Default Option Exercise over the Financial Crisis and Beyond [*]

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Abstract

We document increased ruthlessness of mortgage default option exercise over the financial crisis and beyond. For a given level of negative equity, borrower propensity to default rose markedly over the 2007 – 2012 period and among hard-hit metropolitan areas. We show that elevated default option exercise was more salient to crisis-period defaults than were adverse shocks to home equity. Analysis of time-series and panel data indicates that proxies for the local business cycle, 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) on borrower default option exercise.

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1. Introduction

Default on residential mortgages skyrocketed during the late-2000s, giving rise to widespread financial institution failure and generalized economic downturn. In the wake of severe crisis-related outcomes, academic, business, and policy analysts have sought new insights and improved modeling of factors associated with default. While much media attention has focused on the role of widespread negative equity to crisis-period defaults, few analyses have addressed the ruthlessness of borrower default option exercise in the presence of negative equity. In this paper, we provide new evidence of more ruthless option exercise and show its salience to default outcomes during the crisis period. We find that dynamic shifts in option exercise were driven by a myriad of factors, notably including local economic fundamentals, sentiment, and unintended effects of federal crisis-related policy.

In literature dating to the 1980s, default is modeled in terms of borrower exercise of the mortgage put option (see literature reviews by Quercia and Stegman, 1992 and Kau and Keenan, 1995). Indeed, empirical findings show that default is importantly driven by borrower negative equity, a proxy for the intrinsic value of the put option (see, for example, Giliberto and Ling, 1992, Quigley and Van Order, 1995, and Deng, Quigley and Van Order, 2000). That same literature, however, acknowledges that borrowers do not always default when facing negative equity. For example, research suggests that high levels of transactions costs or expectations of price recovery may delay borrower default, whereas trigger events or liquidity constraints could have the opposite effect (see, for example, Vandell, 1995; Ambrose, Buttimer and Capone, 1997; Foote, Gerardi, and Willen, 2008; Elul et al, 2010; Campell and Cocco, 2015). Recent analyses point to aggressive default option exercise, even in those cases where the borrower has the capacity to service the loan, an action known as strategic default (see, for example, Guiso, Sapienza, and Zingales, 2013 and Mayer et al, 2014). Mayer et al show an increased willingness to strategically default in response to lender loan modification programs. While recent studies provide new insights as to default behavior, little is known about temporal variation or spatial heterogeneity in the ruthlessness of option exercise as well as drivers thereof over the crisis period and beyond. In this paper, we employ an expansive micro dataset on loan performance to study these issues.[1]

To identify the dynamics of default option exercise, we estimate hazard models of mortgage default allowing for time-varying betas on negative equity. Here the negative equity beta is a measure of borrower ruthlessness or propensity to default in the presence of negative equity.[2] The estimates derive from well-specified default hazard models (see, for example, Deng and Gabriel, 2006; An et al, 2012), where, in

[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.
[2] Here and throughout the paper, we use the term "propensity to default" to describe borrower sensitivity to negative equity, which is the negative equity beta estimated in the default hazard model.

addition to negative equity, a large number of other covariates including the incentive to refinance, and numerous borrower and loan characteristics are included as control variables. Also included are measures of borrower financial hardship, given recent research indicating the importance of borrower liquidity constraints to default outcomes during economic downturns (see, e.g., Foote, Gerardi, and Willen, 2008; Elul et al, 2010; Campell and Cocco, 2015). Rolling window hazard model estimates show marked run-up in the negative equity beta from 0.13 in 2007 to 0.80 in 2012 (Figure 1), translating into substantially higher default probabilities for a given level of negative equity. For example, in 2007, a mortgage loan with 20 percent negative equity had only a 10 percent greater chance of entering into default relative to a loan with 5 percent negative equity. In marked contrast, by 2012, a loan with 20 percent negative equity had over a 200 percent chance of entering into default as compared to a loan with 5 percent negative equity (Figure 2). These findings suggest that fluctuations in the negative equity beta during the crisis period were highly salient to the default rate. Indeed, upward movement in the negative equity beta outweighed declines in borrower home equity in determination of the spike in defaults.

To inform our assessment of the negative equity beta, we build on existing literature to provide a simple theoretical framework that captures key elements of the borrower default decision (see, for example, Kau et al, 1992; Riddiough and Wyatt, 1994b; Ambrose, Buttimer and Capone, 1997; Campbell and Cocco, 2015; and Corbae and Quintin, 2015). In the model, the borrower has rational expectations and engages in default to maximize wealth. Benefits to default option exercise include elimination of negative equity and gains from possible loan modification. In the case of default option exercise, the borrower incurs transaction costs and loses the opportunity to default in the future. The model suggests that the negative equity beta can vary over time due to factors such as changing house price expectations, household liquidity constraints, conditional probability of foreclosure (workout), and default transaction costs. For example, binding income constraints and/or pessimism about future house price trends could make the borrower more sensitive to a negative equity position. Similarly, expectations of lender loan modification could also lead to more ruthless option exercise. On the other hand, optimism about the future path of housing or labor markets could serve to delay borrower option exercise.

We then empirically test drivers of the negative equity beta as informed by (the above) theory. We control for local economic fluctuations via various business cycle controls. Results indicate that a coincident indicator of economic activity as well as innovations in MSA (or State) unemployment rates explain a significant portion of the variation in negative equity beta. A difference-in-difference analysis based on a propensity score-matched sample further confirms the importance of the business cycle to borrower default propensity. Conditional on business cycle controls, we also find that borrower default propensities are sensitive to consumer sentiment, where our sentiment measure is orthogonalized to economic fundamentals.

We find a structural break in the negative equity beta in 2009, which coincides with federal policy intervention to the mortgage market via the Home Affordable Modification Program (HAMP). A difference-in-difference analysis shows that the HAMP program caused elevated default option exercise. In that regard, those eligible for HAMP loan modification become significantly more sensitive to negative equity in the wake of program implementation, relative to the non-HAMP eligible control group. This result suggests that while HAMP may have reduced the incidence of foreclosure among defaulted borrowers, it may also have induced large numbers of borrowers to enter into default in order to benefit from loan modification. This finding 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 (see, for example, Riddiough and Wyatt, 1994a; Jagtiani and Lang, 2011; Guiso, Sapienza and Zingales, 2013; Mayer, et al, 2014).[3]

Finally, results show heterogeneity in the default option beta time-series across metropolitan markets. Indeed, the MSA-specific beta time-series differ both in slope and turning point. This variability is consistent with the notion that business cycles are not fully synchronized across metropolitan economies and that local foreclosure mitigation efforts were implemented 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.

Note that results shown below account for non-linearities in negative equity. We also test whether variations in the negative equity beta are an artifact of uncontrolled borrower liquidity constraints in the hazard model. Results show that even among borrowers who are least likely to be liquidity constrained, variation in the negative equity beta with respect to the aforementioned factors remains salient.

Bear in mind that our sample is comprised of non-traditional subprime and Alt-A loans rather than conventional GSE-conforming loans. Accordingly, we test whether our results apply to prime conforming loans purchased by Fannie Mae and Freddie Mac. In that regard, we re-estimate our models using a Freddie Mac loan sample. Results show a similar pattern of time variance in the negative equity beta as well as a similar role for business cycle, sentiment, HAMP and other effects.

To assess robustness of estimation findings, we tested different house price indices (FHFA vs. Case Shiller and MSA-level vs. zip code-level), different forms of the negative equity measure (continuous vs. categorical variable), and variation in the size of the estimation rolling window (3 years vs 2 years). Results

[3] Piskorski and Tchistyi (2011) also argue that bailing out the most distressed borrowers in the crisis period encourages irresponsible financial behavior during the boom. Ghent and Kudlyak (2011) find that borrowers in non-recourse states are more sensitive to negative equity.

are robust to these variations. We also test different model specifications, e.g., we include a default burn-out term as well as age effects in both the negative equity beta and the baseline to the hazard model. Finally, we estimate the model using annual cohorts to address the concern that a changing mix of borrowers may have contributed to the observed cyclical variation in the negative equity beta. Findings throughout show a similar pattern of negative equity beta variance over the financial crisis and beyond.

Our findings contribute to the existing literature in several important ways. Firstly, our findings provide new insights into borrower default decisions, particularly as regards the salience of changing ruthlessness of borrower default option exercise to the 2000s mortgage and housing crisis. Among crisis-related research and policy papers (see, for example, Gerardi, et al, 2008; Mayer, Pence and Sherlund, 2009; Demyanyk and Van Hemert, 2011; Mian and Sufi, 2009, 2011; Keys, et al, 2010; Mian, Sufi, and Trebi, 2010, 2015; Agarwal et al, 2011, 2012, 2013, 2014; An, Deng and Gabriel, 2011; Haughwout, et al, 2011, 2014; Li, White, and Zhu, 2011; Brueckner, Calem and Nakamura, 2012; Case, Shiller and Thompson, 2014; Piskorski, Seru, and Witkin, 2015; Rajan, Seru, and Vig, 2010, 2015; Willen, 2014; Cheng, Raina and Xiong, 2014; Corbae and Quintin, 2015; Cotter, Gabriel, and Roll, 2015; and Bayer, Ferreira and Ross, 2016), shifts in behavior among mortgage borrowers have received only limited attention. Here we show that changes in mortgage default option exercise were material to crisis-period outcomes. Indeed, the sharp run-up in defaults during the crisis reflected declines in home equity compounded by a markedly elevated borrower negative equity beta.

More broadly, our findings suggest the appropriateness of time-varying coefficient default hazard models. The longstanding assumption of a static negative equity beta can result in significant risk management problems. In that regard, recent studies show substantial underestimation of default risk in an adverse market environment (see, for example, An et al ,2012 and Frame, Gerardi and Willen, 2015). We document marked time variance in the negative equity beta over a relatively long timeframe and identify major drivers of that variance. The time varying coefficient hazard model better characterizes borrower default behavior and it is operationally feasible in predicting default for pricing and risk management purposes. It is our hope that our results will speed the adoption of a new generation of risk-management and regulatory models.

Third, our findings have important policy implications. While HAMP saved many defaulted borrowers from foreclosure, findings suggest this program also may have induced many borrowers to enter into default. While we are silent on the ultimate impact of HAMP on borrower well-being and social welfare, it appears that the efficacy of HAMP in mitigating home foreclosure may have been diminished by an increase in homeowner default as a direct consequence of the program. In that regard, policy makers need to consider possible behavioral change in response to policy aimed at foreclosure mitigation.

The remainder of the paper is organized as follows. In the next section, we lay out a theoretical framework that identifies sources of variation in the negative equity beta; in section 3, we discuss our data; in section 4, based on hazard model estimates, we document the time series pattern in the negative equity beta; in section 5, we document factors that drive the negative equity beta, notably including business cycle, sentiment, and HAMP effects; robustness analysis is contained in section 6; and section 7 provides concluding remarks

2. The Theoretical Framework

The modern mortgage termination literature emanates from an option-based contingent claims framework whereby mortgage default and prepayment are options to put and call the contract, respectively (see, e.g., Kau et al, 1992). Several empirical studies (see, for example, Quigley and Van Order, 1995) provide explicit tests of contingent claims framework. In a competing risks hazard model, Deng, Quigley and Van Order (2000) proxy for the default option value using the time-varying value of mortgage loan negative equity.

Recent literature has extended the option-based contingent claims model to a more general household utility/wealth maximization framework. There mortgage borrowers exercise the default option to maximize utility/wealth, subject to liquidity constraints and other exogenous shocks. Campbell and Cocco (2015) propose a dynamic model of households' mortgage decisions that accounts for borrower characteristics, different mortgage contract terms, and mortgage affordability measures. Corbae and Quintin (2015) develop a structural model that incorporates household heterogeneity and underwriting variation to help identify the impact of leverage on market crises.

Following the above literature and to set the stage for our empirical tests, we propose a simple theoretical framework of the borrower default decision. In our model, 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. Note that the default option is a compound option in that a borrower who does not default but instead continues to service the loan receives the right to default in the future.

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 (negative equity is thus $H_t - M_t$). Default eliminates borrower negative equity. This is often modeled as a boundary condition of the traditional default option model (see, e.g., Schwartz and Torous, 1992; Kau, et al, 1992; Ambrose, Buttimer and Capone, 1997).

Following Riddiough and Wyatt (1994b) and others, we consider the possibility of a loan workout in the wake of default. Accordingly, 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 (Cunningham and Hendershott, 1984, Foster and Van Order, 1985). There will also be intangible foreclosure transaction costs S_t, which include stigma effects and possible psychic costs (Kau and Keenan, 1995; 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

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

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. 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

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

as there's no remaining next period default option.

It has long been recognized that certain trigger events such as loss of job could cause default. Foster and Van Order (1984) and Vandell and Thibodeau (1985) describe such an outcome as suboptimal default, whereas Campell and Cocco (2015) and Corbae and Quintin (2015) model income shocks that serve to force default. More generally, such trigger events may be described in terms of borrower budget constraints. 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 sale of the property 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 associated with property sale. We denote such transaction costs as W_t. Further we denote the probability that the borrower falls into insolvency as q_t. The ultimate benefit of default to the borrower at decision point t is then

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

The default condition is $G_t \geq 0$.

Model solution 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 inferences that 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 the insolvency probability and transaction costs terms. As such, the sensitivity of default probability to negative equity (the first-order derivative of default probability associated with negative equity in the theoretical model and the negative equity beta in a default probability model) is a function of the borrower's expected conditional probability of foreclosure, p_t, borrower insolvency probability, q_t, and transaction costs (a combination of R_t, S_t and W_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.[4]

[4] More formally if we assume house price follows a geometric Brownian motion with time varying drift, such a relation will be obvious from the first-order derivative calculation.

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), transaction costs including sense of distress, and other factors. These observations 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.[5] 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.

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.[6] 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.[7,8] First, BBX loans are matched to

[5] As discussed below in section on robustness, we also fully estimate the model using GSE-conforming conventional prime loans.
[6] HMDA is considered the most comprehensive source of mortgage data, covering about 80 percent of all home loans nationwide (Avery, et al, 2007).
[7]There is no unique common identifier of a loan from these two databases.
[8]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.

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 best-matched HMDA record. Any BBX loan lacking a HMDA loan match using the above criteria is excluded from our sample. On average, our match ratio is about 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.[9] The non-prime loan sample is of sufficient size to allow estimation of the default hazard model. 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 loan sample as well as reliable measures of house price changes as the latter is critical to the 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, Quigley and Van Order, 1996; 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. Another important attribute of 60-day delinquency data is that lenders and servicers typically intervene in the default process only after 60-day delinquency; as such, the 60-day delinquency term reflects borrower choice, as is the focus of this paper. That literature typically assumes the hazard rate of default of a mortgage loan at period T since origination is of the form

[9]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.

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

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.[10] 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[11].

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 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

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

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

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

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

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

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

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 Panel A 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 1 Panel B, 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 1 Panel C shows that over 41 percent of these loans experienced an over 60-day delinquency. Another 37 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 2, we report other descriptive statistics of our sample of 198,375 non-prime loans. Table 2 Panel A 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 42 percent) of sampled non-prime loans carry prepayment penalties. In addition, a substantial number of loans carry second liens (16 percent).

Table 2 Panel B 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.[12] 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 2 Panel C.

The sample statistics of the two key business cycle indicators also are reported in Table 2 Panel C. 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, as a proxy of borrower financial hardship. The average is 1.5 percent, again indicating that the average local unemployment rate was rising over the life of sampled loans.

[12] 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.

4.2. Hazard Model Estimates

4.2.1 Rolling Window Estimates

Figure 1 displays rolling window estimates of the negative equity beta from equation (6). We plot both the point estimate and the confidence band. Clearly evidenced 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 2 the impact of negative equity on default probability in 2007 and 2012. Interestingly, we see that negative equity had a small impact on default probability in 2007 – a loan with 20 percent negative equity had only about a 10 percent additional chance of entering into default relative to a loan with 5 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 20 percent negative equity had over a 200 percent chance of entering into default as compared to a loan with 5 percent negative equity.

As is evident in Figure 1, 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, 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 1, here we pool all observations in estimation of the default hazard model. Results of the model are reported in Table 3. 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 (2015) 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 also include MSA fixed effects as well as interactions of negative equity and the MSA dummies. Note that these terms allow us to control for the possible impact of different foreclosure laws on default probability and the negative equity beta.[13] Further, we control for non-linear effects of negative equity on default probability by including the square term of negative equity in the model.[14]

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 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

[13] We seek to well specify the model in an effort to mitigate concerns about the role of omitted variables in estimation of mortgage default (see, Rajan, Seru and Vig, 2015 for a discussion of omitted variables problem in subprime default models).

[14] We also experiment with higher order polynomials and the results are robust.

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 1. 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.[15]

In addition to negative equity, the literature suggests that trigger events such as borrowers' financial hardship in make monthly payment due to loss of income could cause default. We in our model use change in MSA unemployment rate from loan origination to the current quarter as a proxy of borrower financial hardship. Alternatively, we collect data from the Internal Revenue Services (IRS) and calculate change in zip-code average Adjusted Gross Income (AGI) and use it as a proxy of borrower financial hardship. Results in Appendix Table 1 shows that our findings regarding increasing borrower sensitivity to negative equity during recession is highly robust to this substitution.

Next we experiment with a number of alternative business cycle indicators. Results of that analysis are contained in Table 4. Consistent with estimates from model 2 of Table 3, 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 unemployment rate innovation are positive and significant, suggesting that borrowers are more sensitive to negative equity in the context of a deteriorating local economy[16].

[15] 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.
[16] 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.

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 1, 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 5. As is evident in the first term in Table 5, the Miami loans in general are less sensitive to negative equity during our sample period. However, as shown in the second term in Table 5, 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 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. Appendix Table 2 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 6. 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 (1994a) 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 6 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.[17] 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

[17] 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.

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 3. Over the study period, 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 figure, 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 figure, during the period post 2009Q3, the impact of negative equity on default probability is even more sizable, with the hazard ratio reaching almost 4.

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. 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.[18] As long as one group of borrowers had a higher probability of receiving a HAMP modification than the other group based

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

on borrower *ex ante* expectations, we are able to identify HAMP effects via our difference-in-difference test.

Table 7 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 8, 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 7 in support of the HAMP effect.

In Appendix Table 3, we show our HAMP test results when we narrow the test window, which includes periods before and after the date of policy implementation. Results are robust. We further conduct a placebo test of our difference-in-difference test, where we randomly choose a cutoff point that falls before policy implementation to see whether the difference-in-difference results are illusions caused by the generic difference between our control group and our treatment group. Results in Appendix Table 4 show this is not the case, and thus we are confident in our HAMP difference-in-difference test results.

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 4. 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)[19], the post 2009-Q3 dummy, and an MSA fixed effect. Findings of the panel data analysis in Table 9 are consistent with results of table 6. In that regard, factors including the 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.

In models 5 through 8 of Table 9, we show additional results of panel beta regression, in which house price expectation approximated by lagged HPI return, change in average AGI, and a housing distress index developed in Chauvet, Gabriel and Lutz (2013) are used as regressors. Those results are highly consistent with our rational expectations theory of borrower default behavior change. For example, positive house price expectation would dampen borrower propensity to default while pessimism on the future of house price is associated with higher sensitivity to negative equity.

4.5 Freddie Mac and Subprime-Only Sample Results

We re-estimate the entirety of the analysis using GSE-conforming prime conventional loans in place of our nonprime loan sample. The purpose of that analysis is to alleviate the concern that our estimated increase in ruthlessness of put option exercise might be the artifact of a nonprime loan sample that ceased origination in 2008. Appendix Figure 2 and Appendix Table 5 display very similar findings regarding time series patterns in the negative equity beta as well as drivers of beta changes.

[19] 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.

We also re-run the entirety of the analysis using only subprime loans instead of the combined subprime and Alt-A sample. 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 3 and Appendix Table 6, results are highly consistent with those for the pooled Alt-A and subprime loan sample.

4.6. Borrower Liquidity Constraints

Given the persuasiveness of default trigger events in the form of income shocks and related liquidity constraints during the crisis period, we include in our model proxies of borrower financial hardship, including the MSA unemployment rate and zip-code level income growth. However, because these proxies are imperfect, remaining uncontrolled liquidity constraints might bias our negative equity beta parameter. To further address this concern, we stratify our sample based on payment-to-income ratio, and select the bottom quartile of borrowers (who are least likely to have liquidity issues) and re-run the models. Results in Appendix 7 show that even among the borrowers who are least likely to be liquidity constrained, there remain significant variations in negative equity beta with respect to business cycle, sentiment, and HAMP implementation effects.

In addition to analyzing subsamples based on payment-to-income ratio stratification, we also dynamically sort the loans based on neighborhood income growth. In each year, we sort the loans into four quartiles based on current income growth in the zip code where the property resides and then re-run all the models separately for each of the four quartiles. We are particularly interested in the highest borrower income growth quartiles. Results are presented in Appendix Table 8. Again, even for loans in the highest income growth neighborhoods, where liquidity constraint is least likely an issue, there remain significant variations in negative equity beta with respect to the factors we identified as beta drivers.

4.7 Other Robustness Tests

We conduct a number of additional robustness checks. First, we experiment with expanded model specifications whereby we include addition variables such as a "woodhead" measure (missed default opportunities) and age effects in negative equity beta. Results in Appendix Tables 9 and 10 show that our findings regarding drivers of beta changes are highly robust to those specifications. Second, 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 that not to be the case. Next, 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. Also, we separate owner-occupied property loans from investor loans and run the models only for owner-occupied property loans. Again, results are robust to those re-specifications of the model. Further, 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 11, results are robust to the cohort specification, so as to underscore the primary findings of the paper.

5. Conclusion

In the wake of the late-2000s implosion in house values, mortgage default skyrocketed. The substantially increased incidence of default led to sharp deterioration in the performance of mortgage and housing markets and exacerbated the generalized economic downturn. While default was commonly associated with the sizable run-up in borrower negative equity, that outcome was precipitated as well by increased ruthlessness of default option exercise. Our 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 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 sharp run-up in crisis-period defaults than were declines in home equity.

Our findings provide new insights to shifts in ruthlessness of option exercise relevant to mortgage underwriting and pricing. From the perspective of credit risk management, results underscore the importance of model instability and the appropriateness of time-varying coefficient models. Our study provides guidance on factors governing temporal variation in estimated default option betas. 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. In that regard, there has been substantial debate on whether government should bailout of borrowers via mortgage modification. Arguments against such programs point to borrower moral hazard, whereby anticipated bailout of distressed borrowers may have encouraged irresponsible financial behavior. Our findings 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 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 shaded area shows the confidence interval.

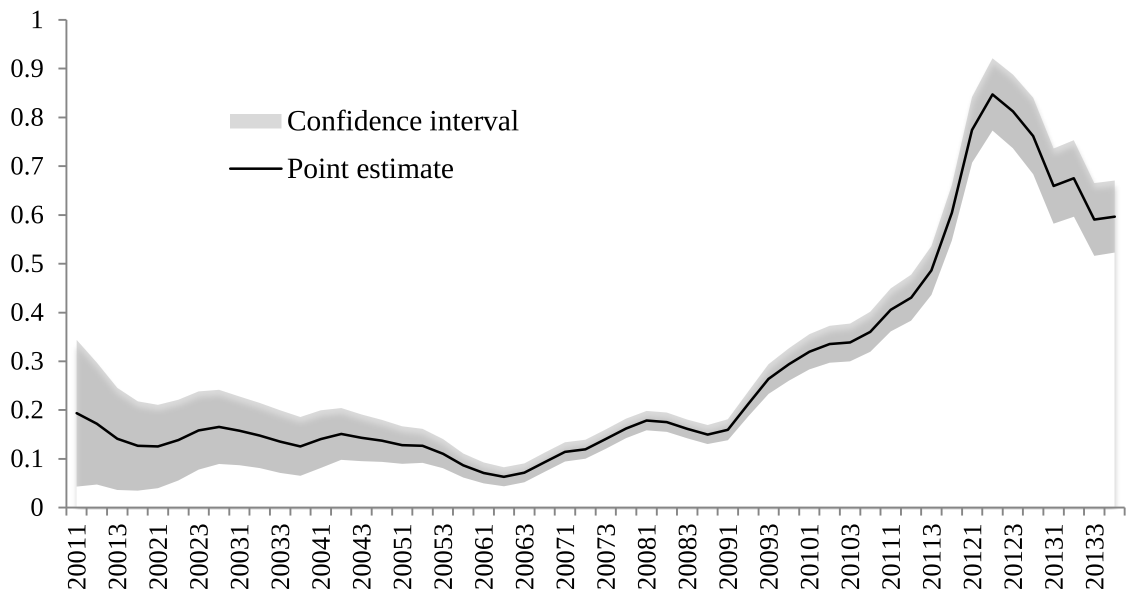


Figure 2 The Impact of Negative Equity on Mortgage Default Probability

This figure shows the simulated impact of negative equity on default probability in different years. Simulations are based on the negative equity beta estimates shown in Figure 1.

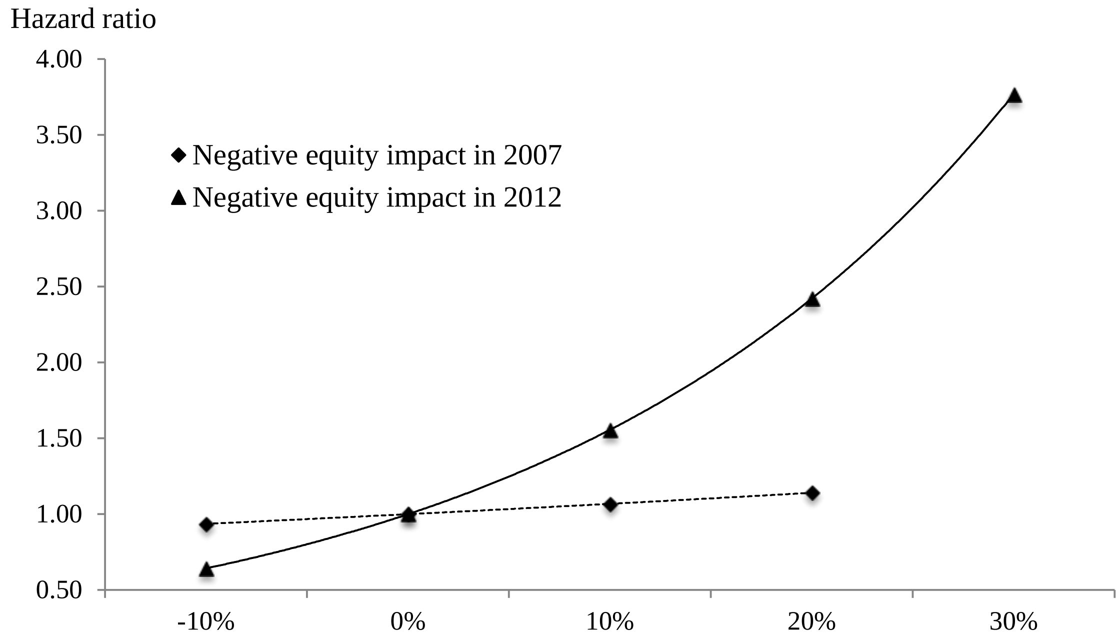


Figure 3 The Impact of Various Risk Factors on Mortgage Default Probability

This figure shows the simulated impact of negative equity on mortgage default probability when drivers of negative equity beta are presented. Simulations are based on the negative equity beta estimates shown in Table 6.

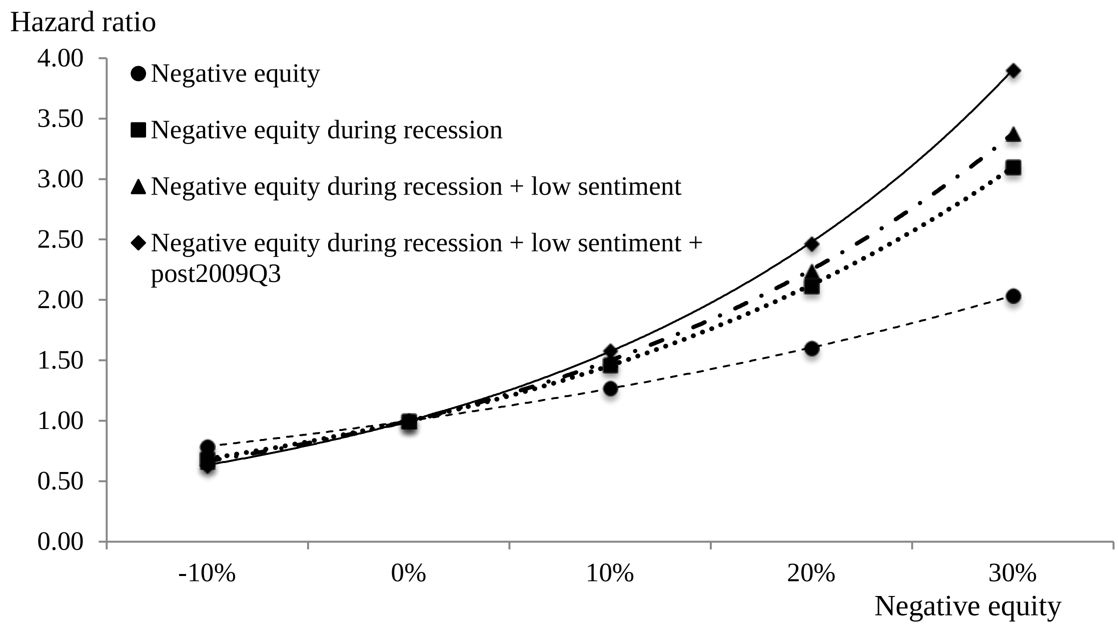


Figure 4 Negative Equity Beta Time Series for the Top 5 MSAs

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.

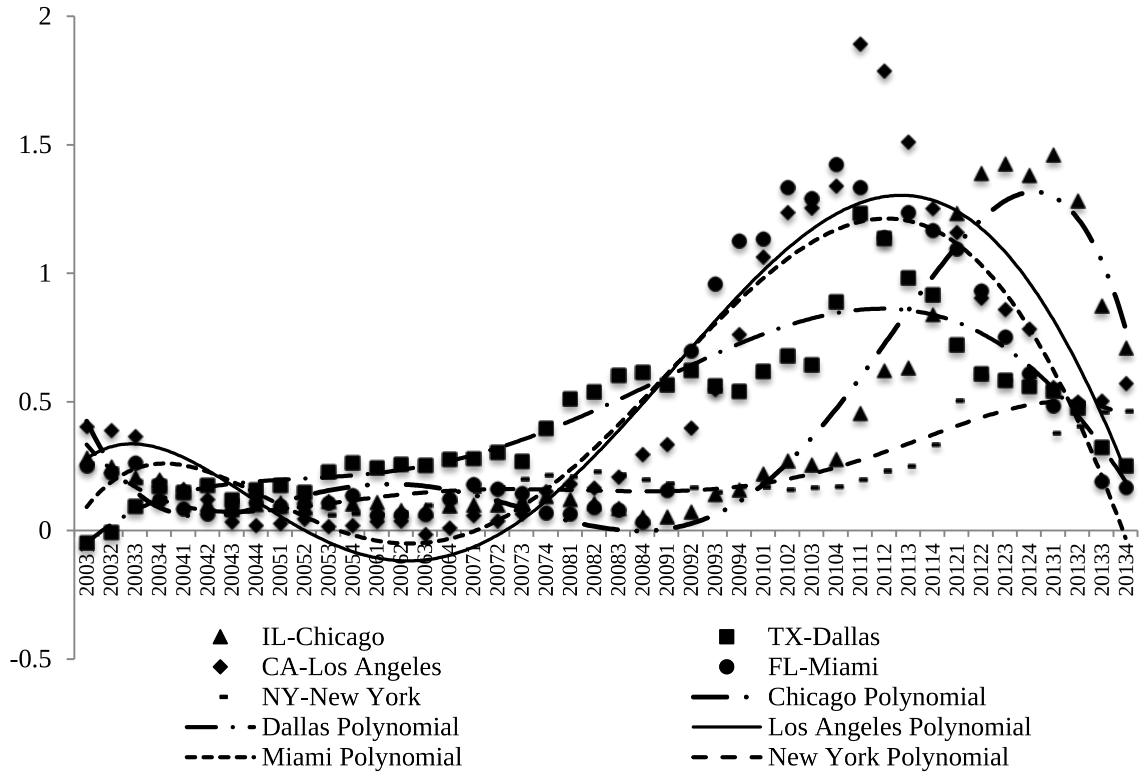


Table 1 Frequency Distributions of Sampled Loans

This table shows the frequency distributions 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 (FRM) 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. 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). We exclude loans with interest only (IO) 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 type or mortgage note rate are also excluded (about 13 percent of the sample). All these loans are securitized by private-label security issuers. 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. Loan termination status is as of January 31, 2014. Default is defined as over 60- day delinquency. Prepayment refers to early repayment of a loan, as a result of borrower move or refinancing for lower interest rates, different loan term or cash out. Current (censor) means that the loan is performing at date of data collection – January 2014. The data is from Blackbox Logic (BBX) based on servicer reports.

Panel A Loan Vintage Distribution

Origination Year	Frequency	Percent	Cumulative Percent
1998	1,165	0.59	0.59
1999	2,825	1.42	2.01
2000	5,166	2.6	4.62
2001	7,197	3.63	8.24
2002	10,931	5.51	13.75
2003	28,472	14.35	28.11
2004	30,362	15.31	43.41
2005	43,268	21.81	65.22
2006	50,898	25.66	90.88
2007	18,039	9.09	99.97
2008	51	0.03	100
Total		198,374	

Panel B Geographic Distribution

MSA Name	MSA Code	Frequency	Percent
Atlanta	12060	13,464	6.79
Boston	14460	8,431	4.25
Chicago	16980	23,491	11.84
Dallas	19100	20,701	10.44
Detroit	19820	14,317	7.22
Los Angeles	31100	29,262	14.75
Miami	33100	27,803	14.02
New York	35620	41,750	21.05
Phoenix	38060	12,186	6.14
Washington DC	47900	6,969	3.51
Total		198,374	
As a share of the national sample		22.79%	

Panel C Loan Termination Status

Termination type	Frequency	Percent
Current	44,009	22.18
Prepay	72,455	36.52
Mature	16	0.01
Default	81,894	41.28
Total	198,374	

Table 2 Summary Statistics on Loan and Event History Samples

This table reports summary statistics of loan and borrower characteristics as well as explanatory variables in our event-history (loan-quarter) sample. Panel A presents the frequency distribution of some important loan and borrower classifications. Panel B shows the mean, standard deviations, and the 5th and 95th percentiles of loan and borrower characteristics as continuous variables, and Panel C provides the mean, standard deviation, and the 5th and 95th percentiles 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. Note rate refers to the coupon rate charged to the borrower (fixed given that all our loans are FRMs). 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 at loan origination. 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. Refinance incentive is the percentage difference between the book value and market value of the loan, where book value is the remaining balance and market value is calculated as the present value of the remaining mortgage payments using the current prevailing mortgage interest rate as the discount rate. Borrower financial hardship is approximated by the change in MSA unemployment rate from loan origination to the current quarter. 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 its four-quarter moving average.

Panel A 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		

Panel B Loan and Borrower Characteristics (Means)

Variable	Mean	Std. Dev.	5th Pctl.	Median	95th 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		

Panel C Event History Data Descriptive Statistics

Variable	Mean	Std. Dev.	5th Pctl.	Median	95th 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	5.63	9.31	-6.13	3.52	23.69
Borrower financial hardship	1.50	2.57	-1.70	0.57	6.53
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
Percentage of loans that ever experienced negative equity			48.28%		
Total number of loan-quarters			4,806,790		

Table 3 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 hazard model is in the form of $h_i(T, Z'_{i,t}) = h_0(T)\exp(Z'_{i,t}\beta)$, where $Z'_{i,t}$ are the risk factors reported in this table. The β is estimated with the standard partial likelihood estimation based on the event-history (loan-quarter) data, where each loan has one record in each quarter of its life. The baseline $h_0(T)$ is estimated non-parametrically and not reported here. Variable definitions are discussed under Table 2. Model 1 is our baseline model without the recession indicator, which is a dummy variable indicating that the current quarter falls under NBER's recession period. In model 2, we include both the recession indicator and its interaction with negative equity trying to capture borrowers' changing sensitivity to negative equity during different phases of the business cycle. 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 * negative equity	0.000*	0.002***
	(0.000)	(0.000)
Negative equity * recession indicator		0.136***
		(0.016)
Negative equity * Alt-A loan indicator	0.152***	0.15***
	(0.016)	(0.016)
Negative equity * Low/no doc indicator	0.072***	0.068***
	(0.011)	(0.011)
Negative equity * Investment property indicator	-0.009	-0.009
	(0.021)	(0.021)
Negative equity * FICO score	0.067***	0.065***
	(0.005)	(0.005)
Refinance incentive * prepayment penalty binding	0.024***	0.025***
	(0.003)	(0.003)
Refinance incentive * not under prepayment penalty	0.000	0.000
	(0.002)	(0.002)
Borrower financial hardship	0.079***	0.080***
	(0.005)	(0.005)
Recession indicator		0.053***
		(0.008)
Alt-A loan	-0.339***	-0.338***
	(0.009)	(0.009)
Low/no doc	0.166***	0.167***
	(0.007)	(0.006)
Investment property	0.139***	0.139***

	(0.012)	(0.012)
FICO score	-0.057***	-0.056***
	(0.005)	(0.005)
FICO score square	0.037***	0.037***
	(0.002)	(0.002)
Payment-to-Income (PTI) ratio	0.018***	0.018***
	(0.001)	(0.001)
Log balance	0.036***	0.035***
	(0.004)	(0.004)
LTV at origination >= 80%	0.133***	0.131***
	(0.006)	(0.006)
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)
With prepayment penalty clause	-0.059***	-0.059***
	(0.015)	(0.015)
Unknown prepayment penalty clause	-0.137***	-0.137***
	(0.015)	(0.015)
Asian borrower	-0.056**	-0.056**
	(0.017)	(0.017)
African American borrower	0.080***	0.08***
	(0.007)	(0.007)
Other non-white borrower	0.020**	0.02**
	(0.007)	(0.007)
Female borrower	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 4 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 3 except that the recession indicator is replaced by the various business cycle variables 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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), 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 5 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 Alt-A and subprime FRM 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, 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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.
N	423,102
-2LogL	200,869
AIC	200,935

Table 6 Test of the Impacts of Sentiment and Structural Break

This table presents the Cox proportional hazard model results based on event-history from 2005Q1 to 2013Q1. We only use data from 2005Q1 to 2013Q1 because the MSA-level consumer distress index is only available from 2005Q1 to 2013Q1. In Appendix Table 2 we show that our main model results in Table 4 are robust to this change in sample. 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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), 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 7 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 Alt-A and subprime FRM loans originated before January 2009 with payment-to-income ratio above 31 percent and a remaining balance of no more than $729,500. 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, 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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), 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 8 DID Test of the HAMP Eligibility 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 originated before January 2009 for owner-occupied properties only with payment-to-income ratio above 31 percent. 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, 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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), 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 9 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 (thus a panel of beta). Loans included in the first stage hazard model estimation are Alt-A and subprime FRM loans in the 10 MSAs. In the second stage panel regression, the number of observations is reduced when we include the MSA-level consumer distress index because the distress index is only available from 2005Q1 to 2013Q1. Similar situation exists in some other specifications. For the housing distress index, refer to Chauvet, Gabriel and Lutz (2013). Panel A shows our main tests, and Panel B shows additional tests. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

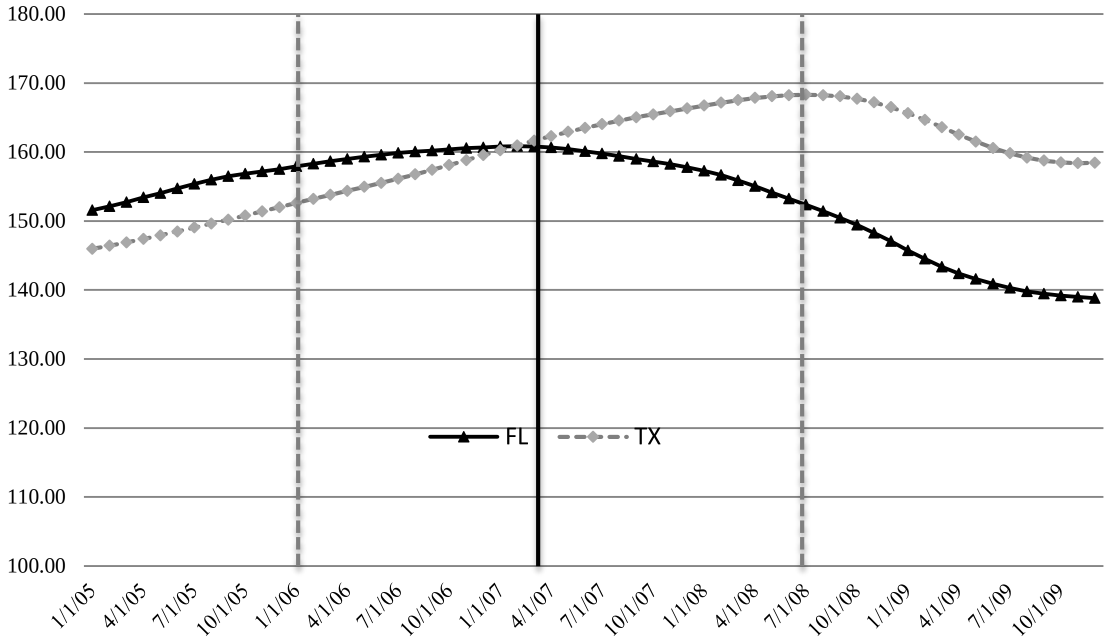
Panel A Main Tests

Explanatory variable	Model 1	Model 2	Model 3	Model 4
	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)
State unemployment rate innovation	0.045*			0.105***
	(0.023)			(0.020)
Orthogonalized MSA distress index		-0.095***		-0.095***
		(0.026)		(0.020)
Post 2009Q3			0.286***	0.324***
			(0.019)	(0.020)
MSA-fixed effect	Yes	Yes	Yes	Yes
N	440	330	440	330
Adjusted R-Square	0.136	0.252	0.436	0.586

Panel B Additional Tests

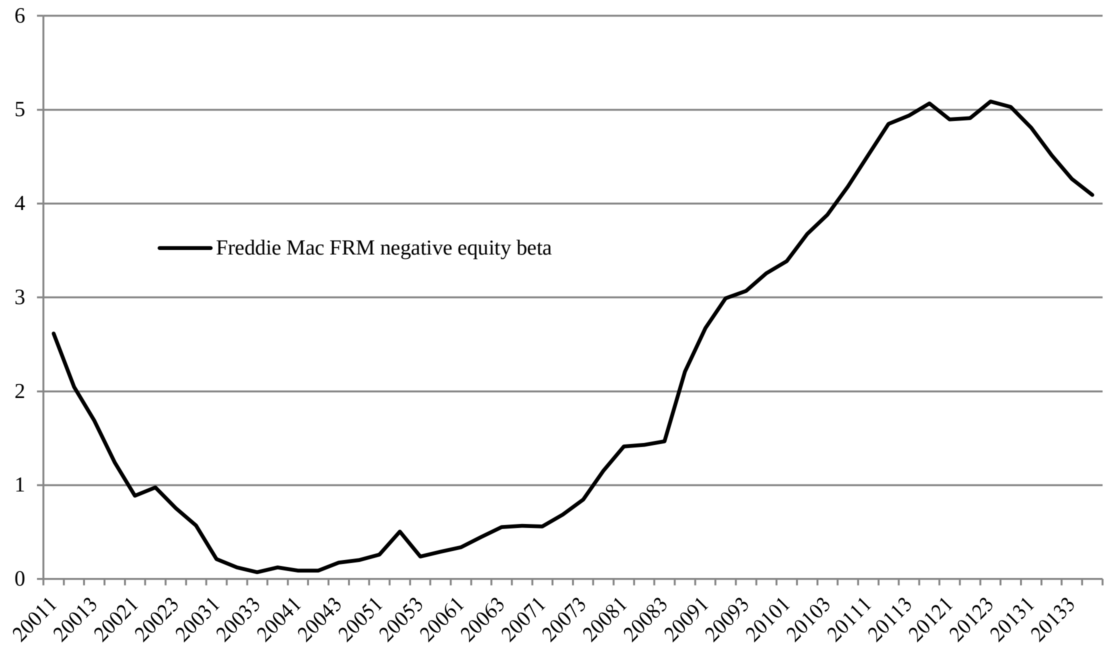
Explanatory variable	Model 5	Model 6	Model 7	Model 8
	Estimate (S.E.)			Estimate (S.E.)
Lagged MSA HPI return	-0.139***			-0.069*
	(0.022)			(0.029)
Change in average AGI		-0.068***		0.054*
		(0.024)		(0.027)
Housing distress index			0.162***	0.148***
			(0.024)	(0.032)
MSA-fixed effect	Yes	Yes	Yes	Yes
N	440	432	396	396
Adjusted R-Square	0.200	0.145	0.248	0.264

Appendix Figure 1 Coincident Indicators of Florida and Texas

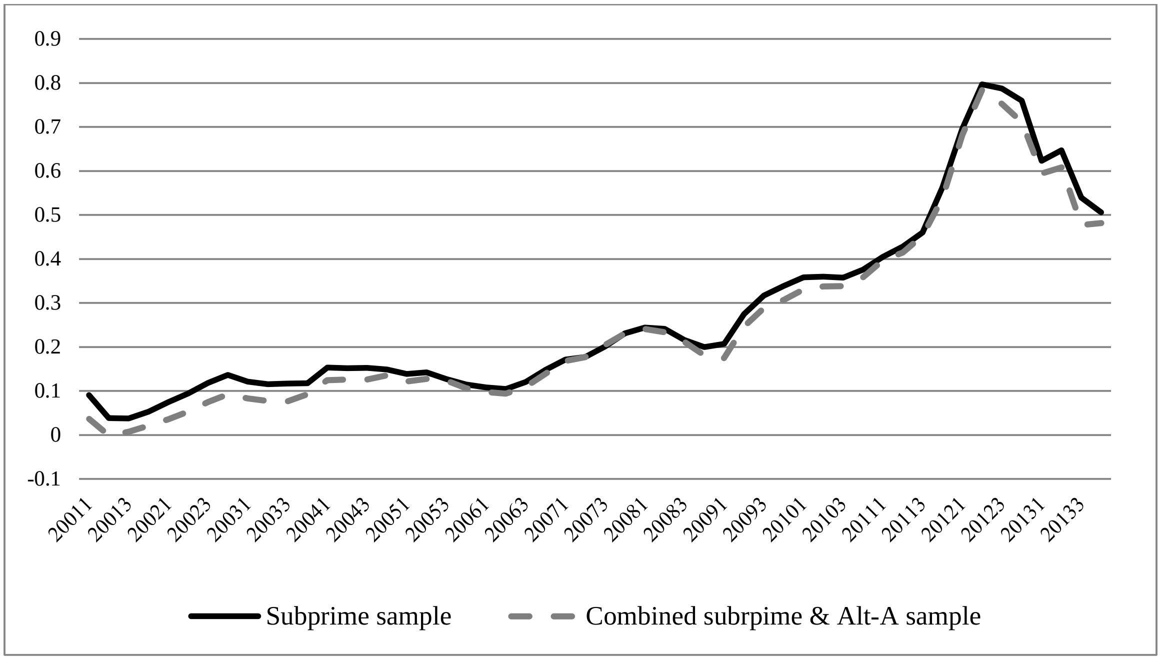


The grey vertical lines indicate our DID test sample starting and ending period. The red vertical line indicates the treatment (negative economic shock) start date. Data source: St. Louis Fed.

Appendix Figure 2 Rolling Window Estimates of Negative Equity Beta based on Freddie Mac Fixed-Rate Mortgage Loans



Appendix Figure 3 Rolling Window Estimates of Negative Equity Beta: Combined Subprime Alt-A sample vs. Subprime sample



Appendix Table 1 Hazard Model Results with Alternative Measure of Borrower Financial Hardship

This table presents the Cox proportional hazard model results for the Alt-A and subprime FRM loan sample for the ten MSAs. Instead of using MSA-level unemployment rate as a proxy for borrower financial hardship (Table 3), we use the IRS zip code level adjusted-gross income (AGI) data to measure borrower financial hardship. Note that due to missing AGI data for some zip codes, we have slightly fewer observations than in Table 3. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

	Estimate (S.E.)	
Covariate	Model 1	Model 2
Negative equity	0.329***	0.292***
	(0.081)	(0.08)
Negative equity * negative equity	0.000*	0.001**
	(0.000)	(0.000)
Negative equity * recession indicator		0.143***
		(0.016)
Negative equity * Alt-A loan indicator	0.176***	0.174***
	(0.018)	(0.018)
Negative equity * Low/no doc indicator	0.061***	0.057***
	(0.012)	(0.012)
Negative equity * Investment property indicator	0.003	0.004
	(0.025)	(0.025)
Negative equity * FICO score	0.068***	0.066***
	(0.006)	(0.006)
Refinance incentive * prepayment penalty binding	0.132***	0.124***
	(0.017)	(0.017)
Refinance incentive * not under prepayment penalty	-0.002	-0.002
	(0.002)	(0.002)
Change in zip-code average Adjusted Gross Income (AGI)	-0.042***	-0.042***
	(0.004)	(0.004)
Recession indicator		0.018*
		(0.008)
Alt-A loan	-0.341***	-0.34***
	(0.01)	(0.01)
Low/no doc	0.169***	0.17***
	(0.007)	(0.007)
Investment property	0.139***	0.139***
	(0.013)	(0.013)
FICO score	-0.058***	-0.057***
	(0.005)	(0.005)
FICO score square	0.037***	0.038***
	(0.002)	(0.002)

Payment-to-Income (PTI) ratio	0.022***	0.022***
	(0.002)	(0.002)
Log balance	0.044***	0.042***
	(0.005)	(0.005)
LTV at origination >= 80%	0.131***	0.128***
	(0.007)	(0.007)
15-year FRM	-0.141***	-0.139***
	(0.012)	(0.012)
Planned-unit development	-0.061***	-0.061***
	(0.011)	(0.011)
Condominium	-0.086***	-0.087***
	(0.011)	(0.011)
Rate/term refinance	-0.284***	-0.283***
	(0.009)	(0.009)
Cash out refinance	-0.029***	-0.028***
	(0.008)	(0.008)
With prepayment penalty clause	-0.059***	-0.058***
	(0.017)	(0.017)
Unknown prepayment penalty clause	-0.133***	-0.132***
	(0.017)	(0.017)
Asian borrower	-0.047*	-0.047*
	(0.019)	(0.019)
African American borrower	0.079***	0.078***
	(0.007)	(0.007)
Other non-white borrower	0.028***	0.028***
	(0.007)	(0.007)
Female borrower	0.000	0.000
	(0.006)	(0.006)
MSA dummy * Negative Equity	Yes	Yes
MSA dummy	Yes	Yes
Vintage fixed-effect	Yes	Yes
N	4,016,792	4,806,790
-2LogL	3,052,152	3,052,068
AIC	3,052,266	3,052,185

Appendix Table 2 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 4. ***, ** 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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), 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

Appendix Table 3 DID Test of the HAMP Eligibility Effect with a Narrower Test Window: 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, similar to the one shown in Table 7 except that we limit the time window of our loan performance records to 2008Q1 to 2009Q4, among which 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	-0.253* (0.109)
Negative equity * Owner-occupied property indicator * Post 2009Q1	0.425*** (0.100)
Post 2009Q1	0.054 (0.050)
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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.
N	605,597
-2LogL	598,807
AIC	598,925

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

This table presents results of a placebo test of the difference-in-difference (DID) test of the HAMP eligibility effect on borrower default option exercise. The test is in the same form as that in Appendix Table 8, except that the time window of our loan performance records is 2006Q1 to 2007Q4, during which there was no HAMP program. ***, **, and * indicate 0.1%, 1%, and 5% significance, respectively.

Covariate	Estimate (S.E.)
Negative equity * Owner-occupied property indicator	-0.100 (0.059)
Negative equity * Owner-occupied property indicator * Post 2007Q1	0.077 (0.042)
Post 2007Q1	-0.061* (0.025)
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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.
N	720,825
-2LogL	396,438
AIC	396,552

Appendix Table 5 Tests of the Impact of Sentiment and Structural Break (2005-2013 sample), *Freddie Mac Loan Sample*

This table presents results of a Cox proportional hazard model using the Freddie Mac loan sample, instead of the non-agency loan sample as in Table 6. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)
Negative equity * state unemployment rate innovation	0.291*** (0.011)
State unemployment rate innovation	0.012 (0.007)
Negative equity * Orthogonalized MSA consumer distress index	-0.160*** (0.009)
Orthogonalized MSA consumer distress index	-0.005 (0.005)
Negative equity * Post 2009Q3	0.552*** (0.035)
Post 2009Q3	0.069** (0.063)
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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.

Appendix Table 6 Tests of the Impact of Sentiment and Structural Break

(2005-2013 sample), *Subprime Loans Only*

This table presents results of a Cox proportional hazard model using only the subprime loan sample, instead of the subprime and Alt-A combined loan sample as in Table 6. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

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 * 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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.

Appendix Table 7 Effects of Business Cycle, Sentiment, and Structural Break: Low vs. High PTI Subsample

This table presents the Cox proportional hazard model results based on subsamples of loans where loans are grouped into low payment-to-income (PTI) subsample and high PTI subsample. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)	
	Low PTI Subsample	High PTI Subsample
Negative equity * state unemployment rate innovation	0.123*** (0.016)	0.152*** (0.015)
State unemployment rate innovation	0.078*** (0.012)	0.072*** (0.011)
Negative equity * Orthogonalized MSA consumer distress index	-0.077*** (0.017)	-0.099*** (0.015)
Orthogonalized MSA consumer distress index	-0.056*** (0.009)	-0.028*** (0.009)
Negative equity * Post 2009Q3	0.057* (0.023)	0.151*** (0.049)
Post 2009Q3	0.126*** (0.037)	0.067* (0.036)
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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.	
N	949,443	953,283
-2LogL	536,370	745,834
AIC	536,496	745,960

Appendix Table 8 Effects of Business Cycle, Sentiment, and Structural Break with Loan Portfolios Sorted by Income Growth

This table presents the Cox proportional hazard model results based on subsamples of loans where loans are dynamically sorted into three buckets based on current annual income growth in the zip code. The sorting is dynamic so the same loan can fall into different categories based on the current income growth in the zip code. Income growth data is from IRS. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Low income growth (lower quartile)	Moderate income growth	High income growth (Upper quartile)
Negative equity * state unemployment rate innovation	0.211*** (0.015)	0.165*** (0.020)	0.128*** (0.016)
State unemployment rate innovation	0.011 (0.010)	0.080*** (0.014)	0.119*** (0.012)
Negative equity * Orthogonalized MSA consumer distress index	-0.026** (0.011)	-0.031** (0.015)	-0.021 (0.013)
Orthogonalized MSA consumer distress index	-0.075*** (0.006)	-0.080*** (0.009)	-0.082*** (0.008)
Negative equity * Post 2009Q3	0.289*** (0.041)	0.300*** (0.065)	0.220*** (0.050)
Post 2009Q3	0.050 (0.028)	0.070* (0.040)	0.124*** (0.038)
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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.		
N	1,206,771	1,676,960	955,395
-2LogL	943,727	959,045	525,305
AIC	943,817	959,225	525,395

Appendix Table 9 Alternative Hazard Model Specification Inclusive of a Burn Out Variable

This table presents results of a Cox proportional hazard model with a burn out variable. Comparing to the model specification in Table 6, we add "missed default opportunities" as an additional variable to control for the burn out effect. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)
Negative equity * Missed default opportunity	-0.206*** (0.037)
Missed default opportunity	0.174*** (0.021)
Negative equity * state unemployment rate innovation	0.103*** (0.013)
State unemployment rate innovation	0.108*** (0.008)
Negative equity * Orthogonalized MSA consumer distress index	-0.067*** (0.012)
Orthogonalized MSA consumer distress index	-0.036*** (0.006)
Negative equity * Post 2009Q3	0.095*** (0.029)
Post 2009Q3	0.118*** (0.023)
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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.

Appendix Table 10 Alternative Hazard Model Specification with Age (Seasoning) Effect on Negative Equity Beta

This table presents results of a Cox proportional hazard model with age (seasoning) effect on negative equity. Comparing to the model specification in Table 6, we add the interaction between negative equity and the age (seasoning) of the loan. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)
Negative equity * state unemployment rate innovation	0.146*** (0.011)
State unemployment rate innovation	0.065*** (0.007)
Negative equity * Orthogonalized MSA consumer distress index	-0.080*** (0.010)
Orthogonalized MSA consumer distress index	-0.026*** (0.005)
Negative equity * Post 2009Q3	0.301*** (0.038)
Post 2009Q3	0.026 (0.024)
Negative equity * [loan age of 1 quarter, loan age of 2 quarters, …, loan age of 64 quarters]	Yes
Other 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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), MSA fixed effect in negative equity beta, MSA-fixed effect, vintage-fixed effect.

Appendix Table 11 Estimates of the Cox Proportional Hazard Model by Vintage

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

This table presents results of Cox proportional hazard models with separate vintage loans. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)			
	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, refinance incentive, borrower financial hardship, payment-to-income ratio, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development indicator, condominium indicator, rate/term refinance indicator, cash-out refinance indicator, second/vacation home indicator, prepayment penalty indicators, borrower race (Asian, African American, other non-white), borrower gender (female), 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