Neighborhood Foreclosure Concentration and the Decision to Default*

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1. Introduction

In recent years, the United States has experienced a nation-wide crisis in the mortgage market with unprecedented number of defaults and foreclosures. However, mortgage defaults and foreclosures were not evenly distributed across space. Miami, Las Vegas, Phoenix, Detroit and Los Angeles are the hard-hit metropolitan (metro) areas with intensive foreclosures. Other metros such as Seattle, Houston and Atlanta have much lower foreclosure rates. Also within cities, foreclosures are more concentrated in some neighborhoods than in others. For example, in Los Angeles, the foreclosure rate in zip code 90056 (Ladera Heights in South Los Angeles) is about forty times more than that in zip code 90403 (Santa Monica in West Los Angeles) in April 2014[1]. Questions arise as what socio-economic consequences those concentrated foreclosures bring to urban neighborhoods.

Existing research has found foreclosures generate externalities to urban neighborhoods. For example, they lower the values of nearby properties, increase neighborhood violent crimes and cause high property turnovers (see, e.g., Harding, Rosenblatt and Yao, 2009; Immergluck and Smith, 2006a; Gerardi and Willen, 2009). In this paper, we take a novel

[1] According to RealtyTrac, May 2014, Los Angeles County Real Estate Trends & Market Info. http://www.realtytrac.com/statsandtrends/foreclosuretrends/ca/los-angeles-county. Foreclosure rate is defined as the number of foreclosures divided by the total number of housing units in the zip code.

approach to try to answer a new question, which is how concentrated foreclosures affect the default decision of mortgage borrowers in the surrounding area. The question we address can be intuitively understood as how seeing foreclosure signs in one's neighborhood affects someone's likelihood of and attitude towards exercising her mortgage default option to enter into default.

From a game-theoretic perspective, concentrated foreclosures in one's neighborhood can discourage the borrower's exercise of default option. This is because intense foreclosures in a neighborhood can send out a signal to nearby borrowers that should they choose to default they are likely to be similarly foreclosed instead of receiving a favorable loan modification. This information effect is similar to that discussed by Riddiough and Wyatt (1994) and Guiso, Sapienza and Zingales (2013) where borrower's strategic default decision depends on her belief of what the lender's reaction would be.

However, on the other hand, concentration of foreclosure can induce more defaults due to contagion. Such foreclosure contagion can arise from observational learning: seeing foreclosures in one's neighborhood can cause the borrower to adjust down her property valuation or to strengthen her belief of a declining market, and thus increase her chance of exercising the default option (Agarwal et al, 2011). Foreclosure contagion can also arise due to ethical reasons – knowing that many others in the neighborhood have defaulted their mortgage loans might change someone's view that default is immoral or ease the stigma effect of default. In addition, it can come from behavioral responses such as herding (Seiler, Lane and Harrison, 2012).

Therefore, the ultimate impact of neighborhood foreclosure concentration on borrowers' default decision is an empirical question, which we investigate in this paper. With a rich dataset of individual mortgage loans from BlackBox Logic (BBX), we are able to track the performance of individual loans, to measure foreclosure intensity in each urban neighborhood, and further to estimate a model of mortgage borrowers' delinquency decision that incorporates neighborhood foreclosure concentration effect. Comparing to existing studies, we take a novel approach to not only assess the impact of neighborhood foreclosure concentration on individual borrower's delinquency probability but also estimate the impact of foreclosure concentration on the borrower's sensitivity to negative equity. The latter estimate measures to a certain extent the changing attitude of borrowers towards default option exercise.

In our main analysis, we focus on the Los Angeles-Long Beach-Santa Anna metropolitan statistical area (the Los Angeles MSA). Our sample includes over 12,000 fixed-rate subprime mortgage loans that were originated between 1998 and 2008 and tracked through the first quarter of 2014. Our results show that on average neighborhood foreclosure concentration enhances borrowers' default option exercise during the study period – borrowers are more willing to enter into default when there are intense foreclosures in the neighborhood. However, interestingly, the impact of foreclosure concentration varies in different regimes: before 2007, higher neighborhood foreclosure intensity is associated with reduced borrower sensitivity; entering into the crisis period (2007-2011), the impact turns from negative to positive; and post 2012, the impact becomes insignificant. We believe such variations reflect the balancing of the information effect and the contagion effect we discussed above. For example, during the crisis period, the foreclosure contagion effect might have been the dominant force and outweighed the information effect, so we see a positive *net* impact.

The net impact of neighborhood foreclosure concentration on borrowers' sensitivity to negative equity also varies across different borrower groups. For example, the positive impact is significantly stronger among Asian borrowers than among non-Asian borrowers, but smaller among female borrowers than among male borrowers. There is a U-shape in the relation between neighborhood average FICO score and the impact of foreclosure concentration on borrowers' sensitivity to negative equity. Both very high and very low FICO neighborhoods see increased borrower sensitivity. Finally, lower income neighborhoods see stronger relation between foreclosure concentration and borrower sensitivity. These heterogeneities are also consistent with the notion that the balancing of the information effect and the contagion effect is likely to differ across different borrower groups.

The aforementioned results can be generalized to the whole state of California. And these results are robust to alternative house price index (HPI) and different measures of neighborhood foreclosure concentration.

Understanding how mortgage borrowers make their default decisions is critical to mortgage default risk management, pricing and underwriting. Traditional studies of borrower decision focus on mortgage borrowers' own socio-economic status such as the borrower's FICO score, income constraint, and equity position. Recently, some researchers have tried to place borrowers into social networks to understand their default decisions (see, e.g., Seiler, Collins and Fefferman, 2013; Gangel, Seiler and Collins, 2013; Guiso, Sapienza and Zingales, 2013). We follow this line of thoughts. But different from existing studies that rely on simulated data or survey data, we use actual default data. Our findings indicate that peer behavior has great influence on borrower's actual default choice. Therefore, default models should incorporate such network effects.

From a policy perspective, understanding the impact of foreclosure concentration on borrower's delinquency decision is also important. Delinquency is the first step of loan default, and foreclosure is usually the last step. Typically, large numbers of foreclosures follow the wave of delinquencies. Interestingly, what we find in this paper is that concentrated foreclosures can feedback onto borrower delinquency. Therefore, during the crisis, mortgage default can be self-enforcing in certain neighborhoods – increased delinquencies lead to more foreclosures, and concentrated foreclosures further lead to even more delinquencies. From this perspective, timely intervention by the government to reduce foreclosure is important to break the loop and to stop the foreclosure cascade.

The rest of the paper is organized as follows: in the next section, we will explain our data and present some results regarding neighborhood foreclosure concentration; in section 3, we will discuss our hypothesis development, model, and empirical results regarding the impact of foreclosure concentration on borrower delinquency; concluding remarks are in a final section.

2. Data and Measures of Foreclosure Concentration

2.1. Data Sources

Our first and main data comes from the loan-level data furnished by BlackBox Logic (hereafter BBX). The BBX aggregates data from mortgage servicing companies. The most recent BBX data contains roughly 22 million non-agency (including jumbo, Alt-A, and subprime) mortgage loans throughout the United States, making it a comprehensive source for mortgage default studies[1]. BBX provides detailed information on the borrower and the loan at loan origination, including the borrower's FICO score, original loan balance, interest rate, loan term (30 year, 15 year, etc.), loan type (fixed-rate, 5-1 ARM, etc.), loan purpose (home purchase, rate/term refinance, cash out refinance), occupancy status, prepayment penalty indicator and other characteristics. BBX also tracks the performance (default, prepayment, mature, or current) of each loan in every month.

Another key data source is the Home Mortgage Disclosure Act (HMDA) implemented by the Federal Reserve Board, which requires that lending institutions report virtually all mortgage application and origination data. HMDA is considered the most comprehensive source of mortgage data, covering about 80 percent of all home loans nationwide and an even higher share of loans originated in metropolitan statistical areas (Avery, et al, 2007). In particular, it provides a nearly complete universe of 122 million U.S. mortgage applications over the period 2001–2010. The key reason for using HMDA is that it covers borrower characteristics such as applicant's race, sex, and annual income that are not

[1] The BBX data is comparable to other well-known datasets such as the CoreLogic data.

contained in the BBX data. HMDA also provides abundant information on the loan characteristics at the stage of loan application, including loan amount (in thousands), loan purpose (home purchase or refinancing or home improvement), borrower-reported occupancy status (owner-occupied or investment), (in the case of originated loans) whether the loan was sold to the secondary market within the year of origination, and other characteristics. Property-related variables available in HMDA are geographic location (census tract level identification) and property type (one-to-four-family or manufactured housing or multifamily).

Given the existence of common variables in the BBX data and the HMDA data, we match BBX loan-level data with selected HMDA loan data using step-by-step criteria.[1,2] First, BBX loans are matched to HMDA loans with the same loan purpose and occupancy status of the borrowers. Second, based on the origination dates of BBX loans, HMDA loans within the same year of origination are considered. In addition, BBX loans are only matched to HMDA loans with the same zip code. Last, loans from BBX should have the same original loan amount as those from HMDA. For all possible HMDA matches for each BBX loan (with the same BBX identifier but different HMDA identifiers), we keep only the first record for the same BBX identifier. Any BBX loan that has no corresponding HMDA loans matched using the above criteria is a non-match and is excluded from our sample[3].

[1] There is no unique common identifier of a loan from these two databases.

[2] In order to match with BBX data, only loan applications marked as originated in HMDA data are considered. Those loans originated by FNMA, GNMA, FHLMC and FAMC are removed. Those with loan type of FSA (Farm Service Agency) or RHS (Rural Housing Service) are excluded as well.

[3] The success rate of our match is about 70 percent.

Furthermore, we merge the loan-level data with macro variables such as the MSA-level unemployment rate from Bureau of Labor Statistics, the CoreLogic Case-Shiller zip code-level Home Price Index, and the S&P Case-Shiller MSA-level Home Price Index. Treasury bond rate and interest rate swap rate from the Federal Reserve, and mortgage interest rate from Freddie Mac are also matched into the data.

For our main tests, we focus on first-lien, fixed-rate subprime mortgage loans for the Los Angeles-Long Beach-Santa Anna metropolitan statistical area (the Los Angeles MSA).[1] The advantage of focusing on one particular MSA rather than pooling MSAs is that we can insulate our analysis from the cross-MSA disparities in borrower behavior that is due to legal and institutional differences, and thus gain cleaner inference from our model. Later we generalize our analysis to the whole state of California. We focus on the subprime mortgage loan sample that contains enough number of delinquencies, which enable us to estimate a sensible delinquency model.

2.2. Measures of Foreclosure Concentration

We create a number of neighborhood foreclosure concentration measures at the zip-code level. Our main measure is the foreclosure intensity calculated as the total number of foreclosures in the past two quarters (e.g. for 2009Q1 it is 2008Q4 and 2008Q3) divided by the total number of housing units (in thousands) in each zip code. We further create a foreclosure intensity rank order of all zip codes in the Los Angeles MSA in each quarter

[1] A series of filters is also applied: we first exclude loans originated before 1998 for accuracy consideration; we also exclude those loans with interest only periods or those not in metropolitan areas (MSAs); loan occupancy status indicated as second home or vacancy home, loans with missing or wrong information on loan origination date, original loan balance, property type, refinance indicator, occupancy status, FICO score, loan-to-value ratio (LTV), documentation level or mortgage note rate are excluded.

and then define a dummy variable "High foreclosure intensity" as the zip-quarter that ranks in the 90th percentile of all zip-quarters.

We also calculate alternative foreclosure intensity as the total number of foreclosures in the recent four quarters (current quarter plus the past three quarters) divided by the total number of housing units in each zip code (in thousands). Accordingly, a "High foreclosure intensity" dummy variable is created based on rank order.

Finally, instead of using the total housing units as the denominator to calculate foreclosure intensity we use the total population in each zip code to calculate per capita foreclosure intensity measures.

Figure 1 shows some maps of foreclosure intensity. The first map shows the aggregate foreclosure intensity from all years. We see that there is great variation in foreclosure concentration across neighborhoods. Generally, zip codes in the inland cities have greater foreclosure intensity than those along the coast; zip codes in northern cities experience greater foreclosure intensity than those in west and east cities. Among all cities in this metropolitan area, Santa Clarita Valley, Antelope Valley and San Fernando Valley experienced the highest foreclosure intensity: for every one thousand housing units in these zip codes, 50-135 loans during the period of 1998-2008 turned into foreclosures. San Gabriel Valley and Gateway Cities also suffered great waves of foreclosure during this period, ranging from 10 to 50 foreclosures per thousand housing units per zip code. Westside Cities, located in the west of this area, are shown to have the least foreclosure concentrations, with less than 10 foreclosures for every thousand housing units at the zip code level.

We further create the foreclosure intensity maps for each individual year and show the years of 2003, 2006, 2009 and 2012 in Figure 2. We see that foreclosure intensities vary significantly across the four years. 2003 and 2006 overall have small average foreclosure intensities (0.11 and 0.75 foreclosures per thousand housing units, respectively), in contrast to 3.05 and 1.81 foreclosures per thousand housing units in 2009 and 2012. Specifically, in 2003, more than half of the metropolitan area has foreclosure intensity of less than 1 per thousand, while in 2006, zipcodes in northern and southern cities experienced high foreclosure intensities, reaching 5 to 8 per thousand. In 2009, we observe even greater increases in the foreclosure concentration in the north, south and central area, with the greatest concentration in the northern part (25-50 per thousand). The foreclosure intensity in 2012, although still at a pretty high level compared with that in 2003 and 2006, starts to decrease, with the highest intensity of 20 per thousand housing units at the zip code level. The possible explanation for these phenomena is that the strong house price appreciation during 2003-2005 helped most of the loans in 2003 and 2006 out of foreclosure troubles, while the sharp and far-reaching house price decline starting from 2006 led to the much higher foreclosure concentration later in 2009 and 2012. The gradually recovering housing market in 2012 helped to reduce foreclosures. Among all cities in this area, Antelope Valley from the northern part experienced the most serious foreclosure problems through the four years, while San Gabriel Valley, the city located in the east of this area, remains at very low foreclosure intensity across the whole study period.

2.3. Descriptive statistics

Before digging into our main analyses, we take a preliminary look at our sample. Table 1 reports the number of originated loans in our sample by vintage, and Table 2 presents the numbers of loans at loan termination by the choice of default, prepay or current (censor).[1] As shown in Table 1, the number of loans originated rise slowly from 1998 (105 loans) to 2002 (512 loans), while starting from 2003 through 2006, there is a sharp jump in the observation numbers, with the highest number in 2005 (3,719 loans, 26% of the total sample) and lowest in 2003 (1,848 loans, 15% of the total sample). Since 2007, the loan number has declined quickly, with only about 61 percent less than that in 2006. The origination year distribution of our sample reflects the development of the subprime mortgage market. By looking at the loan numbers by termination status in Table 2, we can see that among 12,007 loans in our sample, around 39% of loans have been defaulted, around 42% have been prepaid, and only 19% remain current by the time of January 2014.

Table 3a reports frequencies of some loan and borrower characteristics of our subprime FRM sample. Although approximately 52% of loans have full documentation of income, asset or employment, there are 26% of loans with low or even no documentation. Among

[1] The terminations status of a loan is classified into default, prepay, and censor, whichever is the earliest at the end of January 2014. Default is defined as over 60- day delinquency. Prepay refers to early repayment of a loan, often as a result of refinancing to take advantage of lower interest rates. Current (censor) means that the loan is alive at the end of January 2014.

the 12,007 loans in our sample, 10,394 loans (87%) have origination LTV greater than 80. Only 5% of loans are 15-year FRMs, which are usually thought to be less risky than 30-year FRMs. 97% of loans are classified as owner-occupied, compared with investment purpose (3%). Regarding property type, single family group ranks first (around 89% of the total loans), followed by condominium group. In terms of loan purpose, cash-out refinance and rate/term refinance account for about 94% of the total loans, while purchase loans only account for 6%. Consistent with the usual characteristics of subprime loans, about 87% of loans in our sample have prepayment penalty clause in the mortgage contracts, which might limit the subprime borrower's ability to refinance into more affordable loans and thus increase the chance of default. In terms of borrower characteristics, White and African American borrowers take up 49% and 12% of the total sample, while Asian borrowers are only 6%. More than 60% of the borrowers are male borrowers.

Table 3b shows the descriptive statistics of important loan and borrower characteristics. Because of high housing costs in Los Angeles MSA, our loans had an average original loan balance of $263,130. The average FICO score is 582, and the current interest rate reaches 7.22 on average. Borrower's debt-to-income ratio is around 28 percent on average. The average original LTV and combined LTV are both around 65 percent.

3. The Impact of Foreclosure Concentration on Borrower Delinquency

3.1. Hypothesis Development

We start with a brief explanation of the default process. Typically borrower's failure to make monthly mortgage payment constitutes a default[1], which can result in a sale of the collateral to fulfill the borrower's debt obligation. However, default is not a one-stage process. It is actually a multiple-stage lengthy process. The borrower first decides whether to miss a scheduled monthly payment. If a payment is missed and the loan becomes 30-day delinquent, late fees will be charged. Subsequently when a mortgage loan is 60-day overdue, a notice of default (NOD) is usually sent to the borrower, and the servicing of the loan will be transferred from the general servicer to a special servicer, who will first seek a workout if appropriate. If a workout is unsuccessful, the lender (through special servicer) will start the foreclosure process, which typically occurs after the loan is over 90-day delinquency. The actual foreclosure sale (trustee sale in non-judicial foreclosure states like California) typically takes another several months to occur because foreclosure has to be publicized fully (e.g., notification sent to the borrower, notice published at the local newspaper, and signs to be put on the property). Finally, if a sale is successful, the lender receives sales proceeds net of all the fees and legal costs. An unsuccessful foreclosure/trustee sale leads to real estate owned (REO), in which the lender obtains the title of the property. Therefore, we can see that borrower delinquency is the beginning of the default process while foreclosure is in the subsequent stage of default, which can be many months away down the road.

Many believe that mortgage borrowers are strategic in their delinquency decisions in a sense that they not only consider their ability to make the monthly payment, the current equity position (whether the house is worth more than the remaining loan balance) and

[1] Technically, borrower's failure to pay taxes or insurance premiums, failure to keep the property in repair, or violations of other loan covenants can also lead to default.

house price trend (the possibility of a future recovery from the current negative equity position) but also consider what the lenders' reactions are. The logic is as follows: given that foreclosure is costly to lenders as sale proceeds from a foreclosure sale usually fall short of the remaining balance plus all the transaction costs, lenders usually first seek to "workout" a delinquent loan. A loan workout can take the form of a reduced interest rate/payment, reduction in loan principal, and extension of the mortgage term, which are typically in the borrower's favor. Foreclosure is typically the worst outcome not only to the lender but also to the borrower, because it causes the borrower to lose her home and incur significant credit impairment. Therefore, from a game-theoretic perspective, borrower's delinquency decision depends upon her own strategic perspective on the consequential gains or losses from acceptance, rejection, or a counter-offer from the lender and the likelihood of each response. Riddiough and Wyatt (1994) argue that borrower's delinquency decision depends on how tough the lender is. Guiso, Sapienza and Zingales (2013) also argue that borrower's attitude towards strategic default depends on her assessment of the probability of getting sued by the lender (a foreclosure)[1]. Following this line of thoughts, we would expect that the incidences of foreclosure, especially large number of foreclosures in one's neighborhood can serve as a signal to the borrower that the chance of receiving a favorable loan modification or short sale is low while the chance of being foreclosed is high should she chooses to enter into default. Therefore, foreclosure concentration will discourage the borrower's choice of delinquency. We define this effect as an information effect.

[1] Strategic default is when the borrower is able to make the monthly payment but chooses not to do so in anticipation of a favorable loan modification after she is delinquent on her loan.

On the other hand, recently there has been a growing literature on foreclosure contagion. Several studies have found that nearby foreclosed properties lower the price of neighboring properties (see, e.g., Immergluck and Smith, 2006b, Schuetz, Been and Ellen, 2008; Lin, et al, 2009; Harding, Rosenblatt and Yao, 2008; Campbell, Giglio and Pathak 2009). Although the exact mechanism of such foreclosure contagion is still debated in the literature, a compelling explanation is the observational learning suggested by Agarwal et al (2012): homeowners update their beliefs about the value of their homes when they receive signals about house price trend. Foreclosures in one's neighborhood send out a public signal of a declining property market. Based on such a signal, nearby homeowners will adjust their valuation downward, causing an observed negative impact of nearby foreclosure on property values. Such downward adjustment in valuation apparently increase the probability of default as borrowers default their mortgage loans mainly because the value of the property is lower than the mortgage loan balance[1]. Therefore, from this perspective, concentrated foreclosure in one's neighborhood has a positive impact on someone's default decision.

The impact of concentrated foreclosures on borrower's delinquency decision can also arise from herding. People do not always exercise independent judgment due to social influence (Shiller, 1995). Meanwhile, in situations where information is limited individuals can follow the herd in the hope of gaining the superior information of the group (Bikhchandani, Hirshleifer, and Welch, 1998). For these reasons, herd behavior can be a source of mispricing and speculative bubbles (Shiller, 2008). In a recent study,

[1] Some researchers argue that insolvency (e.g., loss of income) also cause default. However, if there is positive equity, the borrower should be able to sell the property and payoff the loan to avoid a default. Therefore, negative equity is the ultimate driver of residential mortgage default.

Seiler, Lane and Harrison (2014) find that homeowners are easily persuaded to follow the herd to strategically default their mortgage loan. Extending this herding rational to mortgage borrower's delinquency decision, we would expect someone who resides in a neighborhood with concentrated foreclosures is exposed to the influence of her neighbors and thus is more likely to exercise her default option when she see many foreclosure signs in her neighborhood.

During the recent mortgage market crisis, there have been heated debates regarding whether it is immoral to default one's mortgage loan (see, e.g., White, 2010; Guiso, Sapienza and Zingales, 2010). Although many Americans think it is immoral to strategically default their mortgage loan, seeing many neighbors have done so might have changed some borrowers' view. In addition, the thought that "I am not doing this alone" can ease the stigma effect of mortgage default and thus cause borrowers to be more willing to enter into default.

In summary, foreclosure concentration can have both positive and negative impacts on borrower's delinquency decision. It is really an empirical question as to what the *net* impact is. Further, one may observe different net impacts in different times and across different borrower groups, depending on how those positive and negative impacts play out differently over time and in the cross section.

3.2. Methodology

In order to empirically assess the impact of foreclosure concentration on borrower's delinquency decision, we estimate a Cox proportional hazard model of mortgage delinquency. The hazard model is widely used in the mortgage literature (see, e.g. Vandell, 1993; Quigley and Van Order, 1995; An, et al, 2012). It is convenient mainly because it allows us to work with our full sample of loans despite some observations being censored when we collect our data. This is an important feature for us because a large portion of our mortgage loan observations is censored.

Assume the hazard rate of default of a mortgage loan at period T since its origination follows the form

$$h_i(T, Z'_{i,t}) = h_0(T)\exp(Z'_{i,t}\beta). \tag{1}$$

Here $h_0(T)$ is the baseline hazard function, which only depends on the age (duration), T, of the loan and is an arbitrary function that allows for a flexible default pattern over time[1]; $Z'_{i,t}$ is a vector of covariates for individual loan i that include all the identifiable risk factors. In this proportional hazard model, changes in covariates shift the hazard rate proportionally without otherwise affecting the duration pattern of default. Commonly used covariates include negative equity, FICO score, loan balance, the loan-to-value (LTV) ratio, payment to income ratio, and change in MSA-level unemployment rate.

Neighborhood foreclosure concentration is the key variable that will be on the right hand side of our delinquency model. However, different from existing studies, we take a novel approach to not only include our measure of foreclosure concentration as a covariate but

[1] Notice that the loan duration time *T* is different from the natural time t, which allows identification of the model.

also interact our foreclosure concentration measure with negative equity. In so doing, we allow the coefficient of negative equity to depend on our measure of foreclosure concentration. The model we estimate is thus

$$h_i(T, Z'_{i,t}) = h_0(T)\exp(Z'_{i,t}\beta)$$

$$Z'_{i,t}\beta = \beta_1 NegEq_{i,t} + \beta_2 ForclRate_{j,t} + \beta_3 ForclRate_{j,t} \cdot NegEq_{i,t} + X'_{i,t}\gamma \,, \tag{2}$$

where $NegEq_{i,t}$ is negative equity of loan i in zipcode j at time t, $ForclRate_{j,t}$ is the neighborhood foreclosure rate of zipcode j at time t, and $X'_{i,t}$ are other control variables such as FICO score, LTV ratio, etc.

Existing studies have found negative equity to be a critical driver of mortgage borrowers' default option exercise (see, e.g., Campbell and Dietrich. 1983; Quigley and Van Order, 1995; Deng, Quigley and Van Order, 2000). However, existing research has also found that mortgage borrowers do not always default when facing negative equity (see, e.g., Vandell, 1995; Deng and Quigley, 2002; Foote, Gerardi and Willen, 2008). Therefore, the coefficient of negative equity in a delinquency model measures the sensitivity or responsiveness of the borrower to negative equity in her choice of delinquency. It can also be viewed as the borrower's attitude to exercise default option. Therefore, β_3 in equation (2) measures the impact of foreclosure concentration on borrowers' attitude to exercise their mortgage default option. Note that by including neighborhood foreclosure rate as a covariate, we are also measuring the direct impact of foreclosure concentration on delinquency probability (the impact is reflected in β_2 in our model). In addition, this variable will control for any unobservable neighborhood characteristics that are orthogonal to house price movement and other measured changes in the neighborhood if there is any such unobservable characteristics.

3.3. Results

We report our first set of estimation results in Table 4. Model 1 is the model without time-fixed effect. In addition to the focus variables we see in equation (2), we have 25 control variables (the X variables). Most of these control variables are significant with signs conforming to existing research or economic theory. For example, low or no doc loans have higher risk of delinquency and borrowers of those loans are more sensitive to negative equity. Owner-occupied loans are less sensitive to negative equity than investor loans. FICO score is negatively correlated with delinquency probability but the function is concave. In addition, higher FICO score borrowers are more sensitive to negative equity. Large loans and loans with high LTV (over 80 percent) are more likely to enter into default, everything else equal. Rate/term refinance loans are less likely to be delinquent while cash-out refinance loans are more likely to become delinquent. Loans with higher payment to income ratio have higher delinquency risk, and African American borrowers and female borrowers are more likely to enter into default. Finally, increase in MSA level unemployment rate causes more delinquency.

We now turn to discuss our focus variables. Consistent with findings in the existing literature, negative equity is a highly significant factor of mortgage delinquency. The higher the negative equity is the more likely the loan will be delinquent (the positive β_1). In addition, we can see from the significant positive coefficient of the square term of negative equity that the function is convex, which is as expected – borrowers become extremely sensitive when they have a large negative equity. The more interesting findings here are on the zip-level foreclosure rate and its interaction with negative equity. We see that zip-level foreclosure rate itself is significant but negatively correlated with the probability of delinquency (the negative β_2). This tends to support the game-theoretic view that borrowers take nearby foreclosures as an indication of the chance of being foreclosed should she chooses to default, and thus nearby foreclosures lower the neighboring borrower's likelihood of becoming delinquent on her loan. But as we just discussed, this variable can also be measuring some unobservable neighborhood characteristics that are orthogonal to other measured changes in the neighborhood. Therefore, we do not want to over-interpret this result. The clearer inference should be from the interaction term. The coefficient of $ForclRate_{j,t} \cdot NegEq_{i,t}$ is positive and significant (the positive β_3) meaning that the higher the foreclosure rate is in neighborhood, the more sensitive borrowers are to negative equity in their delinquency choice. This positive *net* impact of neighborhood foreclosure concentration on delinquency suggests that the foreclosure contagion effect likely outweighs the information effect.

To account for possible changes in borrower's sensitivity to negative equity due to other reasons such as the overall market sentiment, we include the interaction of current year dummies with negative equity in Model 2. We see that there is no material change to the results we just discussed. β_3 is still positive and highly significant.

In Table 5, we report results of our models where we use a dummy variable to indicate where a specific zip code during a specific quarter has high foreclosure rate comparing to other zip-quarters. Here high foreclosure rate means that it is in the 90^{th} percentile of all zip-quarters. Other than this change, the model specification is exactly the same here in Table 5 as in Table 4. Results are consistent with those in Table 4. β_3 is still positive and highly significant, suggesting strong positive *net* impact of neighborhood foreclosure concentration on borrower's propensity to exercise default option.

It is reasonable to assume that the information effect of neighborhood foreclosure concentration to be stable over time. However, the contagion effect might vary in different regimes. Before 2007, the housing market was glorious. There were very few foreclosures and foreclosure was not a serious concern. Therefore, we would expect the foreclosure contagion effect to be minimal. These are exactly what we find in the next a few tests. In Table 6, we show results of a model where we allow the impact of neighborhood foreclosure concentration to vary in different regimes. We divide the whole study period into four regimes: pre-2007 is the period of housing boom; 2007 to 2009 is when we had the first wave of the housing and mortgage market crisis; 2010-2011 is when we had the second wave of the crisis during which Los Angeles had a second downturn in the housing market after a short recovery in the second half of 2009; post 2012 is when the Los Angeles housing market had a real recovery. We see that the *net* impact of neighborhood foreclosure concentration is indeed negative pre-2007, consistent with the notion that foreclosure contagion effect was small if not zero while the information effect was significant and negative. During 2007-2009, the *net* impact turned positive, likely due to the fact that foreclosure contagion became significant and prevalent. In 2010 and 2011, the *net* positive impact became even stronger compared to that during 2007-2009, possibly because of stronger contagion effect due to the desperation brought by the second wave of the crisis. Finally, post-2012 the *net* impact is not significant, likely due to a balance of the information effect and the foreclosure contagion effect.

The information effect and contagion effect could also vary with respect to different borrower groups. We conduct such tests subsequently. In order to avoid the confounding effect of housing market regimes, we conduct the tests with the post 2007 subsample. We first test whether Asian borrowers behave differently from the rest of the population. Table 7 shows the results. Interestingly, we see that the *net* impact of neighborhood foreclosure concentration for Asian borrowers is significantly different from non-Asian borrowers. Both its impact on delinquency probability and its impact on borrower's sensitivity to negative equity are stronger among Asian borrowers than among non-Asian borrowers. A possibly explanation is that due to cultural differences Asians are more susceptible to herd behavior[1]. Table 8 shows the comparison between African American borrowers and the rest of the population. We see almost no difference between African Americans and non-African Americans.

Next, we turn to compare female borrowers and male borrowers. Interestingly, we see from Table 9 that females have smaller β_3, suggesting that either the contagion effect is

[1] For example, Chiang and Zheng (2010) find stronger evidence of herding in Asian stock market than in the US and Latin American markets.

weaker or the information effect is stronger among female borrowers. A possibly explanation is that females have higher opportunity cost of homeownership and are more concerned with the negative consequences of foreclosure, which makes the information effect to be stronger and offsets more of the contagion effect.

We further test whether the foreclosure concentration effects vary in different neighborhoods. We first classify neighborhoods by average FICO score. For each zip code, we calculate the average FICO score of fixed-rate subprime mortgage loans originated during our study period and rank order all zip codes in the Los Angeles MSA. Then we use a dummy variable to indicate whether a neighborhood is in the upper or lower quartile in average FICO score. Finally, we interact these dummy variables with our focus variables. Table 10 shows the model results. Interestingly, we see that there is a U-shape in the relation between neighborhood average FICO score and the impact of foreclosure concentration on borrowers' sensitivity to negative equity. β_3 is significantly higher in very high and very low average FICO neighborhoods, while the middle tier FICO neighborhoods see decreased borrower sensitivity. Notice that we have already found that borrowers with higher FICO score are more sensitive to negative equity (the positive coefficient of the interaction term between negative equity and FICO score), which is suggestive that borrowers with higher FICO score are more financially sophisticated and more responsive to financial opportunities. Our finding that the neighborhood foreclosure concentration impact is more profound among high FICO neighborhood is consistent with such a financial sophistication explanation. In a separate test, we classify neighborhoods based on average income and find that lower-income neighborhoods see stronger relation between foreclosure concentration and borrower sensitivity to negative equity, while there is no significant difference between moderate-income neighborhoods and high-income neighborhoods in terms of the impact of foreclosure concentration on borrowers' sensitivity to negative equity.

Lastly, we generalize our analysis to the whole state of California. Results in Table 12 show that the impact of neighborhood foreclosure concentration in Califronia is very similar to what we find in Los Angeles MSA.

We also conduct a number of robustness tests including the use of different house price index to construct the negative equity measure as well as alternative foreclosure rate measure (e.g., per capital vs. per housing unit foreclosure rate). Results are robust.

4. Conclusions

Existing research has found foreclosure to be contagious in that foreclosure reduces the price of nearby non-distressed sales. In this paper, we find another type of foreclosure contagion – foreclosures can induce nearby mortgage borrowers to exercise their default option more ruthlessly. This type of foreclosure contagion is especially prominent during a downturn of the housing market. Therefore, during the mortgage market crisis, we saw a large number of mortgage loans become delinquent, many of which subsequently were foreclosed. Those foreclosures were definitely bad results for the borrowers, the lenders and the investors. But the damage was not limited to the borrowers and lenders who are directly involved in the default process. Those foreclosures generate externalities to the neighborhood – they induce more borrowers in the surrounding area to enter into default. This circular reaction can go on and on and lead to foreclosure cascades. Therefore, it is important for the government and lenders to take timely actions to stop or reduce foreclosures and thus to break the loop of such a crisis.

Certainly, the impact of neighborhood foreclosure concentration on borrower default behavior is not limited to the contagion effect. We actually find that sometimes the impact can be on the opposite direction – foreclosures can discourage borrower's delinquency if borrowers take foreclosures as a signal of how lenders will deal with delinquencies. This information effect can dominate the contagion effect during the market boom. From this perspective, borrowers are strategic in their default decisions. Credit risk modelers thus should take this game feature of mortgage default into consideration to achieve better understanding and estimation of mortgage default risk.

Future research should try to establish the exact mechanism of the foreclosure contagion we discover in this paper, and assess the relative roles of observational learning, herding and other channels in generating such foreclosure contagion.

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Table 1 Number of Loans in Our Sample by Vintage

This table shows the frequency distribution of loan originations in our sample. We include first-lien, fixed-rate subprime mortgage loans for the Los Angeles-Long Beach-Santa Anna metropolitan statistical area (the Los Angeles MSA), and exclude those loans with interest only periods or those with missing or wrong information. All the loans are originated during the period 1998—2008.

Origination Year	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1998	105	0.87	105	0.87
1999	123	1.02	228	1.9
2000	184	1.53	412	3.43
2001	245	2.04	657	5.47
2002	512	4.26	1169	9.74
2003	1848	15.39	3017	25.13
2004	2625	21.86	5642	46.99
2005	3179	26.48	8821	73.47
2006	2290	19.07	11111	92.54
2007	895	7.45	12006	99.99
2008	1	0.01	12007	100

Table 2 Performance of Loans in Our Sample

This table presents the frequency distribution of loan termination status in our sample, by the choice of default, prepay or current (censor), whichever is the earliest at the end of January 2014. Default is defined as over 60- day delinquency. Prepay refers to early repayment of a loan, often as a result of refinancing to take advantage of lower interest rates. Current (censor) means that the loan is alive at the data collection point—January 2014.

Termination type	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Current	2245	18.7	2245	18.7
Prepay	5118	42.63	7363	61.32
Default	4644	38.68	12007	100

Table 3 Summary Statistics of Loan and Borrower Characteristics

Table 3 reports the summary statistics of loan and borrower characteristics in our sample. Table 3a presents the frequency distribution of some important loan and borrower characteristics, while Table 3b shows the mean, standard deviations, minimum and maximum of some numerical variables. Documentation type is an indicator whether a particular loan has full, low, do or reduced documentation of income, asset or employment. LTV greater than 80 percent is equal to Yes if the original loan-to-value (LTV) ratio is greater than 80 percent. Race refers to the racial group that the borrower belongs to, and Gender indicates whether the borrower is a male or female. Loan type means whether the durations of the FRM loan is 30 years or 15 years. Property type refers to the classification of the property securing the mortgage: i.e. Single family, PUD (planned urban development) and Condo (condominium). Loan purpose indicates the primary reason the mortgage was taken out by the borrower. Occupancy status means the use of the home such as investment, owner-occupied (primary residence), etc. Prepayment penalty type is an indicator denoting that a fee will be charged to the borrower if they elect to make unscheduled principal payments. Loan with a second lien is Yes if a second mortgage is taken out on the same property. Original loan amount is defined as the amount of principal on the closing date of the mortgage. FICO SCORE refers to the FICO (formerly the Fair Isaac Corporation) borrower credit score at the time of the loan closing. Current interest rate refers to the coupon rate charged to the borrower for the most recent remittance period. LTV (%) refers to the ratio of the original loan amount to the property value at loan origination, while Combined LTV (%) means the ratio of all loan amounts on the property at the time of origination to the property value at loan origination. Payment-to-income ratio refers to the percentage of monthly mortgage payment to borrower's monthly income.

Table 3a Frequency Distribution of Loan and Borrower Characteristics

		Frequency	Percent	Cum. Freq.	Cum. Pct.
Documentation type	Full doc	6245	52.01	6245	52.01
	Low doc	3028	25.22	9273	77.23
	No doc	147	1.22	9420	78.45
	Reduced doc	143	1.19	9563	79.65
	Unknown doc	2444	20.35	12007	100
LTV greater than 80 percent	No	10394	86.57	10394	86.57
	Yes	1613	13.43	12007	100
Race	White	5831	48.56	9147	48.56
	Asian	684	5.7	930	54.26
	Black	1430	11.91	2360	66.17
	Other	4062	33.83	12007	100
Gender	Male	7315	60.92	7315	60.92
	Female	4089	34.06	11404	94.98
	Unknown information	603	5.02	12007	100
Loan type	30-year FRM	11358	94.59	11358	94.59
	15-year FRM	649	5.41	12007	100

Table 3a Frequency Distribution of Loan and Borrower Characteristics (Continued)

		Frequency	Percent	Cum. Freq.	Cum. Pct.
Property type	Single family	10631	88.54	10631	88.54
	PUD	341	2.84	10972	91.38
	Condo	1035	8.62	12007	100
Loan purpose	Home purchase	725	6.04	725	6.04
	Rate/term refinance	2142	17.84	2867	23.88
	Cash-out refinance	9140	76.12	12007	100
Occupancy status	Owner-occupied	11611	96.7	11611	96.7
	Investment property	396	3.3	12007	100
Prepayment penalty type	No	116	0.97	116	0.97
	Yes	10396	86.58	10512	87.55
	Unknown	1495	12.45	12007	100
Loan with a second lien	No	10043	83.64	10043	83.64
	Yes	1964	16.36	12007	100
Total number of loans		12,007			

Table 3b Means, Standard and Deviations of Loan and Borrower Characteristics

Variable	Mean	Std. Dev.	Minimum	Maximum
Original loan amount	263,130	131,013	22,000	2,500,000
FICO SCORE	582	34	417	804
Current interest rate (%)	7.22	1.11	1.64	13.83
LTV (%)	65	17.17	6	139
Combined LTV (%)	65	18	6	125
Payment-to-income ratio	0.28	0.16	0.01	11.37
Total number of loans		12,007		

Table 4 MLE Estimates of the Cox Proportional Hazard Model

This table presents the Cox proportional hazard model result for the refined Subprime sample in the Los Angeles MSA, during the period 1999-2013. Negative equity is calculated with the contemporaneous house value (based on MSA level HPI) and the market value of the mortgage loan outstanding, adjusted by MSA-level house price volatility. Zip-level Foreclosure unit is calculated as the permillage of the total number of foreclosures in the past two quarters (e.g. for 2009Q1 it is 2008Q4 and 2008Q3) in the total number of housing units in each zip code. Log balance refers to the log of the original loan amount. Call option is computed the difference between the par value of the mortgage and the present value of the remaining payments evaluated using the current market mortgage rate. Change in MSA unemployment rate refers to the difference between the unemployment rate at current time and at origination time. The other explanations of the variables are shown in Table 3. Parameter estimates are reported standard errors are included in the parentheses. Note that ***, ** and * indicate 1%, 5% and 10% significance, respectively.

Covariate	Estimate (S.E.)	Estimate (S.E.)
Negative equity	0.655***	2.61***
	(0.144)	(0.177)
Negative equity square	0.003***	0.011***
	(0.000)	(0.002)
Negative equity *Zip-level Foreclosure unit	0.192***	0.169***
	(0.04)	(0.042)
Zip-level Foreclosure unit	-0.069**	-0.052*
	(0.028)	(0.029)
Negative equity *Low/no doc indicator	0.088*	0.048
	(0.046)	(0.042)
Low/no doc indicator	0.175***	0.179***
	(0.029)	(0.029)
Negative equity *Owner-occupied property indicator	-0.259*	-0.226*
	(0.141)	(0.135)
Owner-occupied property indicator	0.065	0.059
	(0.082)	(0.081)
Negative equity *FICOSCORE	0.176***	0.136***
	(0.017)	(0.016)
FICOSCORE	-0.132***	-0.116***
	(0.012)	(0.012)
FICOSCORE*FICOSCORE	0.041***	0.041***
	(0.004)	(0.004)
Log balance	0.117***	0.09***
	(0.016)	(0.017)
LTV at origination >=80%	0.074**	0.078**
	(0.035)	(0.035)
Call option in the money but covered by prepayment penalty	0.066***	-0.015
	(0.011)	(0.013)

Table 4 MLE Estimates of the Cox Proportional Hazard Model (Continued)

Covariate	Estimate (S.E.)	Estimate (S.E.)
Call option in the money and out of prepayment penalty coverage	0.006	0.006
	(0.007)	(0.007)
15-year FRM	0.067	0.049
	(0.062)	(0.062)
Planned-unit development	-0.127*	-0.121**
	(0.066)	(0.066)
Condominium	-0.025	-0.044
	(0.044)	(0.044)
Rate/term refi	-0.471***	-0.473***
	(0.057)	(0.057)
Cash out refi	0.113**	0.056
	(0.05)	(0.05)
With prepayment penalty clause	0.203	0.186
	(0.154)	(0.154)
Unknown prepayment penalty clause	0.121	0.128
	(0.156)	(0.157)
Change in MSA unemployment rate	0.322***	0.417***
	(0.02)	(0.024)
Payment-to-Income (PTI)	0.018**	0.016*
	(0.009)	(0.009)
Asian	-0.056	-0.035
	(0.051)	(0.051)
Black	0.064*	0.062*
	(0.037)	(0.037)
Other race	-0.025	-0.011
	(0.026)	(0.026)
Female	0.042*	0.037
	(0.024)	(0.024)
Time Fixed Effects	NO	Current year-fixed effect in negative equity beta
N	263,656	263,656
-2LogL	136,406	135,952
AIC	136,462	136,036

Table 5 Hazard Model Estimates based on Alternative Neighborhood Foreclosure Concentration Measure

This table presents the Cox proportional hazard model result for the refined Subprime sample in the Los Angeles MSA based on alternative neighborhood foreclosure concentration measure, during the period 1999-2013. High Foreclosure Intensity equals one if the zip-quarter ranks in the 90th percentile of all zip-quarters for its foreclosure intensity. The other explanations of the variables are shown in Table 3 and Table 4. Parameter estimates are reported standard errors are included in the parentheses. Note that ***, ** and * indicate 1%, 5% and 10% significance, respectively.

Covariate	**Estimate (S.E.)**	**Estimate (S.E.)**
Put option*High Foreclosure Intensity	0.633*** (0.124)	0.626*** (0.125)
High Foreclosure Intensity	-0.255*** (0.079)	-0.241*** (0.079)
Time Fixed Effects	NO	Current year-fixed effect in negative equity beta
Control variables	Negative equity, negative equity square, negative equity * low/no doc indicator, low/no doc indicator, negative equity * owner-occupied property indicator, owner-occupied property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, call option value, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, prepayment penalty indicator, prepayment penalty unknown indicator, change in MSA unemployment rate from origination to current, payment-to-income ratio, Asian borrower, African American borrower, other non-white race borrower, female borrower.	
N	263,887	263,887
-2LogL	136,410	135,947
AIC	136,466	136,033

Table 6 Hazard Model Estimates w.r.t. Different Housing Market Regimes

This table presents the Cox proportional hazard model result for the refined Subprime sample in the Los Angeles MSA with respect to different housing market regimes, during the period 1999-2013. The other explanations of the variables are shown in Table 3 and Table 4. Parameter estimates are reported standard errors are included in the parentheses. Note that ***, ** and * indicate 1%, 5% and 10% significance, respectively.

Covariate	Estimate (S.E.)
Put option *Zip-level Foreclosure unit * Pre 2007	-0.317*** (0.090)
Put option *Zip-level Foreclosure unit*Yr2007_2009	0.208*** (0.051)
Put option *Zip-level Foreclosure unit*Yr2009_2012	0.369*** (0.085)
Put option *Zip-level Foreclosure unit*Post 2012	0.062 (0.06)
Zip-level Foreclosure unit * Pre 2007	-0.20** (0.086)
Zip-level Foreclosure unit*Yr2007_2009	-0.07** (0.035)
Zip-level Foreclosure unit*Yr2009_2012	-0.278*** (0.057)
Zip-level Foreclosure unit*Post 2012	0.251*** (0.051)
Control variables	Negative equity, negative equity square, negative equity * low/no doc indicator, low/no doc indicator, negative equity * owner-occupied property indicator, owner-occupied property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, call option value, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, prepayment penalty indicator, prepayment penalty unknown indicator, change in MSA unemployment rate from origination to current, payment-to-income ratio, Asian borrower, African American borrower, other non-white race borrower, female borrower.
N	263,656
-2LogL	136,282
AIC	136,350

Table 7 Asian Borrowers vs. Non-Asian Borrowers

This table presents the Cox proportional hazard model result for the refined Subprime sample in the Los Angeles MSA by comparing Asian and non-Asian borrowers, during the period 2007-2013. The other explanations of the variables are shown in Table 3 and Table 4. Parameter estimates are reported standard errors are included in the parentheses. Note that ***, ** and * indicate 1%, 5% and 10% significance, respectively.

Covariate	Estimate (S.E.)
Put option * Zip-level Foreclosure unit *Non-Asian borrower	0.198*** (0.051)
Zip-level Foreclosure unit * Non-Asian borrower	-0.078** (0.035)
Put option * Zip-level Foreclosure unit * Asian borrower	0.674*** (0.236)
Zip-level Foreclosure unit * Asian borrower	-0.465*** (0.172)
Non-Asian borrowers	--
Asian borrower	-0.092 (0.079)
Control variables	Negative equity, negative equity square, negative equity * low/no doc indicator, low/no doc indicator, negative equity * owner-occupied property indicator, owner-occupied property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, call option value, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, prepayment penalty indicator, prepayment penalty unknown indicator, change in MSA unemployment rate from origination to current, payment-to-income ratio, African American borrower, other non-white race borrower, female borrower.
N	165,747
-2LogL	110,641
AIC	110,905

Table 8 African American Borrowers vs. the Rest of the Population

This table presents the Cox proportional hazard model result for the refined Subprime sample in the Los Angeles MSA by comparing African American and the rest of the population, during the period 2007-2013. The other explanations of the variables are shown in Table 3 and Table 4. Parameter estimates are reported standard errors are included in the parentheses. Note that ***, ** and * indicate 1%, 5% and 10% significance, respectively.

Covariate	Estimate (S.E.)
Put option * Zip-level Foreclosure unit * Non-African American borrower	0.208*** (0.056)
Zip-level Foreclosure unit * Non-African American borrower	-0.086** (0.038)
Put option * Zip-level Foreclosure unit * African American borrower	0.202** (0.082)
Zip-level Foreclosure unit * African American borrower	-0.086 (0.064)
Non-African American borrower	--
African American borrower	0.079 (0.056)
Control variables	Negative equity, negative equity square, negative equity * low/no doc indicator, low/no doc indicator, negative equity * owner-occupied property indicator, owner-occupied property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, call option value, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, prepayment penalty indicator, prepayment penalty unknown indicator, change in MSA unemployment rate from origination to current, payment-to-income ratio, Asian borrower, other non-white race borrower, female borrower.
N	165,747
-2LogL	110,647
AIC	110,707

Table 9 Female vs. Male Borrowers

This table presents the Cox proportional hazard model result for the refined Subprime sample in the Los Angeles MSA by comparing female and male borrowers during the period 2007-2013. The other explanations of the variables are shown in Table 3 and Table 4. Parameter estimates are reported standard errors are included in the parentheses. Note that ***, ** and * indicate 1%, 5% and 10% significance, respectively.

Covariate	Estimate (S.E.)
Put option * Zip-level Foreclosure unit * male borrower	0.220*** (0.058)
Zip-level Foreclosure unit * male borrower	-0.092** (0.04)
Put option * Zip-level Foreclosure unit * female borrower	0.177** (0.07)
Zip-level Foreclosure unit * female borrower	-0.072 (0.049)
Male borrower	--
Female borrower	0.054 (0.036)
Control variables	Negative equity, negative equity square, negative equity * low/no doc indicator, low/no doc indicator, negative equity * owner-occupied property indicator, owner-occupied property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, call option value, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, prepayment penalty indicator, prepayment penalty unknown indicator, change in MSA unemployment rate from origination to current, payment-to-income ratio, Asian borrower, African American borrower, other non-white race borrower.
N	165,747
-2LogL	110,646
AIC	110,706

Table 10 High FICO vs. Low FICO Neighborhoods

This table presents the Cox proportional hazard model result for the refined Subprime sample in the Los Angeles MSA by comparing the lower, middle and upper quartiles of FICO SCORE at zipcode level during the period 2007-2013. Lower_FICO (Upper_FICO) equals one if the zip-quarter ranks in the 10th (90th) percentile of all zip-quarters for its FICO SCORE. The other explanations of the variables are shown in Table 3 and Table 4. Parameter estimates are reported standard errors are included in the parentheses. Note that ***, ** and * indicate 1%, 5% and 10% significance, respectively.

Covariate	Estimate (S.E.)
Put option * Zip-level Foreclosure unit * Lower_FICO	0.251*** (0.08)
Zip-level Foreclosure unit * Lower_FICO	-0.118** (0.057)
Put option * Zip-level Foreclosure unit * Middle_FICO	0.145** (0.06)
Zip-level Foreclosure unit * Middle_FICO	-0.021 (0.042)
Put option * Zip-level Foreclosure unit * Upper_FICO	0.315*** (0.095)
Zip-level Foreclosure unit * Upper_FICO	-0.193*** (0.067)
Lower_FICO	--
Middle_FICO	-0.067 (0.045)
Upper_FICO	0.037 (0.051)
Control variables	Negative equity, negative equity square, negative equity * low/no doc indicator, low/no doc indicator, negative equity * owner-occupied property indicator, owner-occupied property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, call option value, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, prepayment penalty indicator, prepayment penalty unknown indicator, change in MSA unemployment rate from origination to current, payment-to-income ratio, Asian borrower, African American borrower, other non-white race borrower.
N	165,747
-2LogL	110,637
AIC	110,705

Table 11 High Income vs. Low Income Neighborhoods

This table presents the Cox proportional hazard model result for the refined Subprime sample in the Los Angeles MSA by comparing the lower, middle and upper quartiles of borrower median income at zipcode level during the period 2007-2013. Lower_Income (Upper_Income) equals one if the zip-quarter ranks in the 10^{th} (90^{th}) percentile of all zip-quarters for its median income. The other explanations of the variables are shown in Table 3 and Table 4. Parameter estimates are reported standard errors are included in the parentheses. Note that ***, ** and * indicate 1%, 5% and 10% significance, respectively.

Covariate	Estimate (S.E.)
Put option * Zip-level Foreclosure unit * Lower_Income	0.269** (0.132)
Zip-level Foreclosure unit * Lower_ Income	-0.206** (0.093)
Put option * Zip-level Foreclosure unit * Middle_ Income	0.188*** (0.059)
Zip-level Foreclosure unit * Middle_ Income	-0.06 (0.041)
Put option * Zip-level Foreclosure unit * Upper_ Income	0.203*** (0.07)
Zip-level Foreclosure unit * Upper_ Income	-0.082 (0.05)
Lower_ Income	0.137** (0.06)
Middle_ Income	0.03 (0.039)
Upper_ Income	--
Control variables	Negative equity, negative equity square, negative equity * low/no doc indicator, low/no doc indicator, negative equity * owner-occupied property indicator, owner-occupied property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, call option value, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, prepayment penalty indicator, prepayment penalty unknown indicator, change in MSA unemployment rate from origination to current, payment-to-income ratio, Asian borrower, African American borrower, other non-white race borrower.
N	165,747
-2LogL	110,639
AIC	110,707

Table 12 Hazard Model Results for All Subprime Loans in the State of California

This table presents the Cox proportional hazard model result for the refined Subprime sample in the State of California, during the period 1999-2013. Negative equity is calculated with the contemporaneous house value (based on MSA level HPI) and the market value of the mortgage loan outstanding, adjusted by MSA-level house price volatility. Zip-level Foreclosure unit is calculated as the permillage of the total number of foreclosures in the past two quarters (e.g. for 2009Q1 it is 2008Q4 and 2008Q3) in the total number of housing units in each zip code. Log balance refers to the log of the original loan amount. Call option is computed the difference between the par value of the mortgage and the present value of the remaining payments evaluated using the current market mortgage rate. Change in MSA unemployment rate refers to the difference between the unemployment rate at current time and at origination time. The other explanations of the variables are shown in Table 3. Parameter estimates are reported standard errors are included in the parentheses. Note that ***, ** and * indicate 1%, 5% and 10% significance, respectively.

Covariate	Estimate (S.E.)	Estimate (S.E.)
Negative equity	0.442***	2.383***
	(0.072)	(0.095)
Negative equity square	0.004***	0.005***
	(0.000)	(0.001)
Negative equity *Zip-level Foreclosure unit	0.154***	0.113***
	(0.022)	(0.024)
Zip-level Foreclosure unit	-0.07***	-0.051***
	(0.013)	(0.013)
Negative equity *Low/no doc indicator	0.115***	0.033
	(0.032)	(0.029)
Low/no doc indicator	0.169***	0.191***
	(0.018)	(0.017)
Negative equity *Owner-occupied property indicator	0.001	-0.011
	(0.071)	(0.062)
Owner-occupied property indicator	-0.089**	-0.091**
	(0.041)	(0.04)
Negative equity *FICOSCORE	0.172***	0.122***
	(0.011)	(0.01)
FICOSCORE	-0.102***	-0.088***
	(0.006)	(0.006)
FICOSCORE*FICOSCORE	0.047***	0.05***
	(0.002)	(0.002)
Log balance	0.132***	0.128***
	(0.008)	(0.008)
LTV at origination >=80%	0.106***	0.108***
	(0.017)	(0.017)
Call option in the money but covered by prepayment penalty	0.066***	0.025***
	(0.006)	(0.007)

Table 12 Hazard Model Results for All Subprime Loans in the State of California (Continued)

Covariate	Estimate (S.E.)	Estimate (S.E.)
Call option in the money and out of prepayment penalty coverage	-0.004	-0.003
	(0.005)	(0.005)
15-year FRM	-0.093***	-0.098***
	(0.035)	(0.035)
Planned-unit development	-0.103***	-0.097***
	(0.035)	(0.035)
Condominium	0.019	0.031
	(0.031)	(0.031)
Rate/term refi	-0.381***	-0.378***
	(0.03)	(0.03)
Cash out refi	0.172***	0.134***
	(0.026)	(0.026)
With prepayment penalty clause	0.058	0.01
	(0.082)	(0.082)
Unknown prepayment penalty clause	-0.04	-0.065
	(0.084)	(0.084)
Change in MSA unemployment rate	0.31***	0.373***
	(0.011)	(0.012)
Payment-to-Income (PTI)	0.022***	0.022***
	(0.004)	(0.004)
Asian	-0.093***	-0.074**
	(0.032)	(0.032)
Black	0.036	0.043*
	(0.024)	(0.024)
Other race	-0.018	-0.011
	(0.014)	(0.014)
Female	0.034**	0.029**
	(0.014)	(0.014)
Time Fixed Effects	NO	Current year-fixed effect in negative equity beta
N	748,241	748,241
-2LogL	489,080	487,835
AIC	489,136	487,919

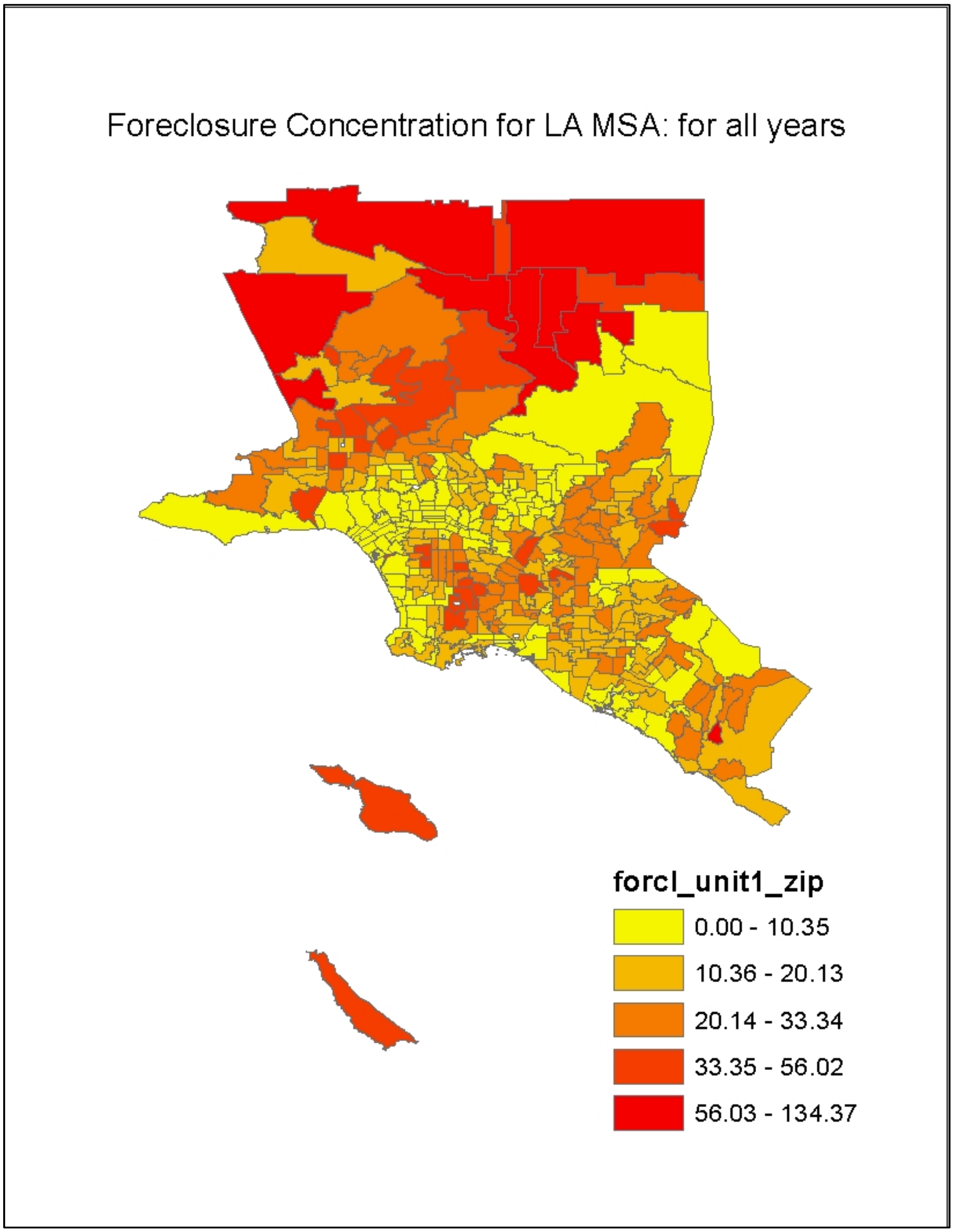

Figure 1 Foreclosure Concentration for LA MSA: for all years

This figure shows the foreclosure concentration rate for LA MSA, across the whole sample period. Foreclosure concentration is calculated as the total number of foreclosures in the past two quarters (e.g. for 2009Q1 it is 2008Q4 and 2008Q3) divided by the total number of housing units (in thousands) in each zip code.

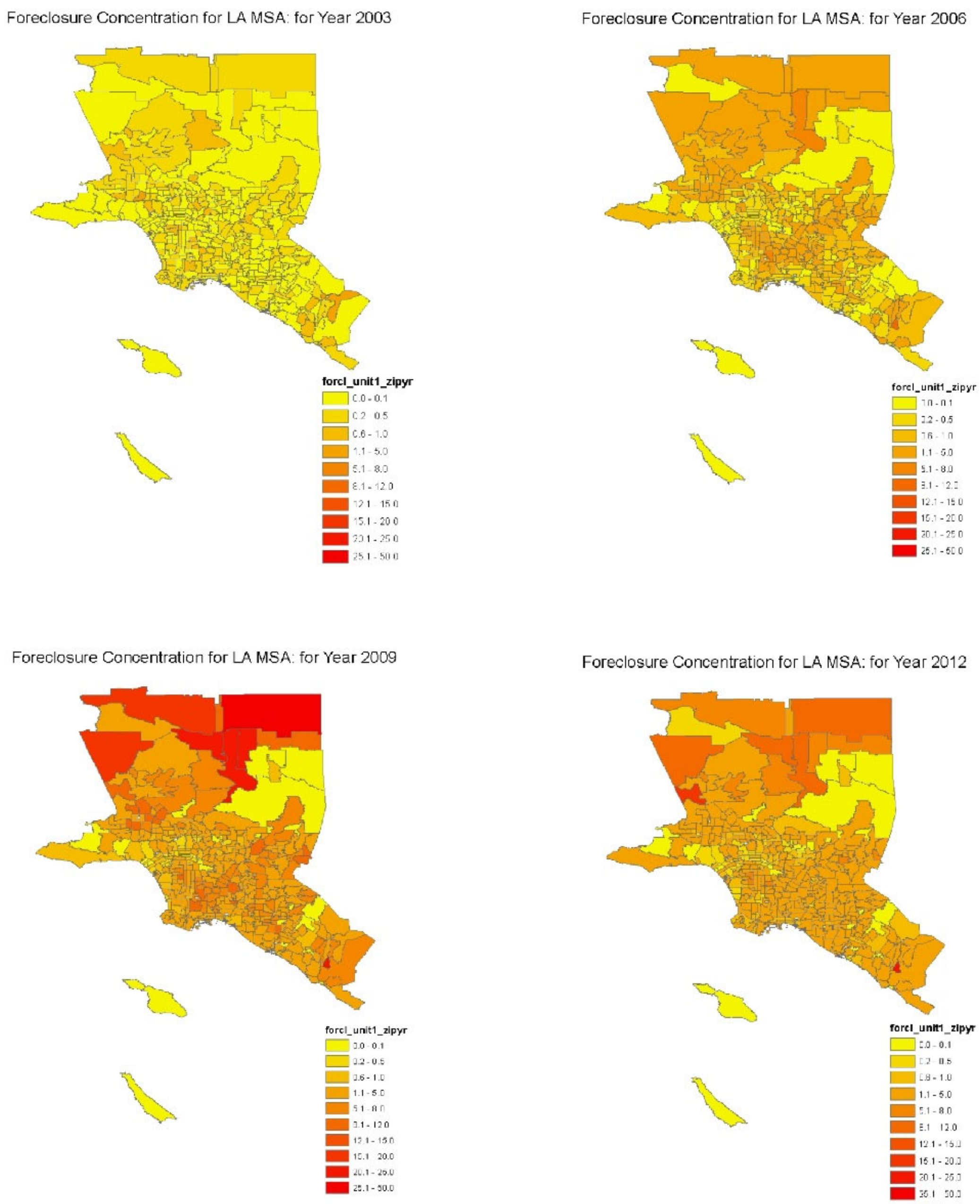

Figure 2 Foreclosure Concentration for LA MSA by year

This figure shows the foreclosure concentration rate for LA MSA, for Year 2003, 2006, 2009 and 2012. Foreclosure concentration is calculated as the total number of foreclosures in the past two quarters (e.g. for 2009Q1 it is 2008Q4 and 2008Q3) divided by the total number of housing units (in thousands) in each zip code.