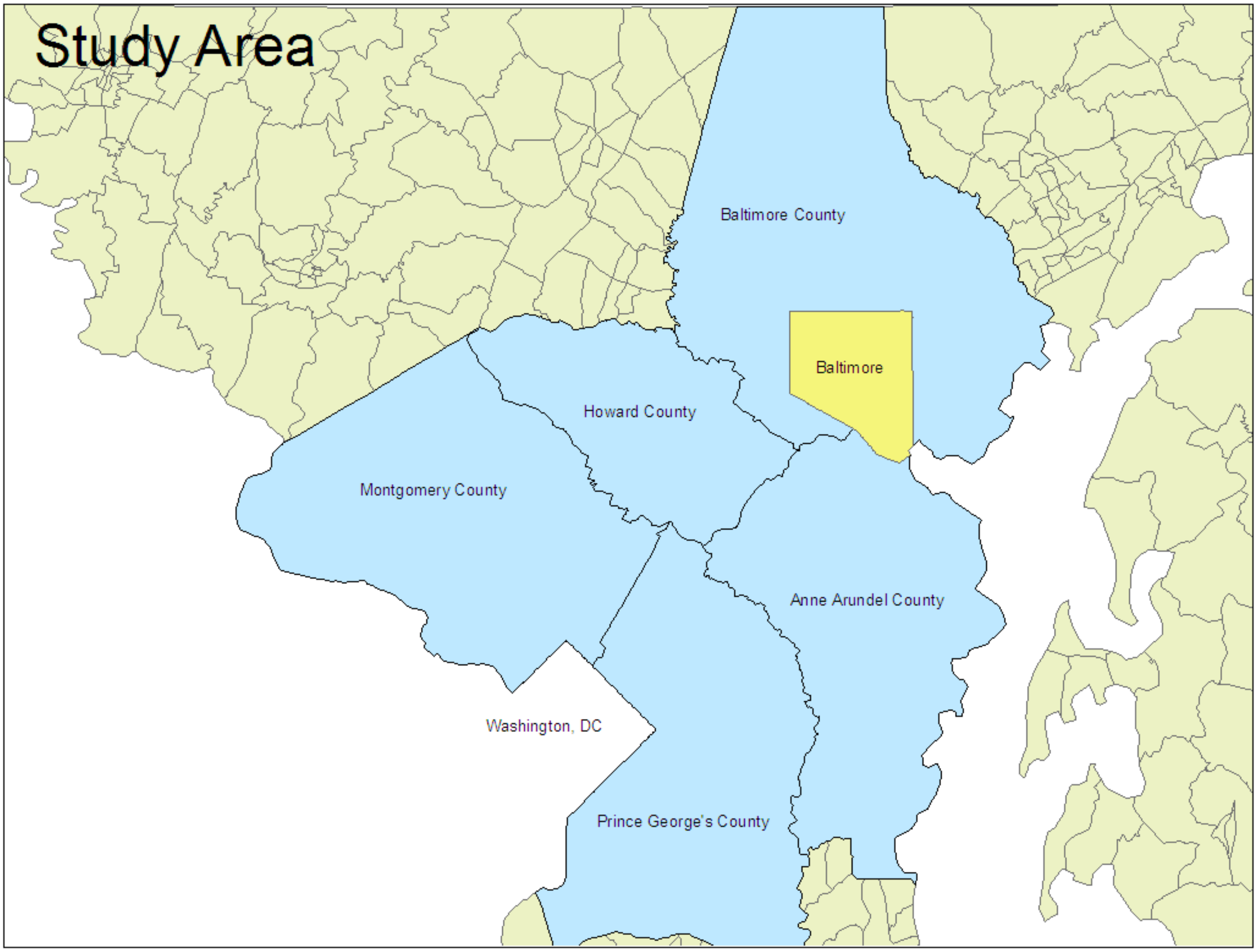


Figure 2: 2006 Foreclosure activity

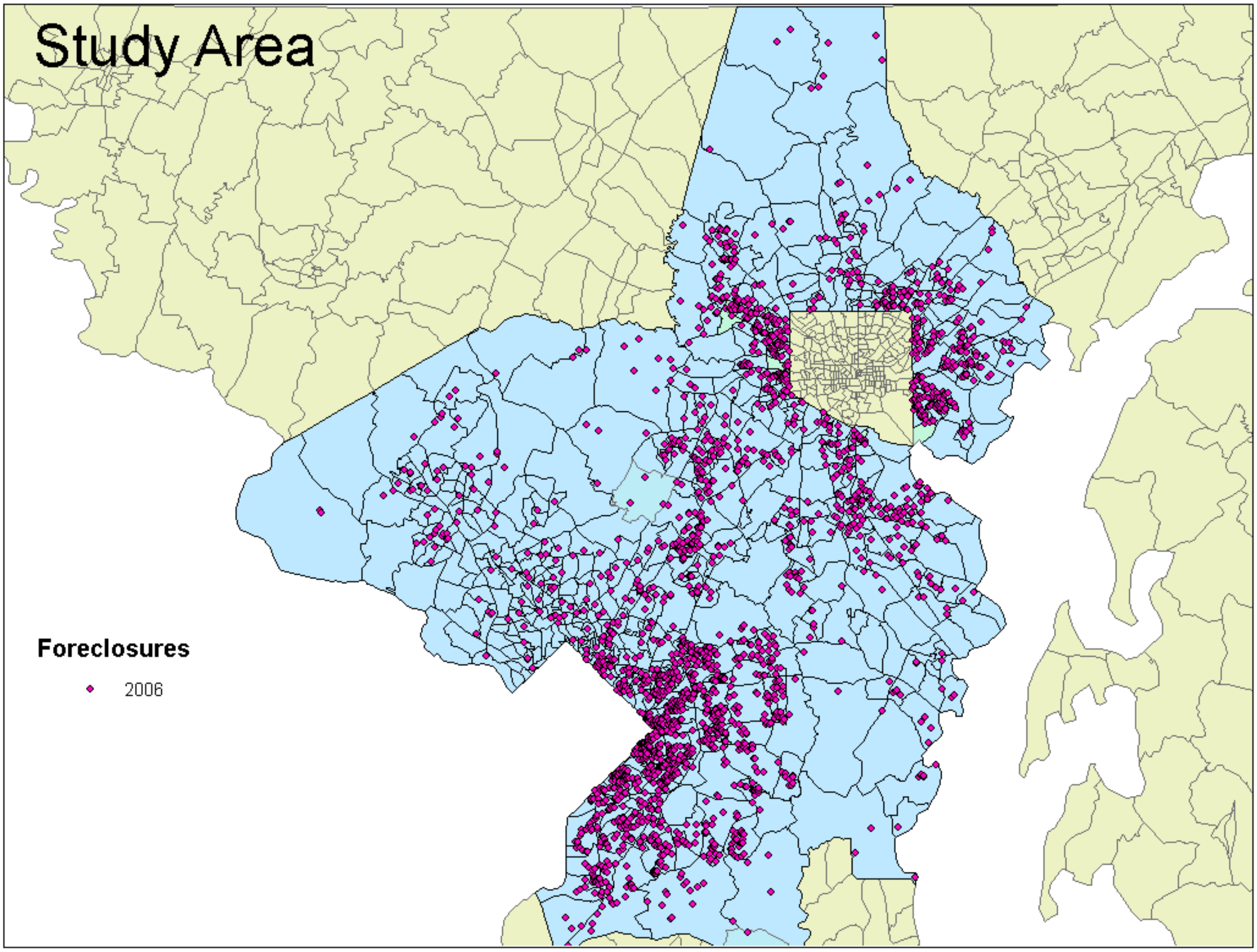


Figure 3: 2006-2009 Foreclosure activity

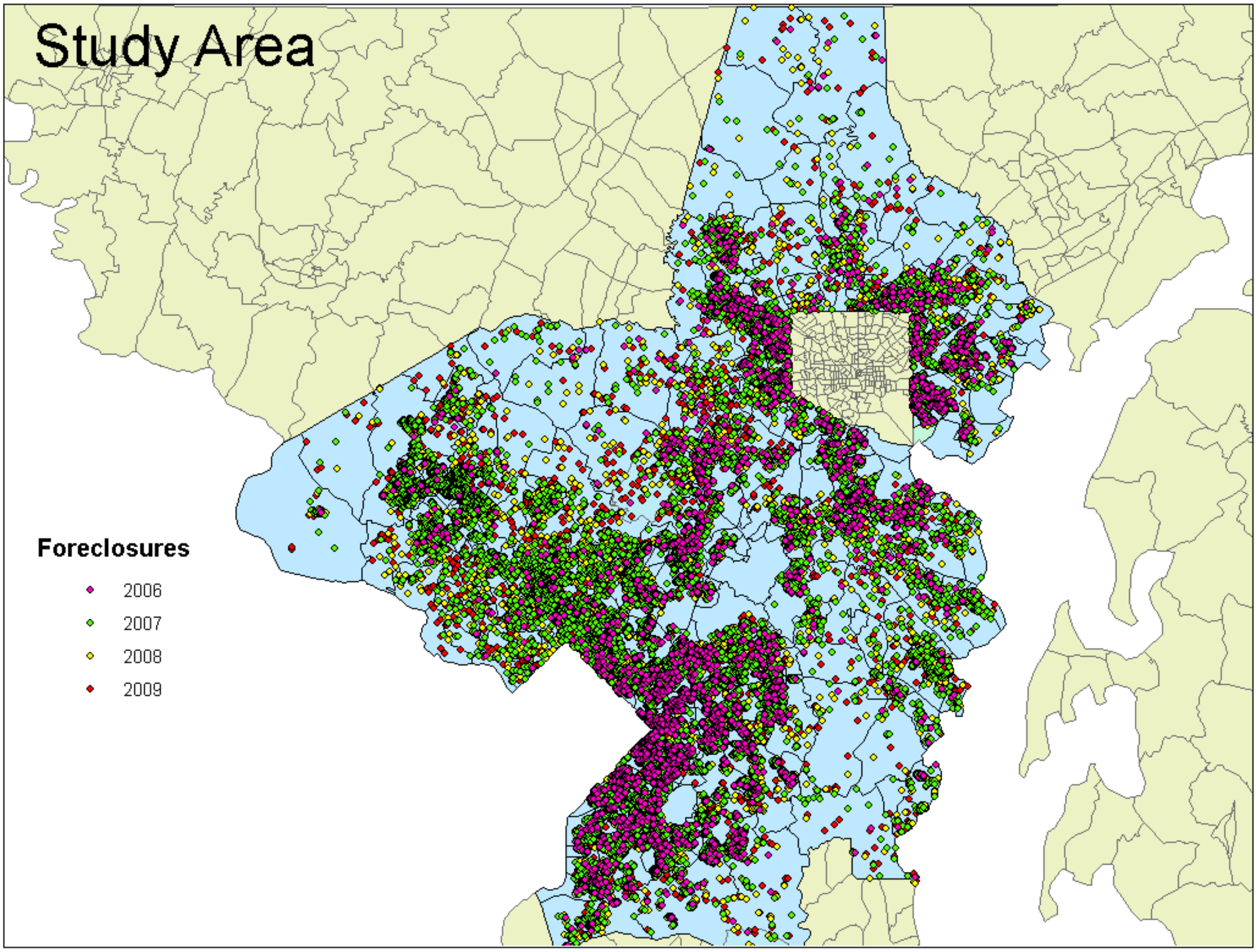
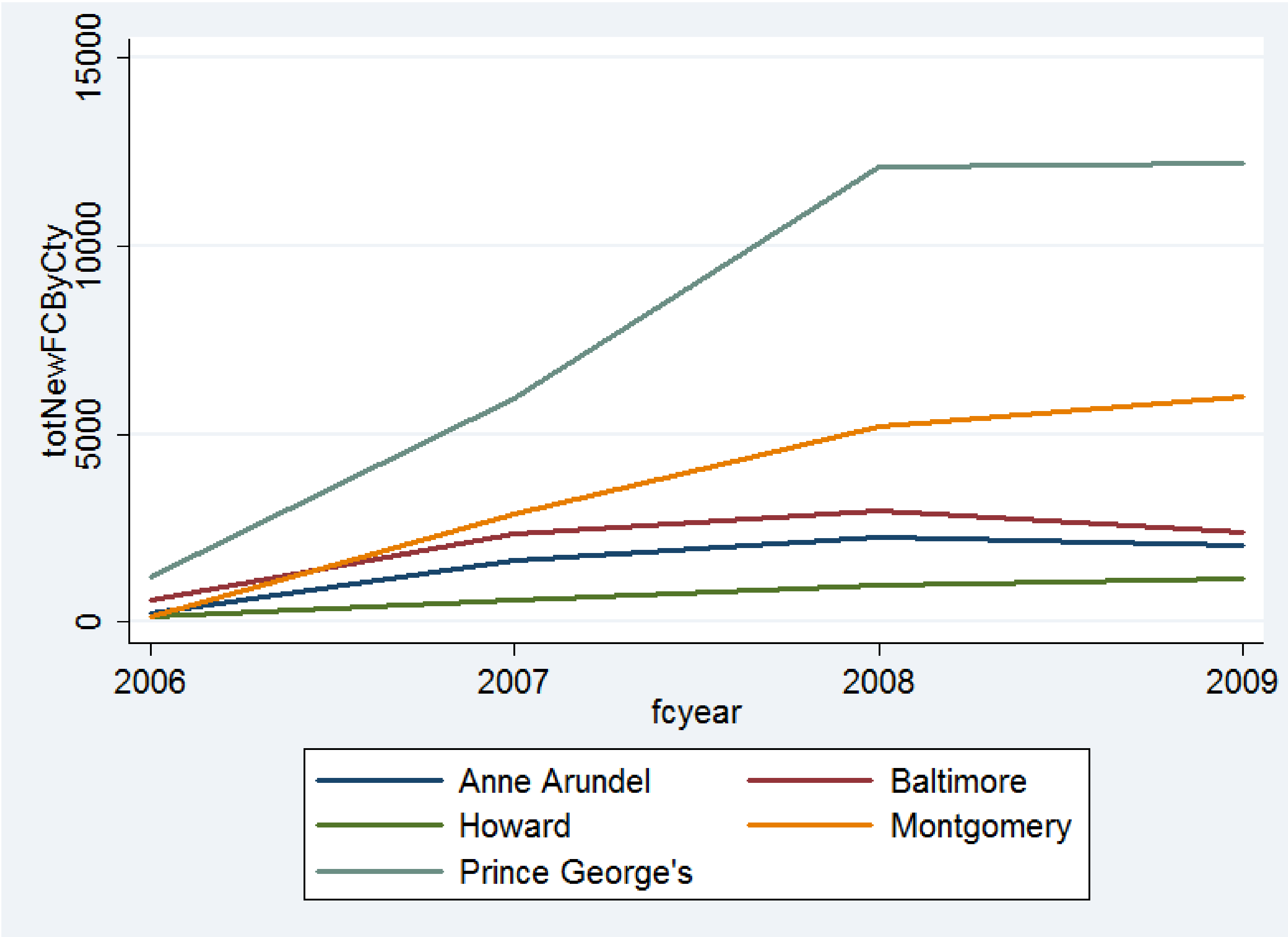


Figure 4: Number of Foreclosure events by year and county.



Note: FC through 3Q of 2009

Figure 5: Buffer illustration for dense area.

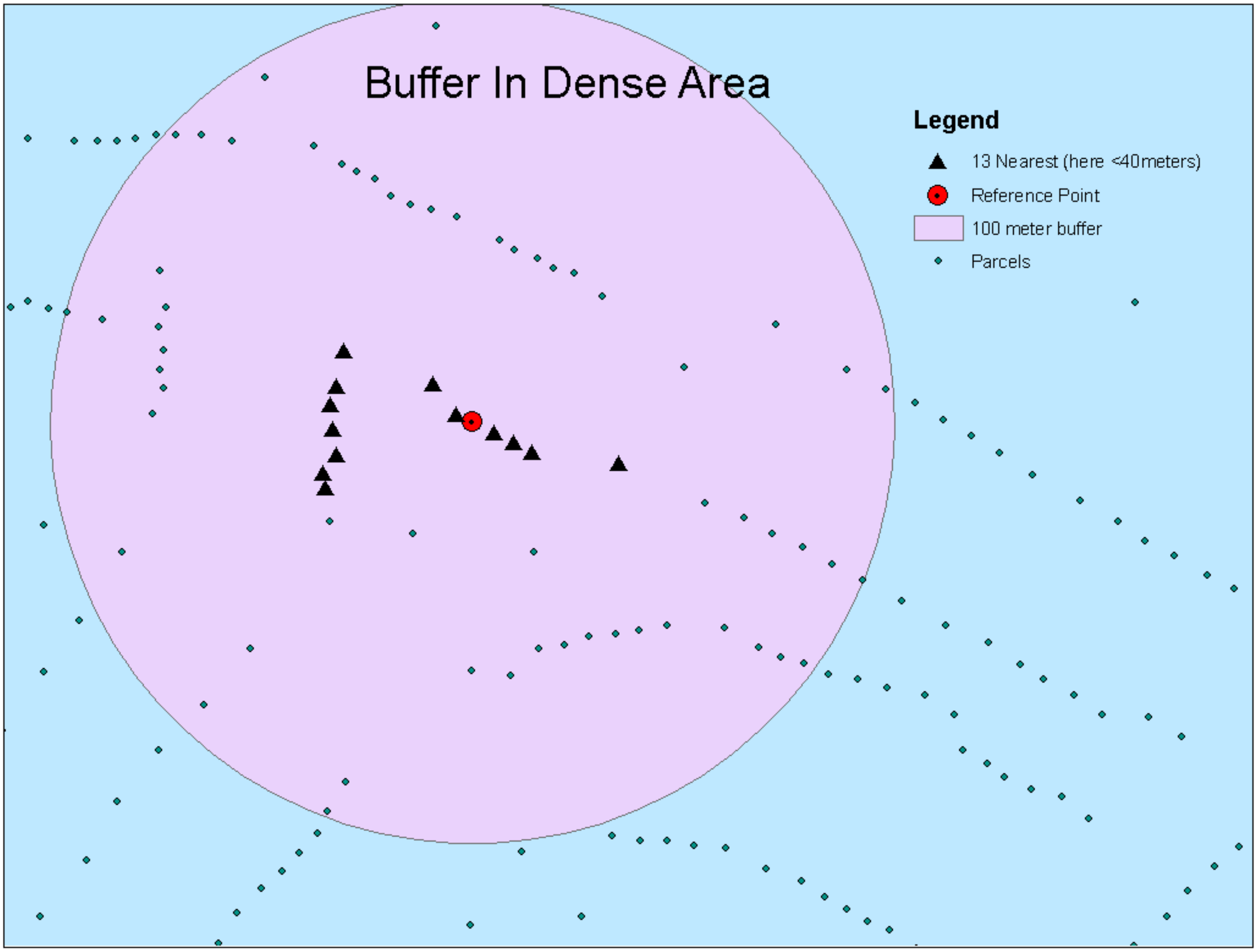


Figure 6: Buffer illustration in rural area.