Default Option Exercise over the Financial Crisis and Beyond *

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Abstract

We provide new evidence of cyclical variation in mortgage default option exercise. For a given level of negative equity, borrower propensity to default rose markedly during the financial crisis and among hard-hit metropolitan areas. Results show that shifts in borrower behavior were more salient to crisis-period defaults than were adverse shocks to home equity. Analysis of time-series and panel data indicates that local economic conditions, consumer sentiment, and federal foreclosure mitigation programs explain much of the rise in the negative equity beta. Difference-in-difference tests further corroborate unintended consequences of the Home Affordable Modification Program (HAMP) in boosting borrower default option exercise.

Keywords: Mortgage default; option exercise; negative equity beta; HAMP

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1. Introduction

While substantial research and policy debate have focused on housing, financial market, and regulatory antecedents to the 2000s mortgage crisis (see, for example, Gerardi, et al, 2008; Mayer, Pence and Sherlund, 2009; Demyanyk and Van Hemert, 2009; Mian and Sufi, 2009; Keys, et al, 2010; Haughwout, et al, 2011; An, Deng and Gabriel, 2011; Agarwal et al, 2011, 2012, 2013(a), 2013(b), 2015; Brueckner, Calem and Nakamura, 2012; Corbae and Quintin, 2014; Piskorski, Seru, and Witkin, 2014; Rajan, Seru, and Vig, 2010, 2014; Willen, 2014; Cheng, Raina and Xiong, 2014; Campbell and Cocco, 2015; Cotter, Gabriel, and Roll, 2015), shifts in behavior among mortgage borrowers have received only limited attention. Among recent papers, Guiso, Sapienza and Zingales (2013) apply survey data to show substantial borrower and temporal heterogeneity in attitudes toward strategic default. Piskorski and Tchistyi (2011) and Mayer et al (2014) also document changes in strategic behavior among mortgage borrowers in response to government and lender policy aimed at crisis amelioration. While those and other papers are suggestive of dynamic shifts in borrower default option exercise over the 2000s financial crisis and beyond, few systematic analyses have been undertaken. In this paper, we apply micro data on loan performance to show that changes in mortgage default option exercise were highly salient to crisis-period outcomes.[1]

In the mortgage default literature, default is importantly driven by homeowner negative equity (see, e.g., Quigley and Van Order, 1995; Deng, Quigley and Van Order, 1996, 2000; Kau and Keenan, 1999). However, that same literature acknowledges that mortgage borrowers do not always default when facing negative equity (see, for example, Vandell, 1995; Deng and Quigley, 2002; and Foote, Gerardi and Willen, 2008; Bhutta, Dokko, and Shan, 2010). Unfortunately, little is known about the time variation or drivers of the mortgage negative equity beta. For example, do borrowers exercise the default option more ruthlessly during a period of economic weakness? If so, could such changes in behavior materially worsen mortgage outcomes so as to exacerbate the market downturn?

Below we provide new evidence of changes over the business cycle in mortgage borrowers' propensity to default in the presence of negative equity (negative equity beta). Our findings show, all things equal, that for a given level of negative equity, borrower propensity to default rose markedly during the crisis period and among hard-hit metropolitan areas. Consistent with a theory of rational

[1] In the related literature on corporate default, Duffie et al (2009) find evidence of dynamic variation in the role of common latent factors in prediction of firm level default. Also, Duan, Sun and Wang (2012) point out the challenges in appropriately addressing the time dynamics of the state variables to multiperiod mortgage default prediction. Case, Shiller and Thompson (2014) similarly provide survey-based evidence of changing homebuyer behavior in hot and cold markets.

default (see below), the documented trending up in the negative equity beta during the crisis period could be due to increased borrower income constraints and/or pessimism about future house price and income dynamics. Also, analysis of default propensity time-series and panel data indicates the importance of local economic conditions and consumer sentiment in explanation of changes in borrower sensitivity to negative equity. Among other explanatory factors, we find that HAMP Program innovations designed to curb home foreclosures may have inadvertently resulted in elevated default propensities. This result is consistent with the notion that mortgage borrowers are strategic and are more likely to become delinquent when they expect lenders to modify defaulted loans (Riddiough and Wyatt, 1994; Jagtiani and Lang, 2011; Guiso, Sapienza and Zingales, 2013).[2]

To identify the dynamics of mortgage default option exercise, we estimate hazard models of mortgage default allowing for time-varying betas on negative equity. Our estimates show that mortgage borrowers are more sensitive to negative equity in bad economic times. Further, the estimated changes in borrower behavior are economically significant: the negative equity beta in the hazard model moved up from less than 0.1 in 2006 to over 0.8 in 2012 (Figure 1), translating into substantially higher default probabilities for a given level of negative equity. For example, in 2006 a mortgage loan with 15 percent negative equity had only a 5 percent greater chance of entering into default than a loan with 0 percent equity; in marked contrast, by 2012, a loan with 15 percent negative equity was 150 percent more likely to default than a loan with 0 percent equity (Figure 2). These findings suggest that fluctuations in the negative equity beta during the crisis period were material to the default rate. Indeed, the explosion in defaults during the crisis reflected declines in home equity compounded by a markedly elevated borrower negative equity beta. Results (below) indicate that upward movement in the negative equity beta during the crisis period outweighed the effects of declines in borrower home equity in determination of the spike in defaults.

Analysis of the negative equity beta time-series indicates the salience of local economic activity, notably including changes in coincident indicators of the local business cycle as well as innovations in the unemployment rate at the state and MSA-levels. A difference-in-difference analysis based on a propensity score matched sample confirms the impact of business cycle effects. These findings are consistent with a rational expectations explanation of default option exercise; indeed, borrowers' house price expectations, income constraints, and opportunity costs of default may evolve over the business cycle, resulting in time-varying sensitivities to negative equity. Conditional on those controls, we also

[2] Piskorski and Tchistyi (2011) also argue that bailing out the most distressed borrowers in the crisis period encourages irresponsible financial behavior during the boom. Mayer et al (2014) show that borrowers respond strategically to news of mortgage modification programs.

find that borrower default propensities are sensitive to measures of consumer sentiment, where our sentiment measure is orthogonalized to indicators of economic activity.[3]

We also find a structural break in mortgage default behavior in 2009. As shown in Figures 3, 4, and Table 9, not only does borrower default probability increase significantly after 2009, but so does the propensity to default. The structural break in the negative equity beta time-series is shown to be related to federal policy intervention associated with the Home Affordable Modification Program (HAMP). A difference-in-difference analysis shows that loan modification opportunities associated with the HAMP Program may have boosted borrower propensity to exercise the default option. In that regard, those eligible for HAMP loan modification became significantly more sensitive to negative equity during the program implementation period, compared to the non-HAMP eligible control group. This result suggests that while HAMP saved many defaulted borrowers from foreclosure, it also may have induced many borrowers to enter into default[4]. While this paper is silent on the ultimate impact of HAMP on borrower well-being and social welfare, it appears that the efficacy of the HAMP program in mitigating home foreclosure may have been diminished by increase in homeowner default as a direct consequence of the program.

Finally, we find heterogeneity in the default option beta time-series across metropolitan markets. Indeed, the MSA-specific time-series differ both in slope and turning point. This variability is consistent with the notion that business cycles are not fully synchronized across regions and that different states implemented varying foreclosure mitigation efforts at different points in time. We further analyze the metropolitan beta time-series in a panel data framework. As above, results of the panel data analysis show that roughly 60 percent of the variation in default propensities can be explained by the aforementioned factors, notably including local business cycle indicators, sentiment, and the 2009 structural break.

We further assess the robustness of estimation results. Indeed, we sought to evaluate whether results were sensitive to choice of mortgage lending instrument (subprime, Alt-A, or prime loans), borrower type, house price index, specification of the negative equity term, and size of estimation rolling window. Further, we estimated the model using annual cohorts to address the concern that the changing mix of borrowers may have contributed to the observed cyclical variation in the negative equity beta. Research findings in all cases are robust to the above changes in data or model specification.

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[3] Here and throughout the paper, we use the term "default propensity" to distinguish borrowers' sensitivity to negative equity, which is the negative equity beta in the hazard model, from default probability.

[4] See Cordell, et al (2009) for a discussion of other issues with HAMP.

The remainder of the paper is organized as follows: in the next section, we lay out a theoretical framework that depicts a time-varying borrower sensitivity to negative equity and helps to identify sources of variation; in section 3, we explain our data and methodology; in section 4, we discuss our results; concluding remarks are in section 5.

2. The Theoretical Framework

Mortgage loans are characterized by an embedded default (put) option, in that borrowers can "put" their property to the lender in exchange of a release from the debt obligation. Residential borrowers often exercise that option when the value of the property falls short of the remaining mortgage balance; e.g., when there is negative equity.

Consider a mortgage borrower who faces a decision at time t of whether to continue to make the mortgage payment or to default on the loan. Assume the property value is H_t and the remaining mortgage balance is M_t. If the borrower chooses to default, there will subsequently be two possible outcomes, including foreclosure with probability p_t, and workout with probability $(1 - p_t)$. If foreclosed, the borrower incurs tangible transaction costs R_t, which include moving costs, credit impairment, and the like. There will also be intangible foreclosure transaction costs S_t, which include stigma effects and possible psychic costs (White, 2010). If instead the bank agrees to work-out the loan, the borrower will receive a benefit of $V_t$in terms of payment reduction (reduced interest rate, term extension, and the like) and/or write-off of some portion of principal balance.

Let B_t denote the benefit to the borrower of default. Then

$$\begin{aligned} B_t &= p_t\left[-\left(H_t - M_t\right) - R_t - S_t - \left(1 + r_t\right)^{-1} E_t B_{t+1}\right] + \left(1 - p_t\right) V_t, \\ &\quad \textit{where } B_{t+1} = p_{t+1}\left[-\left(H_{t+1} - M_{t+1}\right)\cdots\right]\cdots \end{aligned} \tag{1}$$

Here the benefit consists of two parts: the first part is the net benefit from possible foreclosure, including the extinguishment of negative equity (H_t - M_t), incurrence of transaction costs ($R_t + S_t$), and loss of the option to default in the net period with a value of $E_t B_{t+1}$discounted back to the current period with a discount rate r_t[5]. The second part is the net benefit of possible work out, V_t. The total benefit is just a weighted average of these two parts.

Upon loan maturity at time T, the net benefit becomes

[5] Ambrose, Buttimer and Capone (1997) present a model that demonstrates the value of delay in default.

$$B_T = p_T \left[\left(H_T - M_T\right) - R_T - S_T \right] + \left(1 - p_T\right) V_T, \tag{2}$$

as there's no remaining next period default option.

Consider now the borrower's budget constraint. For the borrower to be able to continue making monthly payments, her income must be adequate to cover her mortgage payment, other debt payments, and consumption,

$$Y_t \geq P_t + D_t + C_t, \tag{3}$$

where Y_t denotes the borrower's income, P_t is the mortgage payment, D_t is other debt payment and C_t is consumption.

There is a possibility of borrower insolvency such that her income falls short of required debt payments and consumption. In such circumstances, the borrower can sell the property to pay off the loan and thus avoid default. However, there may be substantial transactions costs associated with a fire sale of the property, including commissions paid to the real estate agents, relocation costs, emotional distress, and stigma effects. In the case where expected equity extraction from the fire sale exceeds transaction costs plus remaining mortgage balance, a rational borrower would choose to sell her property and pay off the loan. However, if the equity extracted from the fire sale is inadequate to cover those costs, the rational borrower would default. Therefore, when the borrower is insolvent, there is an additional benefit of choosing to default, which is to avoid the transaction costs of a fire sale. Let's denote such transaction costs as W_t. Further we denote the probability that the borrower falls into insolvency as q_t. Then the ultimate benefit of default to the borrower at decision point t is

$$G_t = (1 - q_t)B_t + q_t(W_t | H_t - M_t > W_t). \tag{4}$$

The default condition is $G_t \geq 0$.

Solution of this default model requires information about the full dynamics of house prices, mortgage interest rates, discount rates, transaction costs, borrower's income, other debt payment, consumption, and the conditional probability of foreclosure given loan default as well as the benefit of a loan workout. While a closed-form solution is difficult, this does not prevent us from making some observations as derive from this model that can inform our subsequent empirical analysis.

First, in the context of the model, the benefit and thus the probability of default is a function of negative equity ($H_t - M_t$). It is also a function of the borrower's expectation of the future price of the home, reflected in the B_{t+1} term. Finally, default probability is a function of transaction costs, borrower assessment of the likelihood of receiving a workout and the workout benefit, and borrower insolvency probability.

Second, default probability is determined by the interaction of negative equity and the borrower's assessment of the conditional probability of foreclosure, as well as the interaction of negative equity and insolvency probability. As such, the sensitivity of default probability to negative equity (the negative equity beta in a default probability model) is a function of the borrower's expected conditional probability of foreclosure, p_t and borrower insolvency probability, q_t.

Third, the sensitivity of default probability to negative equity (the negative equity beta) also depends on expectations of future house values. This is because B_t depends on $E_t H_{t+1}$, which can be a function of H_t and time varying expected price appreciation.[6]

To summarize, the above model suggests that negative equity is a key driver of loan default. Further, as suggested above, the borrower's sensitivity to negative equity can be time varying and driven by changing house price expectations, insolvency probability, the conditional probability of foreclosure (workout), and other factors. We use these observations to inform our below empirical specification.

3. Data and methodology

3.1. Data Sources

Our primary dataset consists of loan-level information obtained from BlackBox Logic (hereafter BBX). The BBX database aggregates data from mortgage servicing companies in the U.S. The BBX data file contains roughly 22 million non-agency (jumbo, Alt-A, and subprime) mortgage loans, making it a comprehensive source of mortgage information.[7] BBX provides detailed information on borrower and loan characteristics at origination, including the borrower's FICO score, origination loan balance, note 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 the like. BBX also tracks the performance (default, prepayment, mature, or current) of each loan in every month, which is crucial to our default risk modeling.

[6] More formally if we assume house price follows a geometric Brownian motion with time varying drift, such a relation will exist.

[7] As discussed below in section on robustness, we also fully estimate the model using GSE-conforming conventional prime loans.

We match the BBX loan files to those in the Home Mortgage Disclosure Act (HMDA) database. The HMDA requires that lending institutions report virtually all mortgage application data.[8] The HMDA data includes borrower characteristics not contained in the BBX file, such as borrower race, gender, and annual income. HMDA also provides additional information on loan geography (census tract), property type (one-to-four-family or manufactured housing or multifamily), loan amount (in thousands of dollars), loan purpose (home purchase or refinancing or home improvement), borrower-reported occupancy status (owner-occupied or investment), and in the case of originated loans whether the loan was sold in the secondary market.

Using variables and loans common to the BBX and HMDA files, we match BBX loan-level data with selected HMDA loan data using a sequential, step-by-step criteria.[9,10] First, BBX loans are matched to HMDA loans with the same loan purpose and occupancy status. Next, based on the origination dates of BBX loans, HMDA loans within the same year of origination are considered. BBX loans are then matched to HMDA loans in the same zip code. Finally, the BBX loans are matched to those in HMDA with the same origination loan amount. For all possible HMDA matches to a BBX loan, we retain only the first HMDA record. Any BBX loan lacking a HMDA loan match using the above criteria is excluded from our sample. Appendix Table 1 shows the match ratio. On average, our match ratio is 75 percent. We then merge the loan-level data with macro variables including the MSA-level unemployment rate from Bureau of Labor Statistics, the CoreLogic Case-Shiller zip code level Home Price Index, the S&P/Case-Shiller MSA-level Home Price Index for the 20 MSAs, Treasury bond rate, interest rate swap rate, Freddie Mac mortgage interest rate, and like information.

In the analysis, we focus on first-lien, 15- and 30-year fixed-rate (FRM) subprime and Alt-A mortgage loans originated in 10 large metropolitan statistical areas (MSAs) of the United States, including New York, Los Angeles, Chicago, Dallas, Miami, Detroit, Atlanta, Boston, Las Vegas and Washington DC.[11] The non-prime loan sample is of sufficient size to allow estimation of the default hazard model. We do not include jumbo loans as many are originated among prime borrowers, who are

[8] HMDA is considered the most comprehensive source of mortgage data, covering about 80 percent of all home loans nationwide (Avery, et al, 2007).

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

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

[11] A series of filters is also applied: we exclude loans originated before 1998; we also exclude those loans with interest only periods or those not in metropolitan areas (MSAs); 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 also excluded.

fundamentally different from Alt-A and subprime borrowers. Our focus on narrowly defined loan types and borrowers (only 15- and 30-year FRMs) allows us to draw inference on default behavior from a relatively homogeneous sample. The distribution of loans among MSAs allows ample spatial variation in our time-series measures. We limit the analysis to major MSAs to ensure we have adequate sample size for measurement of house price changes as is a critical to construction of our negative equity variable.

3.2. Methodology

We follow the existing literature in estimating a Cox proportional hazard model of mortgage default (see, e.g., Vandell (1993), Deng (1997) and An et al (2012) for reviews). The hazard model is convenient primarily because it allows us to work with our full sample of loans despite the censoring of some observations.

As in much of the literature, we define default as mortgage delinquency in excess of 60-days.[12] That literature typically assumes the hazard rate of default of a mortgage loan at period T since origination is of the form

$$h_i(T, Z'_{i,t}) = h_0(T)\exp(Z'_{i,t}\beta) \quad (5)$$

Here $h_0(T)$ is the baseline hazard function, which depends only on the age (duration) T of the loan and allows for a flexible default pattern over time and $Z'_{i,t}$ is a vector of covariates for loan i that includes all identifiable risk factors.[13] In the proportional hazard model, changes in covariates shift the hazard rate proportionally without otherwise affecting the duration pattern of default. Common covariates include negative equity, FICO score, loan balance, loan-to-value (LTV) ratio, payment (debt) to income ratio, and change in MSA-level unemployment rate[14].

In the paper we relax the assumption that β is constant. Specifically, we allow the coefficient of negative equity in the hazard model to be time-varying to reflect possible intertemporal variation in the sensitivity of borrower default probability to negative equity as discussed in the prior section. Therefore, our model becomes a time-varying coefficient (partially linear) model of the form

$$h_i(T, Z'_{i,t}) = h_0(T)\exp(Z'_{i,t}\beta_t), \quad (6)$$

To estimate a time-varying coefficient model, we adopt two approaches well known in the

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[12] An important benefit of working with 60-day delinquency is that lenders and servicers usually only get involved in the default process after 60-day delinquency and thus 60-day delinquency reflects borrower choice, as is the focus of this paper.

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

[14] Change in unemployment rate is often employed as an instrument for change in borrower income (and thus ability-to-pay).

literature. The first approach is local estimation. As the time-varying coefficient model is locally linear, one can assume the coefficients to be constant for each short time window and thus can apply the usual estimation method to obtain the local estimator (see Fan and Zhang, 2008). In that regard, we form quarterly three-year rolling windows to construct our local estimation sample.

The second approach we take is interaction model estimation. Existing literature suggests that if we know the determinants of the time variation in the hazard model coefficient, we can simply include an interaction term between the covariate and the factors that cause beta time variation and estimate the model like a linear model (see Fan and Zhang, 1999). In this case, the model becomes

$$h_i(T, Z'_{i,t}) = h_0(T)\exp[a(t)Z'_{i,t}\beta] \tag{7}$$

Here $a(t)$ is the time series factor that determines the time-varying coefficient. An issue arises as to which time series factors determine the time variation in the hazard model coefficients. That question is informed by our above theoretical discussion.

As discussed above, the focus of this paper is the time-varying coefficient on negative equity. Accordingly, we hold constant the coefficients of the other covariates in our interaction model. As such, we have

$$a(t)Z'_{i,t}\beta = \beta^1 u_t x_{i,t} + W'_{i,t}\gamma, \tag{8}$$

where we decompose $Z_{i,t}$ into negative equity $x_{i,t}$ and the other covariates $W_{i,t}$. Here β^1 measures how the sensitivity of borrower default to negative equity varies with time series factors u_t, which include business cycle indicators and other terms that we discuss in the next section.

4. Results

4.1. Descriptive statistics

Our sample contains 198,375 fixed-rate Alt-A and subprime (hereafter non-prime) mortgage loans. Most of the subprime loans have FICO scores below 620 and most of the Alt-A loans have FICO scores between 620 and 660.

Table 1 shows the origination year distribution of the non-prime loan sample. While only 1,165 sampled loans (less than 0.6 percent of the sample) were originated in 1998, that number grows to 11,000 in 2002 and then to over 28,000 in 2003. Non-prime loan origination peaked in 2006. In that year, our sample includes almost 51,000 loans. A sharp decline in non-prime origination ensued with the onset of the crisis in 2007. With the demise of non-prime markets, the sample includes only 51 non-prime loans in 2008. This sample distribution well characterizes the rise and fall of the non-prime mortgage market.

In Table 2, we report the geographic distribution of our loan sample. Per above, we focus on loans in 10 large MSAs. Among the 10 MSAs, over 21 percent (41,751 loans) come from New York, followed by Los Angeles (15 percent), and Miami (14 percent). Chicago and Dallas each also comprise over 10 percent of the non-rime loan sample. Washington DC has the lowest share of loans at 3.5 percent (6,969 loans). Altogether, the fixed-rate non-prime mortgage loans in our 10 MSA sample represent almost 23 percent of the national total of such mortgages. As discussed below, each of the MSAs has adequate sample to allow us to estimate separate models.

As is broadly appreciated, the non-prime loans contained in the sample were originated among high risk borrowers. These loans experienced poor performance in the wake of the implosion in house values. Table 3 shows that over 47 percent of these loans experienced an over 60-day delinquency. Another 30 percent were prepaid. At the time of data collection (2014-Q1), about 22 percent of our loans were still performing and hence were censored. As expected, subprime loans experienced higher rates of delinquency than Alt-A loans.

In Table 4, we report descriptive statistics of our sample of 198,375 non-prime loans. Table 4A displays frequencies associated with loan and borrower characteristics. For example, almost 30 percent of sampled loans are characterized by low documentation while another 3 percent have no documentation. Roughly 66 percent of loans are characterized by full documentation. Among other notable characteristics, our sample contains a relatively high 27 percent of loans with LTV in excess of 80 percent. African American and Asian borrowers comprise 21 percent and 3 percent of our sample, respectively.

As discussed previously, we focus only on 15- and 30-year FRMs. In fact, in excess of 91 percent of our sample consists of 30-year FRMs. In terms of collateral property type, 84 percent are for single-family homes. Notably, only about 20 percent of originated mortgages were for purpose of home purchase. Cash-out refinance and rate/term refinance mortgages comprised 55 and 24 percent of the sample, respectively. Owner-occupied loans comprise 93 percent of our sample, whereas investment property loans constitute 6 percent.

In contrast to prime mortgages, a large proportion (almost 55 percent) of sampled non-prime loans carry prepayment penalties. In addition, a substantial number of loans carry second liens (16 percent).

Table 4B reports the mean values of some key loan and borrower characteristics. The average loan amount at origination is $211,152 and the average FICO score of sampled borrowers is 609. Non-prime mortgage loans usually carry higher interest rates than prime loans. The average note rate on our sampled loans is almost 8 percent, which is substantially higher than the average note rate on 15-year and 30-year prime FRMs of about 6.5 percent during our study period.[15] The average LTV of our sample is 73 percent and the average combined LTV is 75 percent. We also calculate an average 24 percent mortgage payment (principal and interest) to income ratio.

To estimate the hazard model, we construct quarterly event-history data based on the performance history of each loan reported by BBX. We also construct a number of time-varying explanatory variables. Negative equity is the percentage difference between the market value of the property and the market value of the loan, where the market value of the property is calculated by adjusting property value at origination given subsequent metropolitan house price index (HPI) changes whereas the market value of the loan is calculated based on the market prevailing mortgage interest rate and remaining mortgage payments at each quarter. To account for cross-MSA differences in house price volatility, we calculate a HPI volatility-adjusted negative equity term for use in model estimation. We calculate two refinance incentive values, one for loan-quarters that are covered by a prepayment penalty and the other for loan-quarters that are not covered by a prepayment penalty. Refinance incentive is calculated as the difference between the market value and the book value of a loan. Sample statistics of these two variables are reported in Table 4C.

The sample statistics of the two key business cycle indicators also are reported in Table 4C. Change in the state coincident index is the year-over-year (four-quarter) change in the state coincident index. Following Korniotis and Kumar (2013), the unemployment rate innovation is the current quarter unemployment rate divided by the average of the past four-quarters. The average state unemployment rate innovation is 1.07, which indicates that that on average the state employment rate was rising during our study period. For each loan-quarter, we also calculate change in the MSA unemployment rate from loan origination to the current quarter. The average is 1.5 percent, again indicating that the average local unemployment rate was rising over the life of sampled loans.

As the paper focuses on default risk (probability), negative equity is the key covariate in our analysis. Accordingly, in Figure 1, we plot two key times series, the 60-day loan delinquency rate and the percentage of loans with negative equity. As expected, the plots suggest a strong positive relationship between loan delinquency and the percentage of loans with negative equity, as is consistent with findings in the literature that negative equity is a key driver of default. As suggested above, not all loans with negative equity enter into default. For example, in 2012, over 10 percent of sampled non-prime

[15] As reported in the Freddie Mac mortgage interest rate survey, during 1998-2008, the average note rates of conventional prime 30-year FRM and 15-year FRM are 6.6 percent and 6.1 percent, respectively.

loans were characterized by negative equity whereas only about 5 percent of those loans had defaulted. In comparison, in 2008, the percentage of loans with negative equity was around 3 percent whereas the default rate was in excess of 3 percent[16]. Summary information suggests that borrower sensitivity to negative equity changes over time.

4.2. Hazard Model Estimates

4.2.1 Rolling Window Estimates

Figure 2 displays rolling window estimates of the negative equity beta from equation (6). We plot both the point estimate and the confidence band. Clearly evident are sizable and significant intertemporal variations in the estimated beta. In that regard, the negative equity beta moved in a limited range between 0.1 and 0.2 over the 2000 – 2006 period. Subsequently, in the wake of downside movement in housing and the economy, the negative equity beta ran up to over 0.8 in 2012. From 2012 onwards, a clear trending down in negative equity beta was evidenced; nonetheless, as recently as 2014-Q1, the estimated beta remained elevated at about 0.6. Note that samples sizes are small in early and late years of the sample and the confidence band surrounding the estimates is large. That notwithstanding, results indicate statistically significant differences over estimation timeframe in the negative equity beta.

To provide further insights as to changes in the mean estimated beta, we plot in Figure 3 the impact of negative equity on default probability in 2006 and 2012. Interestingly, we see that negative equity had a small impact on default probability in 2006 – a loan with 30 percent negative equity had only about a 5 percent additional chance of entering into default relative to a loan with 15 percent negative equity. In marked contrast, by 2012 the impact of negative equity on loan default probability was sizable. In that year, a loan with 30 percent negative equity was 150 percent more likely to default than the one with 15 percent negative equity.

As is evident in Figure 2, the estimated movement over time in the negative equity beta appears to be strongly correlated with the business cycle. Early on, in 2000 and 2001 and in the context of macroeconomic weakness, the negative equity beta was relatively high. In the wake of subsequent growth in economic activity, the negative equity beta largely declined through 2006. As boom then turned to bust, the negative equity beta rose quickly. More recently, as economic conditions improved, the negative equity beta again declined. These results coincide with the theory we laid out in section 2. During different phases of the business cycle, borrowers may have different house price expectations,

[16] Insolvency and transaction costs associated with fire sale are apparently issues here, as we discussed in section 2.

and they may face different income constraints and opportunity costs of default, resulting in differing sensitivity to negative equity.

4.2.2 Interaction Model Estimates

Given the above results and the theoretical framework of section 2, we now turn to estimation of the interaction model. In contrast to the 3-year moving window estimates displayed in Figure 2, here we pool all observations in estimation of the default hazard model. Results of the model are reported in Table 5. Model 1 is a baseline benchmark specification that does not account for potential interactions between negative equity and the business cycle indicator. The baseline specification accounts for 31 covariates including the interaction of negative equity and borrower FICO score, the interaction of negative equity and the Alt-A (versus subprime) indicator, a low/no doc loan indicator and an investment property indicator, as well as many other loan and borrower characteristics. In a recent paper, Corbae and Quintin (2014) demonstrate that changes in composition of borrowers can have substantial impact on subsequent default rates. Accordingly, we introduce a large number of controls for borrower, loan, and locational characteristics. We include MSA fixed effects as well as interactions of negative equity with the MSA dummies[17].

Overall, results indicate that model estimates are largely significant and consistent with prior literature. For example, the estimated negative equity beta is positive and highly significant, indicating that a higher percentage negative equity is associated with a larger default probability. Alt-A loans have lower default probabilities than subprime loans, all else equal. However, as evidenced in the interaction of negative equity and the Alt-A loan indicator, Alt-A loans are more sensitive to negative equity. Low/no doc loans are characterized by higher default probabilities and higher sensitivities to negative equity. Investment property loans have significantly higher default probability and also tend to be more sensitive to negative equity.

As expected, the relation between default probability and FICO score is negative and concave. In that regard, high FICO score borrowers are shown to be more responsive to negative equity than low FICO score borrowers. This may owe to the elevated financial literacy of higher FICO score borrowers, who may be more aware of or have more to gain from the exercise of the default option. As expected, loans with higher payment-to-income ratios are more prone to default. After controlling for negative equity and payment-to-income ratio, we find loans with over 80 percent LTV at origination are also

[17] Like Rajan, Seru and Vig (2014), we seek to well specify the model in an effort to mitigate concerns about the role of omitted variables in estimation of mortgage default.

more likely to default. Also, larger loans are more likely to default. Interestingly, we find that the borrower is more likely to default if the refinance incentive is high but the loan carries a prepayment penalty. This finding is consistent with literature indicating that the borrower may use default to terminate an existing loan and refinance during the workout of a troubled loan (see An et al (2013)). Compared to 30-year FRMs, 15-year FRMs have lower default risk. We use change in local unemployment rate from loan origination to the current period as an instrument of borrower income change. As expected, it is a positive and highly significant determinant of default likelihood. Among other borrower characteristics and consistent with established literature (see, for example, Deng and Gabriel (2006)), Asian borrowers are less likely to default while African American borrowers are more likely to default relative to whites and others. All else equal, female borrowers are more likely to default. Finally, many of the MSA fixed effects as well as interactions between negative equity and MSA dummies are significant. To conserve space, we do not show those results in the table.

In model 2, we add an NBER recession indicator as well as a term interacting the NBER recession indicator with borrower negative equity. All else equal, the recession indicator is associated with higher default risk. Moreover, borrowers are more sensitive to negative equity during an economic recession. This latter finding is consistent with the time-series plot of the negative equity beta displayed in Figure 2. As anticipated, borrower sensitivity to negative equity is pro-cyclical – during bad times borrowers are more sensitive to negative equity and are more likely to pull the trigger on default.[18]

Next we experiment with a number of alternative business cycle indicators. Results of that analysis are contained in table 6. Consistent with estimates from model 2 (table 5), findings indicate that alternative business cycle interactions with borrower negative equity are significant in determination of borrower likelihood of default. For example, a negative coefficient is estimated on the interaction of first-differences in the state-level coincident indicator of economic conditions and borrower negative equity, suggesting that borrowers are more sensitive to negative equity during bad economic times. Innovations in the unemployment rate also are often utilized as a business cycle indicator (see, e.g., Korniotis and Kumar, 2013). As expected, results here indicate that interactions with borrower negative equity of both the state-level unemployment rate innovation and the MSA-level

[18] Note also from table 5, that based on the AIC measure model 2 is a better fit of the data, meaning that allowing the coefficient of negative equity to be dependent on business cycle better reflects borrower’s actual default decision.

unemployment rate innovation are positive and significant, suggesting that borrowers are more sensitive to negative equity in the context of a deteriorating local economy[19].

4.2.3 Propensity Score Match and Difference-in-Difference Test of the Business Cycle Effect

To corroborate the above assessment of business cycle effects, we conduct a difference-in-difference (DID) test based on a propensity score-matched sample of loans. Our focus here is on subsamples of loans from Miami (FL) and Dallas (TX). While Florida was among those areas hit hardest by the 2007 downturn, Texas was substantially less affected. Specifically, as shown in Appendix Figure 2, during the 2006Q1 - 2008Q2 period, Texas witnessed steady economic growth whereas Florida recorded an adverse turn in its economy (first quarter of 2007). In the context of our 2006Q1 - 2008Q2 sample period, 2007Q2 can be identified as the starting date of a negative economic shock that affects Miami but not Dallas. Miami is then our treatment group whereas Dallas is our control group. Using these treatment and control groups, we conduct a standard DID test to discern the impact of the business cycle on the negative equity beta.

To assure the comparability of loans in our treatment and control groups, we firstly employ a propensity score matching algorithm to form our test sample. In that regard, we first run a selection model based on the full array of loan and borrower characteristics (previously described) and then match the loans using the propensity score. The DID test is conducted based on the propensity score-matched sample.

DID test results are displayed in Table 7. As is evident in the first term in Table 7, the Miami loans in general are less sensitive to negative equity during our sample period. However, as shown in the second term in Table 7, Miami loans became much more sensitive to negative equity than did loans in Dallas during the treatment period. The DID test results are then highly consistent with the estimated business cycle effects described in the prior section.

4.2.4 Impact of Sentiment and Structural Break

We next test for the effects of sentiment on default option exercise. We obtain our MSA-level consumer distress index from the St. Louis Fed. The index comes from CredAbility and is a quarterly comprehensive measure of the average American household's financial condition. CredAbility is a nonprofit credit counseling and education organization. It uses more than 65 variables from government, public and private sources to convert a complex set of factors into a single index of

[19] To address potential endogeneity issue, we alternatively used one- and two-quarter lags in the business cycle indicators and found the results to be robust.

consumer distress. The index is measured on a 100 point scale with a score under 70 indicating financial distress. The index is available at the national level and at the MSA-level for 70 MSAs. Given that this distress index partially reflects economic fundamentals, and that we seek a measure of pure sentiment that is orthogonalized to economic fundamentals, we first regress the CredAbility consumer distress index on the unemployment rate innovation as well as time- and MSA-level fixed effects. We then use the residual from the aforementioned regression as the orthogonalized MSA-level sentiment index in our model. As the orthogonalized MSA-level consumer distress index is available only from 2005 to 2013, we now limit our study period to that timeframe. We first re-run all models using the restricted sample to verify that our results hold in the restricted sample. Table 8 shows this is the case. Results for the restricted 2005 – 2013 sample are highly consistent with findings for the full sample. We also estimate the model replacing the state-level unemployment rate innovation (the state-level economic indicator) with the raw MSA consumer distress index. Results show that the raw MSA consumer distress index is highly significant and that it improves the model fit. This is as expected because the CredAbility consumer distress index contains information about both economic fundamentals and pure sentiment, as noted earlier.

Results inclusive of the orthogonalized sentiment indicator are displayed in Table 9. As is evident, the orthogonalized MSA consumer distress index is an important factor in determination of default probability. Low levels of consumer sentiment are associated with higher likelihoods of loan default. Moreover, as shown by the significant negative coefficient on the interaction term, when sentiment is low, borrowers are more sensitive to negative equity.

We further control for the effects on default option exercise of new foreclosure prevention and mortgage modification programs. Numerous state and federal foreclosure prevention programs were implemented during 2009 in response to the default and foreclosure crisis. Among these programs, the most notable was the federal Home Affordable Modification Program (HAMP), which was implemented starting in the first quarter of 2009. The HAMP program uses federal subsidies to incentivize lenders to modify the loan rather than foreclose on defaulted borrowers. In the spirit of the "Lucas Critique", we suspect that dissemination and implementation of a major foreclosure abeyance program may have influenced the behavior of mortgage borrowers, e.g., a borrower may be more likely to default to the extent a loan modification would be forthcoming at more favorable terms. Kahn and Yavas (1994) argue that loan renegotiation provides significant value to the nonperforming party while lenders' ability to foreclose is an effective threat in the bargaining between borrower and lender. Also, Riddiough and Wyatt (1994) and Guiso, Sapienza and Zingales (2013) argue that a borrower's delinquency decision may depend on the anticipated toughness of the lender response (for example, likelihood that the borrower would end in foreclosure). In support of that hypothesis, Table 9 provides evidence of a structural break in borrower default option exercise in 2009. All things equal, borrowers are more likely to default after the third quarter of 2009; further, borrowers also become more sensitive to negative equity at that time.[20] These findings are supported by difference-in-difference analysis of possible HAMP program loan termination effects (see section 4.3 below).

In summary, results of hazard model estimation indicate significant interaction effects of borrower default option exercise with controls for state of the economy, orthogonalized sentiment, and the 2009 structural break coincident to HAMP program implementation. To illustrate the separate and cumulative impacts of those three factors, we plot their hazard ratios in Figure 4. Here we assume a loan with 30 percent negative equity. Over the study period, note that the hazard ratio of negative equity is about 1.8, suggesting that all else equal, a loan with 30 percent negative equity is 1.8 times more likely to enter into default than the one without negative equity. However, as indicated in the second bar of Figure 4, the negative equity impact is much stronger during bad economic times. In that regard, the default probability of a loan with 30 percent negative equity during a period of high unemployment is over 2.5 times greater than that of a loan without negative equity. Finally, as shown in the third bar, during the period post 2009Q3, the impact of negative equity on default probability is even more sizable, with the hazard ratio reaching almost 4. Figure 5 depicts the same story, except that we plot the impacts of those factors for different levels of negative equity and show the cumulative effects of high local unemployment rates, damped sentiment, and post 2009Q3 effects.

4.3 HAMP Program Effects

In this section, we undertake difference-in-difference analysis of HAMP program effects on mortgage option exercise. The analysis seeks to further corroborate interpretation of the HAMP-coincident structural break effects documented above. For a loan to qualify for modification under the HAMP program, a number of criteria must be met. First, only owner-occupied loans are eligible and investor loans are not qualified. Second, the loan must be originated prior to January 2009. Third, the remaining loan balance must be below $729,500. Fourth, the borrower's debt-to-income ratio must be over 31 percent as the intent of the modification is to reduce borrowers monthly housing payments to no more than 31 percent of gross monthly income. Finally, there is a HAMP implementation window, which originally was set to be from March 2009 to December 2012 but later was extended through 2016.

[20] We use the Wald test discussed in Andrews (1993) and test a number of alternative dates for the structural break and find 2009Q3 is the most significant structural break point.

We utilize these cutoff rules in the context of our dataset to conduct difference-in-difference (DID) analysis of borrower behavioral change induced by the HAMP program. Agarwal et al (2013) use this strategy to identify the impact of HAMP on loan renegotiations.

In our first test, our DID control group consists of investor property loans that are not qualified for modification under HAMP and our treatment group includes owner-occupied loans which may be qualified for HAMP pending other conditions. We use 2009-Q1 as the treatment date as HAMP did not exist and there was no related HAMP modification prior to that date. To avoid confounding effects and consistent with HAMP program terms, we limit the sample to loans with a remaining balance below the HAMP threshold of $729,500. For similar reasons, we also exclude loans with a payment-to-income ratio below 31 percent. All of our loans were originated prior to January 2009. Note that our DID test does not require a perfect identification of HAMP eligible loans or loans eventually modified via HAMP.[21] As long as one group of borrowers had a higher probability of receiving a HAMP modification than the other group based on borrower *ex ante* expectations, we are able to identify HAMP effects via our difference-in-difference test.

Table 10 presents results of our first difference-in-difference test. Note that our treatment group, owner-occupied loans, typically is less sensitive to negative equity than our control group, investor loans. However, post 2009-Q1, our treatment group became much more sensitive to negative equity. These findings are consistent with and provide further support of the hypothesis that the federal program may have changed borrower behavior by elevating the default propensities of that qualifying group.

In a second difference-in-difference test, we utilize the remaining loan balance threshold of HAMP as only those loans with a remaining balance below $729,500 are HAMP eligible. Here we augment our data with the jumbo loan sample from BBX. This is because there are not sufficient numbers of subprime or Alt-A loans in our sample with a balance over $729,500 to construct an adequate control group. Here we exclude investor loans and focus solely on owner-occupied property loans to avoid a confounding effect. As evidenced in table 11, loans with a remaining balance below the HAMP threshold are less sensitive to negative equity prior to treatment (implementation of the HAMP program). However, subsequent to treatment (post 2009-Q1), those loans become much more sensitive to negative equity. Again, these results are consistent with those in Table 10 in support of the HAMP effect.

[21] Not all HAMP applications that met those five criteria were approved and some fell out of the program after the trial period.

4.4 MSA Panel Analysis

We proceed to estimate rolling window negative equity beta time series by MSA. Unfortunately, prior to 2003, we do not have adequate observations to obtain sensible estimations for many MSAs. Accordingly, results are shown for the post-2003 period. Note also that the substantially smaller number of observations in each MSA compared to the pooled national sample serves to reduce estimation precision. To address the noise in the by-MSA beta series, we plot the polynomial of the default option beta time-series for each of the top 5 MSAs in Figure 6. As is evident, most MSAs display significant time variation in the negative equity beta with countercyclical movement in that estimate over the 2000s boom, bust and crisis aftermath. That said, we do see variation in beta levels and turning points across MSAs. For example, Las Vegas and Boston experienced sharp increases in borrower sensitivity to negative equity during 2007 and 2008, whereas similar hikes for Atlanta were evident starting in 2010. Both New York and Los Angeles witnessed significant declines in borrower sensitivity to negative equity during 2003-2006. While Los Angeles saw substantial run-up in the negative equity beta starting in 2008, that same phenomenon wasn't evident in New York until 2011. Further, Las Vegas, Los Angeles and Detroit have all witnessed significant decline in default option betas since 2011. Finally, we also observe substantially larger volatility in default option betas in certain MSAs, including Las Vegas, Miami and Los Angeles.

Further evident is the decline in beta during the first half of the 2000s followed by a run up in the negative equity beta during the crisis period. We also observe a clear decline in beta post-2012 in four of the five MSAs. The observed heterogeneity in the time series pattern of the estimated betas is consistent with the observation that different regions have non-synchronized local business cycles. It could also be due to the fact that different states implemented varying foreclosure mitigation efforts at different points in time.

We also conduct a panel data analysis of the negative equity betas. Our dependent variable is the beta estimate from the rolling window estimates in each of the 10 MSAs in each quarter. Our independent terms include the local business cycle indicator, consumer sentiment (the orthogonalized MSA consumer distress index)[22], the post 2009-Q3 dummy, and an MSA fixed effect. Findings of the panel data analysis in Table 12 are consistent with results of table 9. In that regard, factors including the

[22] We also include a specification where we use the raw consumer distress index but omit the business cycle indicator given that the raw consumer distress index contains both information about economic fundamentals and pure sentiment.

state of the economy, consumer sentiment and the 2009 structural break were important drivers of the variation of the default option beta. Indeed, those factors explained almost 60 percent of the variation in the estimated beta terms.[23]

4.5 Robustness

We conduct a number of robustness tests. First, we re-run the entirety of the analysis using only subprime loans. The concern here is that subprime loans might differ fundamentally from Alt-A loans in terms of unobservable risk characteristics. As evidenced in Appendix Figure 1 and Appendix Tables 2-4, results are highly consistent with those for the pooled Alt-A and subprime loan sample. Second, we evaluate whether findings are unique to our sample of non-prime loans. Here, we re-estimate the entirety of the model using newly-available loan-level data on conventional, conforming prime mortgages from Freddie Mac. Those results show a very similar rise and fall of the negative equity beta over the sample period (Appendix Figure 3). Third, to address potential concerns of measurement error in estimated negative equity which is proxied by local house price indices (HPIs), we assess the robustness of findings to different HPIs. In place of MSA-level HPI, we use zip-code level HPI to construct our measure of negative equity. Results are robust to the substitution of the zip-code HPI data. We further test whether negative equity beta is sensitive to standard deviations of the point estimates of MSA-level HPI (a measure of noise in HPI) and find it not to be the case. Fourth, we replace the continuous version of the negative equity term with a dummy variable indicating whether the loan is characterized by negative equity or not in the current quarter, regardless of the magnitude of negative equity. Again results are highly consistent with those reported in the paper. Fifth, we separate owner-occupied property loans from investor loans and run the models only for owner-occupied property loans. Results are again robust. Sixth, for purposes of rolling window estimation, we experiment with different window sizes (e.g., 24 months vs. 36 months) and find the results to be consistent. Finally, we estimate the model using annual cohorts. This test addresses the concern that the changing mix of borrowers might have contributed to the observed changes in the negative equity beta, even after controlling for a large set of borrower characteristics. As displayed in Appendix Table 5, results are robust to the cohort specification, so as to underscore the primary findings of the paper.

[23] We additionally included a lagged house price returns term in the panel data model. That term was used to proxy for the role of house price expectations in determination of default option exercise. Consistent with theory, the lagged house price returns term was both statistically and economically significant in determination of variation in the negative equity beta.

4. Conclusions and Discussions

In the wake of the late-2000s implosion in house values, mortgage default skyrocketed. The substantially increased incidence in default led to sharp deterioration in the performance of mortgage and housing markets and exacerbated the generalized economic downturn. While default incidence was commonly associated with the sizable run-up in borrower negative equity, that outcome was precipitated as well by shifts in borrower propensity to default in the presence of negative equity.

In this paper, we provide new evidence of cyclical variation in mortgage default option exercise. Findings indicate that for a given level of negative equity, borrower propensity to default rose markedly during the period of the financial crisis and in hard-hit metropolitan areas. Further analysis of default option betas indicate that local economic conditions, consumer sentiment, and federal policy innovations explain changes in default option exercise. Changes in borrower propensity to default were material to the crisis. Simulation results show that changes in borrower default behavior were more salient to the avalanche of crisis-period defaults than were declines in home equity.

Our findings provide new insights to shifts in borrower option exercise relevant to mortgage underwriting and pricing. From a credit risk management perspective, results underscore the importance of model instability and provide guidance on factors governing temporal variation in estimated default option betas. Indeed, mortgage originators, investors, and regulators need to account for such shifts in their business planning and practice. Our findings also have implications to macroprudential policy. Findings here suggest that federal foreclosure prevention and loan work-out programs may have inadvertently incented higher levels of default, in turn suggesting adverse, unintended consequences of policies designed to mitigate mortgage failure.

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Figure 1 Default Rate versus Percentage of Loans with Negative Equity

This figure shows the percentage of subprime mortgage loans in our sample that had negative equity and that fell into 60-day delinquency during 2005Q1-2013Q1. Delinquency rate is to the left scale and percentage of loans with negative equity is to the right scale. The numbers are based on authors' own calculations.

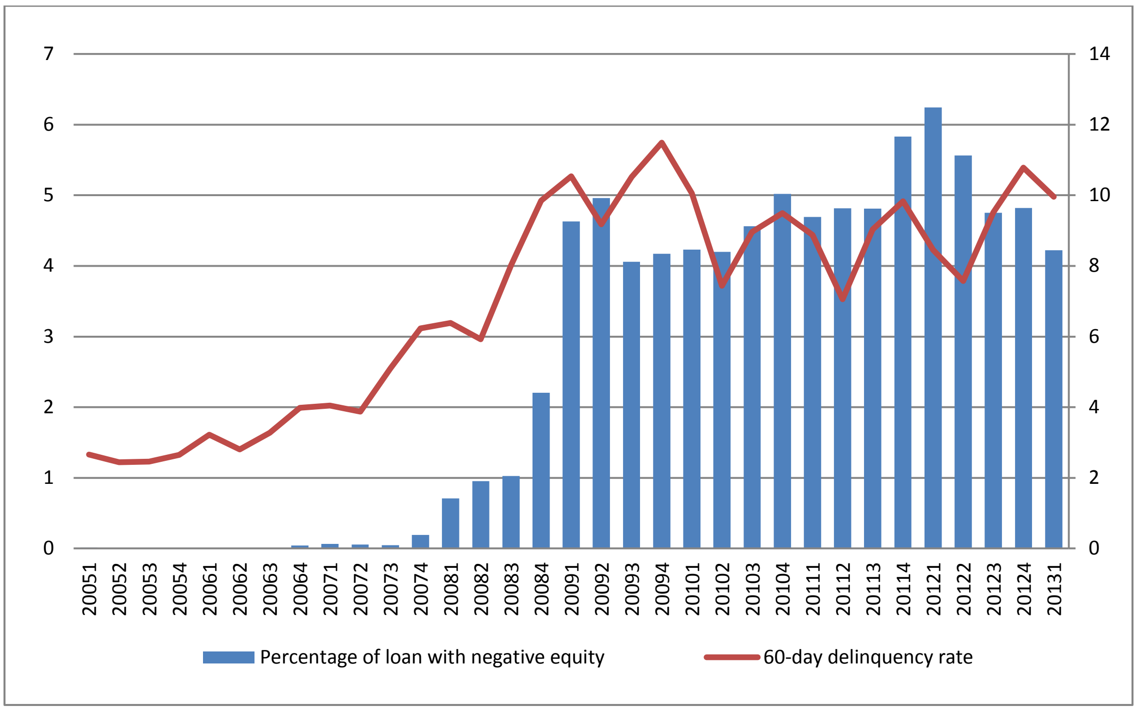


Figure 2 Rolling Window Estimates of the Negative Equity Beta

This figure shows the estimates of negative equity beta in a hazard model. The estimation is based on three-year rolling window samples of subprime and Alt-A loans in 10 MSAs, including New York, NY, Los Angeles, CA, Chicago, IL, Miami, FL, Dallas, TX, Atlanta, GA, Boston, MA, Phoenix, AZ, Detroit, MI, and Washington, DC. The dark line shows the point estimates and the dashed lines shows the confidence interval.

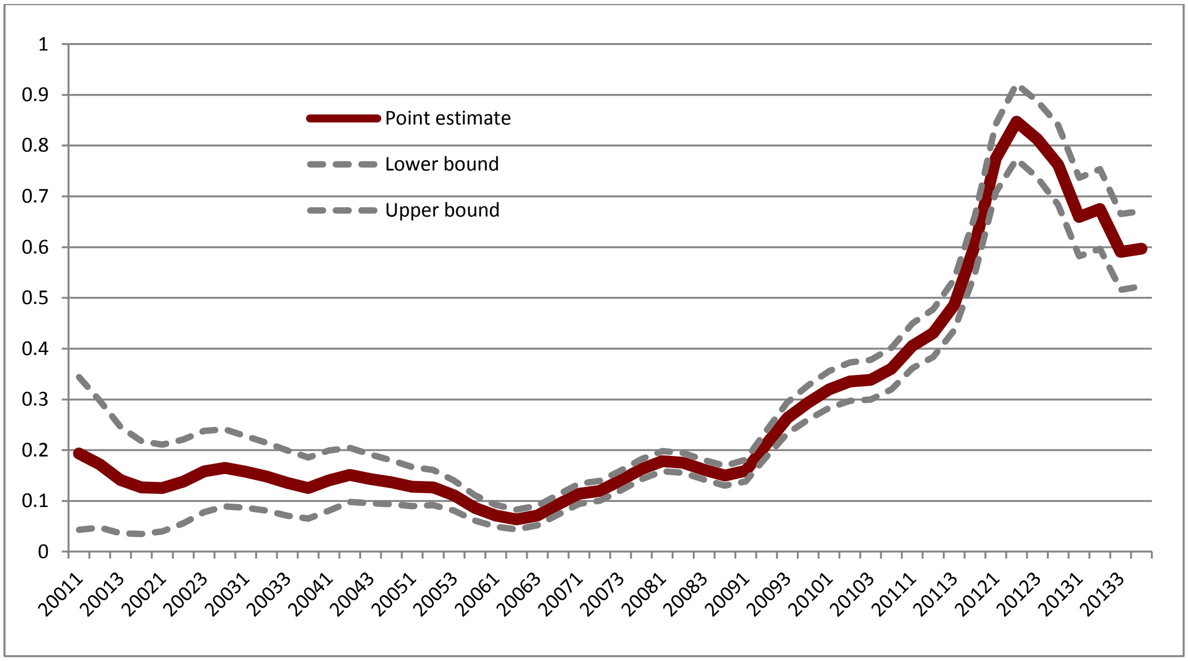


Figure 3 The Impact of Negative Equity on Mortgage Default Probability

This figure shows the simulated impact of negative equity on default probability during different phases of the business cycle. Simulations are based on the negative equity beta estimates shown in Figure 2.

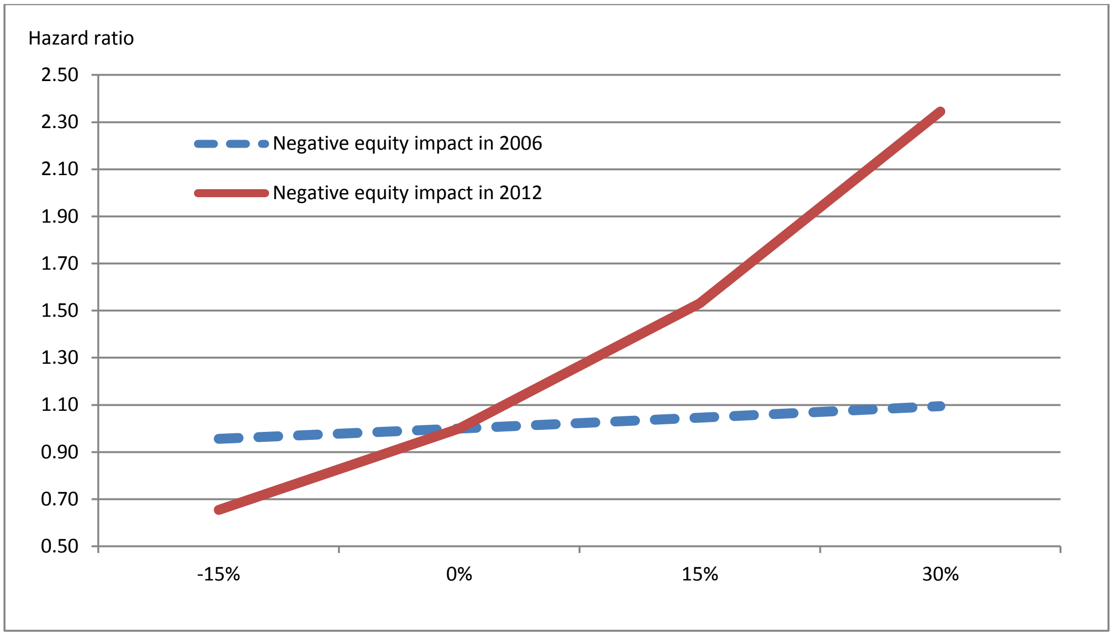


Figure 4 The Impact of Risk Factors on Mortgage Default Probability

This figure shows the simulated impact of negative equity on mortgage default probability when other factors are present. Simulations are based on negative equity beta estimates shown in Table 9.

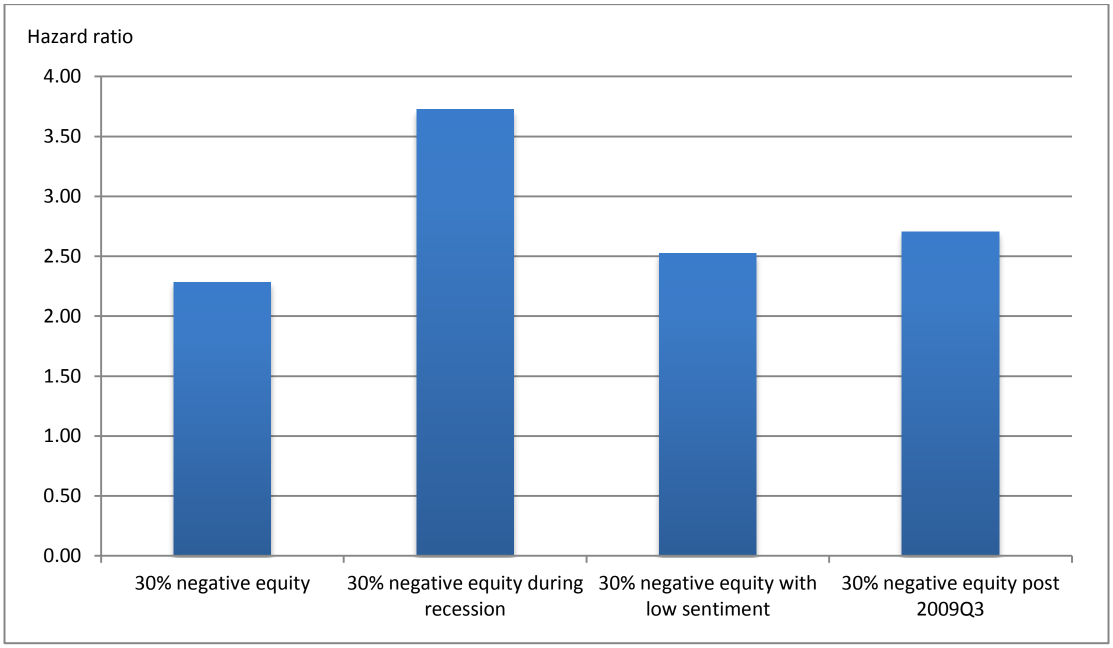


Figure 5 The Impact of Risk Factors on Mortgage Default Probability

This figure shows the simulated impact of negative equity on mortgage default probability when other factors are presented. Simulations are based on the negative equity beta estimates shown in Table 9.

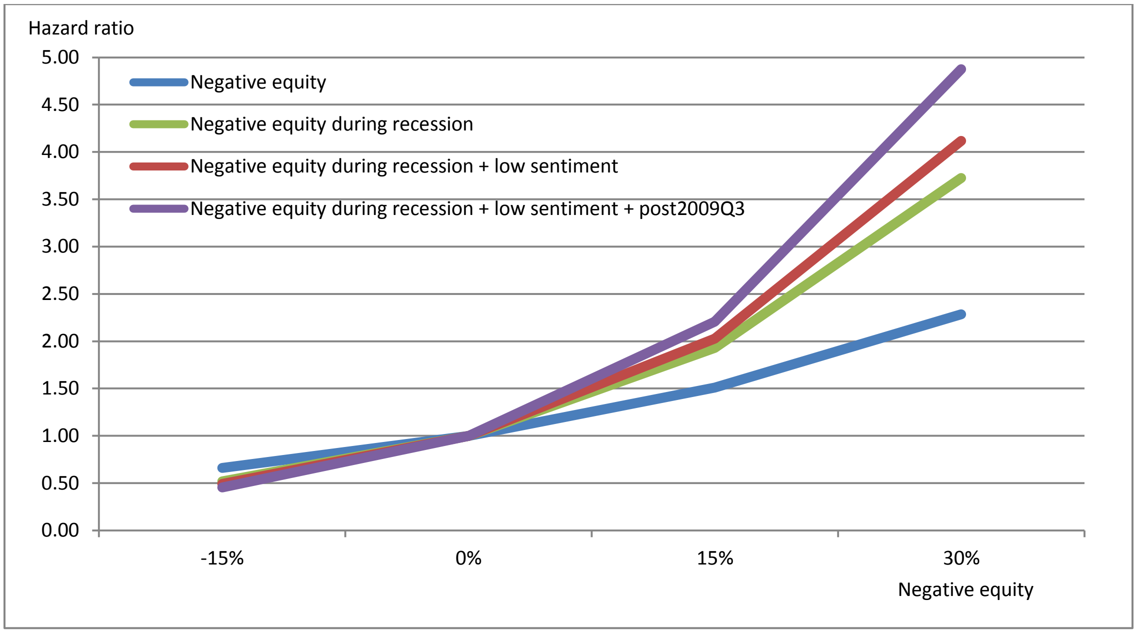


Figure 6 Polynomial of the Negative Equity Beta for the Top 5 MSAs

This figures shows the by-MSA point estimates and their fifth order polynomial of the negative equity beta based on three-year rolling window samples of subprime and Alt-A loans. Given that the estimation accuracy is reduced in the by-MSA sample, we plot the polynomial lines to better illuminate the trend of beta change.

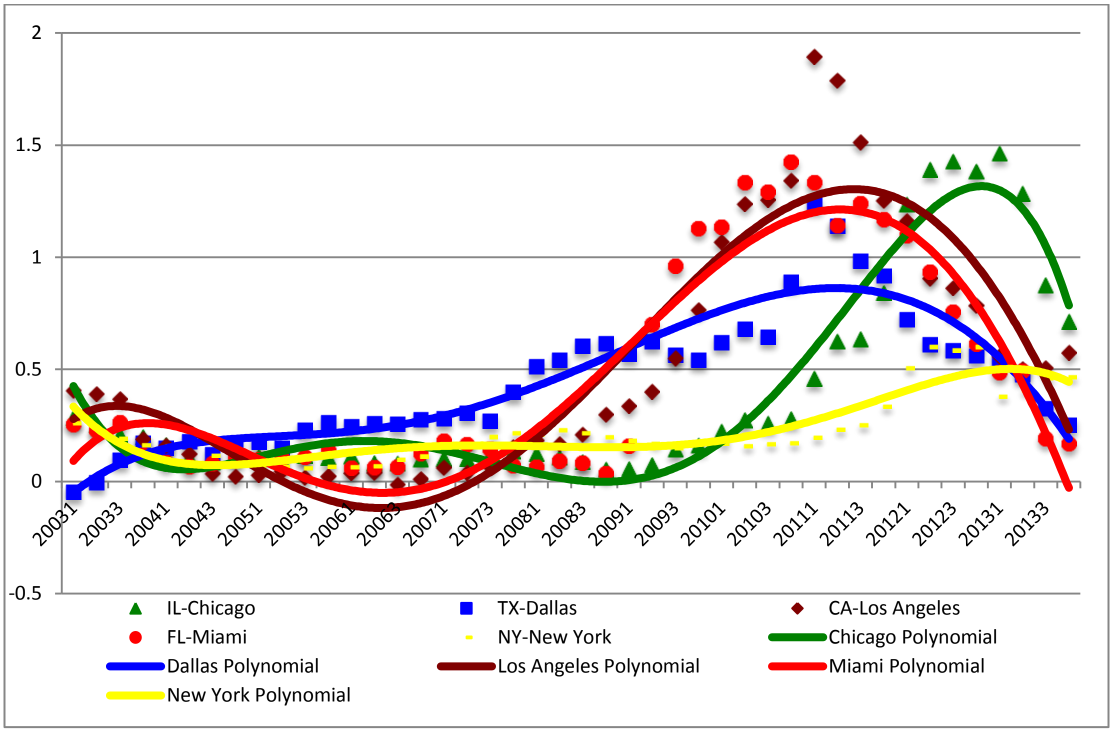


Table 1 Sampled Loans by Vintage

This table shows the frequency distribution of loan originations in our sample. All the loans are originated during the period 1998—2008. We include first-lien, 30-year and 15-year fixed-rate Alt-A and subprime mortgage loans for ten major metropolitan statistical areas (MSAs) including New York, NY, Los Angeles, CA, Chicago, IL, Miami, FL, Dallas, TX, Atlanta, GA, Boston, MA, Phoenix, AZ, Detroit, MI, and Washington, DC. We exclude loans with interest only periods or not in metropolitan areas (MSAs); loans with missing or obvious 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 also excluded (about 13 percent of the sample). All these loans are securitized by private-label security issuers. The data is from Blackbox Logic (BBX) based on servicer reports.

Origination Year	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1998	1165	0.59	1165	0.59
1999	2825	1.42	3990	2.01
2000	5166	2.6	9156	4.62
2001	7197	3.63	16353	8.24
2002	10931	5.51	27284	13.75
2003	28472	14.35	55756	28.11
2004	30362	15.31	86118	43.41
2005	43268	21.81	129386	65.22
2006	50898	25.66	180284	90.88
2007	18039	9.09	198323	99.97
2008	51	0.03	198374	100

Table 2 Geographic Distributions of Sampled Loans

This table shows the distributions of our loan sample among ten major metropolitan statistical areas (MSAs). MSAs are defined by the Office of Management (OMB) and used by the Census Bureau. See OMB (2008) "Update of Statistical Areas and Guidance on Their Uses" for definitions. Here the "national sample" refers to all first-lien, 30-year and 15-year fixed-rate, Alt-A and subprime mortgage loans originated and securitized by private-label (non-agency) security issuers during the period 1998-2008 in U.S.

MSA Name	MSA Code	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Atlanta	12060	13464	6.79	13464	6.79
Boston	14460	8431	4.25	21895	11.04
Chicago	16980	23491	11.84	45386	22.88
Dallas	19100	20701	10.44	66087	33.31
Detroit	19820	14317	7.22	80404	40.53
Los Angeles	31100	29262	14.75	109666	55.28
Miami	33100	27803	14.02	137469	69.3
New York	35620	41750	21.05	179219	90.34
Phoenix	38060	12186	6.14	191405	96.49
Washington DC	47900	6969	3.51	198374	100
As a share of the national sample				22.79%	

Table 3 Performance of Sampled Loans

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

Termination type	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Current	44008	22.18	44008	22.18
Prepay	60565	30.53	104573	52.72
Mature	11	0.01	104584	52.72
Default	93790	47.28	198374	100

Table 4 Summary Statistics on Loan and Event History Samples

Table 4 reports summary statistics of loan and borrower characteristics as well as explanatory variables in our event-history (loan-quarter) sample. Table 4a presents the frequency distribution of some important loan and borrower classifications. Table 4b shows the mean, standard deviations, minimum and maximum of loan and borrower characteristics as continuous variables, and Table 4c provides the mean, standard deviation, minimum and maximum of the key covariates in the event-history sample that are used in the hazard model. Documentation type is an indicator whether a particular loan has full, low, no or reduced documentation of income, asset or employment. LTV greater than 80 percent is equal to 1 if the original loan-to-value (LTV) ratio is greater than 80 percent. Race refers to the racial group of the borrower and Gender indicates whether the borrower is male or female. Loan type refers to whether the duration 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-unit development) or condo (condominium). Loan purpose indicates the primary reason the mortgage was taken out by the borrower. Occupancy status indicates whether the home was used as an investment, owner-occupied (primary residence), etc. Prepayment penalty type is an indicator denoting that a fee will be charged to the borrower if she elects 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 borrowed as of 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. Negative equity is the percentage difference between the market value of the property and the market value of the mortgage loan, where the contemporaneous market value of the property is calculated based on property value at origination plus change therein as indicated by a local house price index (HPI). Volatility adjusted negative equity is the negative equity divided by HPI volatility. Change in state coincident index is the year-over-year (four quarter) change in state coincident index. Unemployment rate innovation is the current quarter unemployment rate divided by the past four-quarter average.

Table 4a Loan and Borrower Characteristics (Frequencies)

		Frequency	Percent	Cum. Freq.	Cum. Pct.
Documentation type	Full doc	104289	52.57	104289	52.57
	Low doc	58139	29.31	162428	81.88
	No doc	6679	3.37	169107	85.25
	Reduced doc	2743	1.38	171850	86.63
	Unknown doc	26524	13.37	198374	100
LTV greater than 80 percent	No	145326	73.26	145326	73.26
	Yes	53048	26.74	198374	100
Race	White	103847	52.35	103847	52.35
	Asian	5859	2.95	109706	55.3
	Black	41005	20.67	150711	75.97
	Other	47663	24.03	198374	100
Gender	Male	115818	58.38	115818	58.38
	Female	69929	35.25	185747	93.63
	Unknown	12627	6.37	198374	100
Loan type	30-year FRM	17549	8.85	17549	8.85
	15-year FRM	180825	91.15	198374	100
Property type	Single family	167060	84.21	167060	84.21
	PUD	15098	7.61	182158	91.82
	Condo	16216	8.17	198374	100
Loan purpose	Home purchase	40190	20.26	40190	20.26
	Rate/term refinance	48280	24.34	88470	44.6
	Cash-out refinance	109904	55.4	198374	100
Occupancy status	Owner-occupied	185087	93.3	185087	93.3
	Second/vacation home	963	0.49	186050	93.79
	Investment property	12324	6.21	198374	100
Prepayment penalty type	No	6795	3.43	6795	3.43
	Yes	83113	41.9	89908	45.32
	Unknown	108466	54.68	198374	100
Loan with a second lien	No	166494	83.93	166494	83.93
	Yes	31880	16.07	198374	100
Total number of loans		198,374			

Table 4b Loan and Borrower Characteristics (Means)

Variable	Mean	Std. Dev.	5^{th} Pctl.	Median	95^{th} Pctl.
Original loan amount	211,153	144,476	57,000	173,000	486,000
FICO SCORE	609	43	525	620	657
Note rate (%)	7.76	1.47	5.90	7.49	10.59
LTV (%)	73	16	41	78	95
Combined LTV (%)	75	17	41	79	100
Payment-to-income ratio	0.24	0.24	0.08	0.23	0.41
Total number of loans			198,374		

Table 4c Event History Data Descriptive Statistics

Variable	Mean	Std. Dev.	5^{th} Pctl.	Median	95^{th} Pctl.
Negative equity (continuous variable)	-0.55	1.08	-1.99	-0.33	0.28
Negative equity dummy	0.19	0.40	0	0	1
Volatility adjusted negative equity	-44.92	95.48	-172.69	-20.60	8.07
Refinance incentive (percentage difference between the book value and market value of the loan)	5.63	9.31	-6.13	3.52	23.69
Change in state coincident index	0.20	1.51	-2.90	0.68	1.95
State unemployment rate innovation	1.07	0.20	0.86	1.00	1.49
Change in MSA unemployment rate (from loan origination to current)	1.50	2.57	-1.70	0.57	6.53
Percentage of loans that ever experienced negative equity			48.28%		
Total number of loan-quarters			4,806,790		

Table 5 MLE Estimates of the Cox Proportional Hazard Model

This table presents the Cox proportional hazard model results for the fixed-rate Alt-A and subprime loan sample for the ten MSAs. The model is estimated with maximum likelihood estimation (MLE) based on the event-history (loan-quarter) data, where each loan has one record in each quarter of its life. Variable definitions are discussed under Table 4. Parameter point estimates are reported with standard errors included in the parentheses. Note that ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

	Estimate (S.E.)	
Covariate	Model 1	Model 2
Negative equity	0.832***	0.787***
	(0.081)	(0.081)
Negative equity square	0.000*	0.002***
	(0.000)	(0.000)
Negative equity * recession indicator		0.136***
		(0.016)
Recession indicator		0.053***
		(0.008)
Negative equity * Alt-A loan indicator	0.152***	0.15***
	(0.016)	(0.016)
Alt-A loan indicator	-0.339***	-0.338***
	(0.009)	(0.009)
Negative equity * Low/no doc indicator	0.072***	0.068***
	(0.011)	(0.011)
Low/no doc indicator	0.166***	0.167***
	(0.007)	(0.006)
Negative equity * Investment property indicator	-0.009	-0.009
	(0.021)	(0.021)
Investment property indicator	0.139***	0.139***
	(0.012)	(0.012)
Negative equity * FICO score	0.067***	0.065***
	(0.005)	(0.005)
FICO score	-0.057***	-0.056***
	(0.005)	(0.005)
FICO score square	0.037***	0.037***
	(0.002)	(0.002)
Log balance	0.036***	0.035***
	(0.004)	(0.004)
LTV at origination >= 80%	0.133***	0.131***
	(0.006)	(0.006)
Refinance incentive * currently under prepayment penalty	0.024***	0.025***

	(0.003)	(0.003)
Refinance incentive * currently not under prepayment penalty	0.000	0.000
	(0.002)	(0.002)
15-year FRM	-0.141***	-0.139***
	(0.011)	(0.011)
Planned-unit development	-0.056***	-0.056***
	(0.01)	(0.01)
Condominium	-0.085***	-0.085***
	(0.011)	(0.011)
Rate/term refinance	-0.287***	-0.287***
	(0.008)	(0.008)
Cash out refinance	-0.018*	-0.018*
	(0.008)	(0.008)
Second/vacation home	-0.027	-0.026
	(0.039)	(0.039)
With prepayment penalty clause	-0.059***	-0.059***
	(0.015)	(0.015)
Unknown prepayment penalty clause	-0.137***	-0.137***
	(0.015)	(0.015)
Change in MSA unemployment rate	0.079***	0.08***
	(0.005)	(0.005)
Payment-to-Income (PTI) ratio	0.018***	0.018***
	(0.001)	(0.001)
Asian	-0.056**	-0.056**
	(0.017)	(0.017)
Black	0.080***	0.08***
	(0.007)	(0.007)
Other non-white race	0.020**	0.02**
	(0.007)	(0.007)
Female	0.003	0.003
	(0.005)	(0.005)
MSA dummy * Negative Equity	Yes	Yes
MSA dummy	Yes	Yes
Vintage fixed-effect	Yes	Yes
N	4,806,790	4,806,790
-2LogL	3,517,853	3,517,752
AIC	3,517,967	3,517,870

Table 6 Alternative Specifications of the Cox Proportional Hazard Model

This table presents additional results for the Cox proportional hazard model results. The model specification is the same as that of model 2 in Table 5 except that the recession indicator is replaced by the business cycle control indicated in this table. The full model results are available upon request. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

	Business cycle indicator		
	Change in state coincident indicator	State unemployment rate innovation	MSA unemployment rate innovation
Negative equity * Business cycle indicator	-0.110*** (0.009)	0.111*** (0.007)	0.140*** (0.008)
Control variables	Negative equity, negative equity square, business cycle indicator, negative equity * Alt-A loan indicator, Alt-A loan indicator, negative equity * low/no doc indicator, low/no doc indicator, negative equity * investment property indicator, investment property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.		
N	4,806,790	4,806,790	4,806,790
-2LogL	3,517,286	3,517,283	3,517,285
AIC	3,517,404	3,517,401	3,517,403

Table 7 Propensity Score Match and DID Test of the Business Cycle Effect: Miami vs. Dallas Loans

This table presents the difference-in-difference (DID) test of the business cycle effect on borrower default option exercise. The DID test is in the form of $Y = \beta_1 T + \beta_2 T * After + \beta_3 After + Z'\gamma$, where T represents the treatment group, $After$ represents the period after which a negative economic shock was realized, and the Z vector represents a vector of control variables. The model estimated is a Cox proportional hazard model. Loans in this test are limited to those fixed-rate Alt-A and subprime loans with a propensity score match between the treatment group and the control group. The treatment group is Miami (FL) loans, which were exposed to the shock in the after-shock period. The control group is Dallas (TX) loans that did not experience the negative shock. 2007Q2 is when the negative shock hit the treatment group Miami (FL). ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)
Negative equity * Miami loan indicator	-0.107** (0.042)
Negative equity * Miami loan indicator * Post 2007Q2	0.598*** (0.094)
Post 2007Q2	0.175*** (0.028)
Control variables	Negative equity, negative equity square, negative equity * Alt-A loan indicator, Alt-A loan indicator, 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%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.
N	423,102
-2LogL	200,869
AIC	200,935

Table 8 Alternative Specifications of the Cox Proportional Hazard Model, 2005~2013 Sample

This table presents the Cox proportional hazard model results based on event-history from 2005Q1 - 2013Q1. The model specification is the same as that in Table 6.
***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

	Business cycle indicator		
	Change in state coincident indicator	State unemployment rate innovation	MSA unemployment rate innovation
Negative equity * Business cycle indicator	-0.197*** (0.012)	0.144*** (0.008)	0.137*** (0.008)
Control variables	Negative equity, negative equity square, business cycle indicator, negative equity * Alt-A loan indicator, Alt-A loan indicator, negative equity * low/no doc indicator, low/no doc indicator, negative equity * investment property indicator, investment property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.		
N	4,091,397	4,091,397	4,091,397
-2LogL	3,100,653	3,100,498	3,100,486
AIC	3,100,772	3,100,616	3,100,604

Table 9 Tests of the Impact of Sentiment and Structural Break (2005-2013 sample)

This table presents the Cox proportional hazard model results based on event-history from 2005Q1 - 2013Q1 (The MSA-level consumer distress index is only available from 2005Q1 - 2013Q1). Orthogonalized MSA consumer distress index is the residual from a regression where MSA-level consumer distress index is regressed on the state-level unemployment rate innovation, MSA fixed effect and year-fixed effect. For the structural break, we test a number of breaking points but find 2009Q3 is the best breaking point based on model fit. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)
Negative equity * state unemployment rate innovation	0.165*** (0.008)
State unemployment rate innovation	0.072*** (0.006)
Negative equity * Orthogonalized MSA consumer distress index	-0.099*** (0.008)
Orthogonalized MSA consumer distress index	-0.025*** (0.004)
Negative equity * Post 2009Q3	0.169*** (0.023)
Post 2009Q3	0.092*** (0.017)
Control variables	Negative equity, negative equity square, business cycle indicator, negative equity * Alt-A loan indicator, Alt-A loan indicator, negative equity * low/no doc indicator, low/no doc indicator, negative equity * investment property indicator, investment property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.
N	4,091,397
-2LogL	3,100,050
AIC	3,100,176

Table 10 DID Test of the HAMP Eligibility Effect: Owner-Occupied vs. Investor Property Loans

This table presents the difference-in-difference (DID) test of the HAMP eligibility effect on borrower default option exercise. The DID test is in the form of $Y = \beta_1 T + \beta_2 T * After + \beta_3 After + Z'\gamma$, where T represents the treatment group, $After$ represents the period after which the policy was implemented, and the Z vector represents a vector of control variables. The model estimated is a Cox proportional hazard model. Loans in this test are limited to those fixed-rate Alt-A and subprime loans with payment-to-income ratio above 31 percent and a remaining balance of no more than $729,500. All loans were originated before January 2009. The treatment group is owner-occupied property loans, which satisfy the HAMP occupancy requirement. The control group is investor property loans that are not HAMP eligible. 2009Q1 is when the HAMP starts to be implemented. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)
Negative equity * Owner-occupied property indicator	-0.129*** (0.026)
Negative equity * Owner-occupied property indicator * Post 2009Q1	0.378*** (0.018)
Post 2009Q1	0.197*** (0.014)
Control variables	Negative equity, negative equity square, negative equity * business cycle indicator (State unemployment rate innovation), business cycle indicator (State unemployment rate innovation), negative equity * Alt-A loan indicator, Alt-A loan indicator, 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%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.
N	4,802,609
-2LogL	3,521,452
AIC	3,521,552

Table 11 DID Test of the HAMP Effect: Loan Size Over vs. Under the HAMP Threshold (Outstanding Balance ≤ $729,500)

This table presents an additional difference-in-difference (DID) test of the HAMP eligibility effect on borrower default option exercise. Loans in this test are limited to those fixed-rate jumbo loans for owner-occupied properties only with payment-to-income ratio above 31 percent. All loans were originated before January 2009. The treatment group includes those loans with remaining balance of no more than $729,500, which satisfy the HAMP loan balance requirement. The control group is those with remaining balance over $729,500 and thus is not HAMP eligible. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

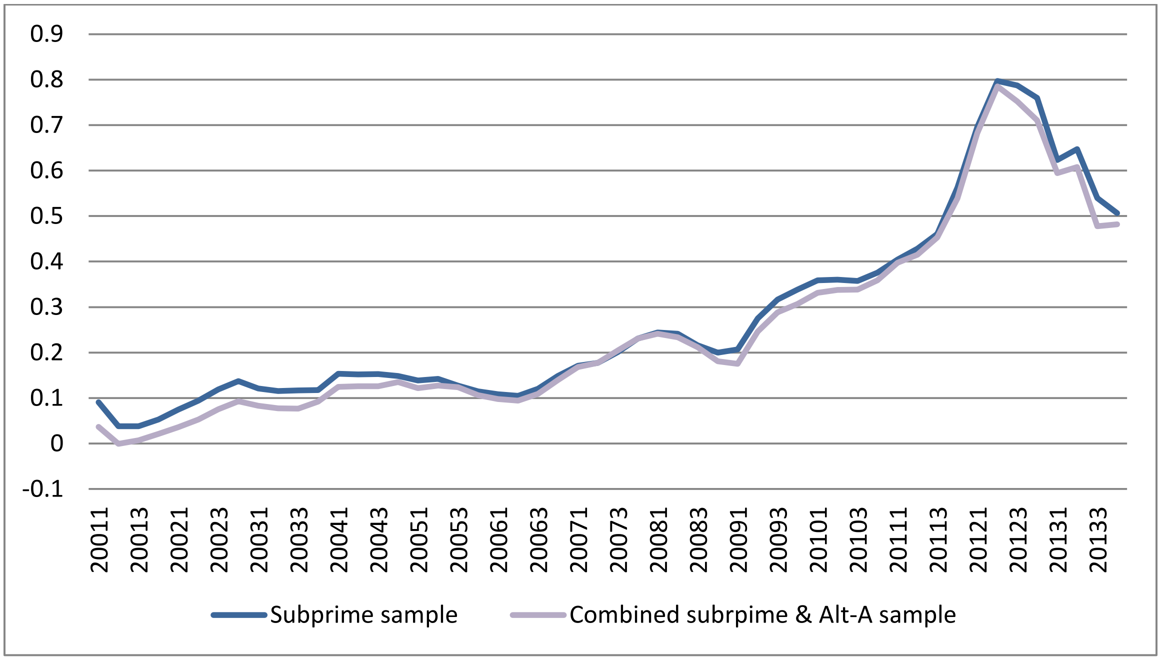
Covariate	Estimate (S.E.)
Negative equity * Outstanding balance ≤ $729,500	-0.082*** (0.035)
Negative equity * Outstanding balance ≤ $729,500 * Post 2009Q1	0.218*** (0.017)
Post 2009Q1	0.224*** (0.016)
Control variables	Negative equity, negative equity square, negative equity * business cycle indicator (State unemployment rate innovation), business cycle indicator (State unemployment rate innovation), 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%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.
N	9,514,331
-2LogL	2,424,487
AIC	2,424,583

Table 12 OLS Estimates of the Panel Data Model of Negative Equity Beta

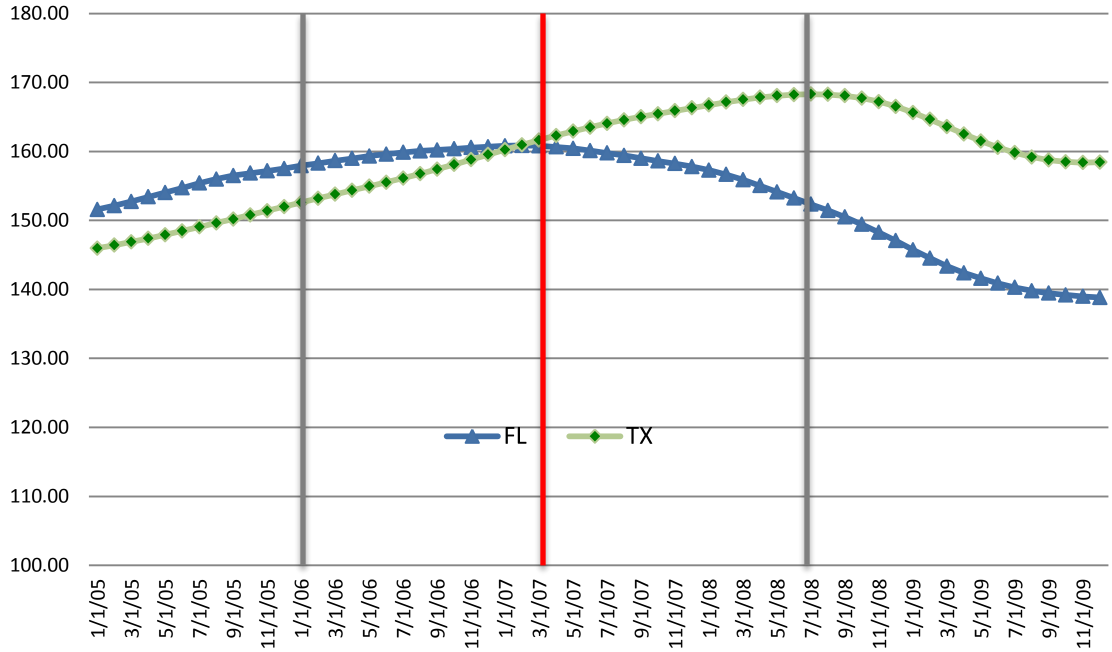
This table shows the regression results of the panel data model of the negative equity beta (the second stage analysis). The dependent variable is the negative equity beta estimate based on the Cox Proportional Hazard Model (the first stage analysis) for each MSA in each rolling window (a panel of beta). Loans included in the first stage hazard model estimation are fixed rate Alt-A and subprime loans in the 10 MSAs. In the second stage panel regression, the number of observations is reduced when we include the MSA-level distress index because the distress index is only available from 2005Q1 to 2013Q1. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Explanatory variable	Model 1	Model 2	Model 3	Model 4	Model 5
	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)
State unemployment rate innovation	0.260*	0.643***	0.555***		0.535***
	(0.131)	(0.104)	(0.108)		(0.104)
Post 2009Q3		0.637***	0.654***		0.655***
		(0.038)		(0.043)	(0.041)
MSA distress index				-0.050***	
				(0.003)	
Orthogonalized MSA distress index					-0.046***
					(0.009)
MSA-fixed effect	Yes	Yes	Yes	Yes	Yes
N	440	440	330	330	330
Adjusted R-Square	0.136	0.482	0.555	0.576	0.586

Appendix Figure 1 Rolling Window Estimates of Negative Equity Beta: Combined subprime Alt-A sample vs. Subprime sample

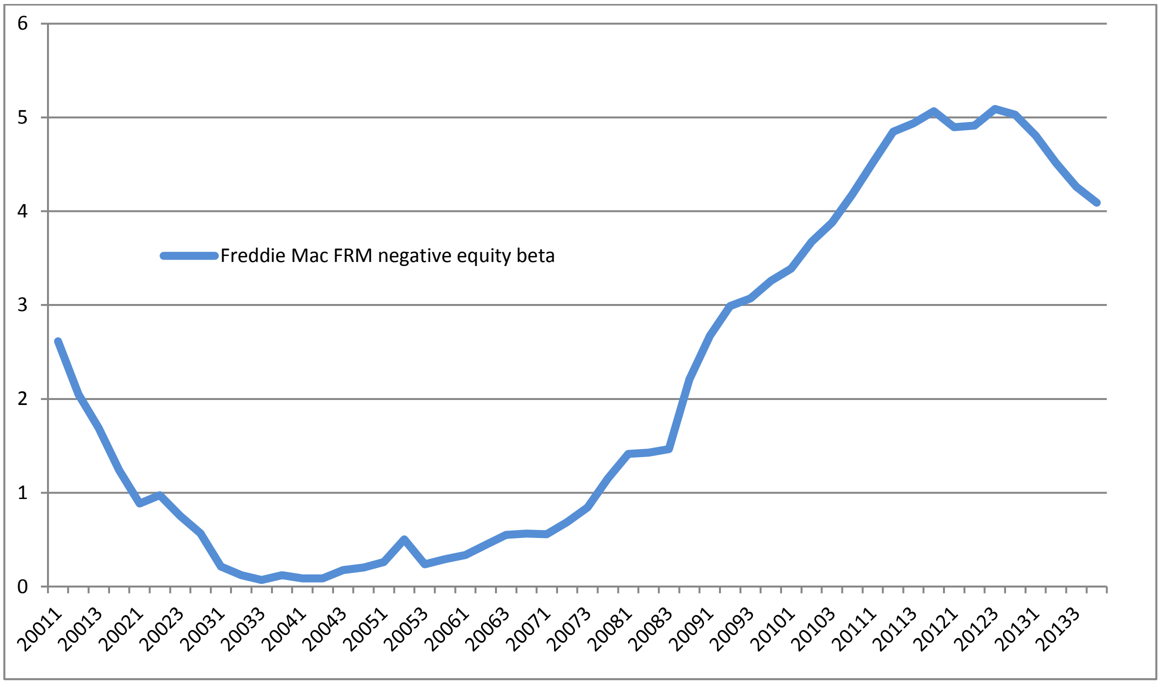


Appendix Figure 2 Coincident Indicators of Florida and Texas



The grey vertical lines indicate our DID test sample starting and ending period. The red vertical line indicates the treatment (negative economic shock) start date. Data source:

Appendix Figure 3 Rolling Window Estimates of Negative Equity Beta based on Freddie Mac Fixed-Rate Mortgage Loans



Appendix Table 1 The Success Rate of the HMDA-BBX Data Match

This table shows the percentage of loans in the BBX data that are successfully matched to the HMDA data. There is no unique identifier between the BBX data and the HMDA data, so we used a number of common variables between the two databases, including loan purpose, occupancy status, origination year, loan balance (rounded to $000s), etc. to match the data.

Origination year	BBX	HMDA matched
1998	3124	1773
1999	7419	4581
2000	15513	9464
2001	21039	13581
2002	21875	14139
2003	31582	25777
2004	38398	30906
2005	61812	49655
2006	76588	59769
2007	27324	20181
2008	79	48
Total	304753	229874
Percentage of matching	75%	

Appendix Table 2 Alternative Specifications of the Cox Proportional Hazard Model, 2005~2013 Sample, Subprime Only

	Business cycle indicator		
	Change in state coincident indicator	State unemployment rate innovation	MSA unemployment rate innovation
Negative equity * Business cycle indicator	-0.135*** (0.015)	0.103*** (0.010)	0.098*** (0.010)
Control variables	Negative equity, negative equity square, business cycle indicator, negative equity * low/no doc indicator, low/no doc indicator, negative equity * investment property indicator, investment property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.		
N	2,095,298	2,095,298	2,095,298
-2LogL	1,729,483	1,729,441	1,729,426
AIC	1,729,597	1,729,555	1,729,540

Appendix Table 3 Tests of the Impact of Sentiment and Structural Break (2005-2013 sample), Subprime Loans Only

Covariate	Estimate (S.E.)
Negative equity * state unemployment rate innovation	0.118*** (0.010)
State unemployment rate innovation	0.073*** (0.007)
Negative equity * Orthogonalized MSA consumer distress index	-0.072*** (0.010)
Orthogonalized MSA consumer distress index	-0.029*** (0.005)
Negative equity * Post 2009Q3	0.159*** (0.030)
Post 2009Q3	0.072*** (0.023)
Control variables	Negative equity, negative equity square, business cycle indicator, negative equity * low/no doc indicator, low/no doc indicator, negative equity * investment property indicator, investment property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.
N	2,095,298
-2LogL	1,729,243
AIC	1,729,365

Appendix Table 4 DID Test of the HAMP Eligibility Effect: Owner-Occupied vs. Investor Property Loans, Subprime Loans Only

Covariate	Estimate (S.E.)
Negative equity * Owner-occupied property indicator	-0.10*** (0.034)
Negative equity * Owner-occupied property indicator * Post 2009Q1	0.376*** (0.025)
Post 2009Q1	0.271*** (0.018)
Control variables	Negative equity, negative equity square, negative equity * business cycle indicator (State unemployment rate innovation), business cycle indicator (State unemployment rate innovation), negative equity * low/no doc indicator, low/no doc indicator, Owner-occupied property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.
N	2,529,607
-2LogL	1,999,876
AIC	1,999,972

Appendix Table 5 Estimates of the Cox Proportional Hazard Model by Vintage

Subprime and Alt-A sample of loans in the 10 MSAs

	Loan vintage			
	2001	2003	2005	2007
Negative equity * State unemployment rate innovation	0.022** (0.010)	0.021*** (0.008)	0.095*** (0.016)	0.041** (0.014)
State unemployment rate innovation	-0.023 (0.036)	0.059* (0.024)	0.012 (0.014)	0.088*** (0.019)
Control variables	Negative equity, negative equity square, business cycle indicator, negative equity * Alt-A loan indicator, Alt-A loan indicator, negative equity * low/no doc indicator, low/no doc indicator, negative equity * investment property indicator, investment property indicator, negative equity * FICO, FICO, FICO square, log loan balance, original LTV greater than 80%, refinance incentive, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home 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, MSA fixed effect in negative equity beta, MSA-fixed effect.			
N	278,870	771,449	961,850	343,235
-2LogL	70,322	248,051	692,056	381,061
AIC	70,418	248,147	692,152	381,157