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 find the marked upturn in default option exercise was even more important to crisis period defaults than was the collapse in home equity. Analysis further indicates that much of the variation in default ruthlessness can be explained by the local business cycle, house price expectations, and consumer distress. Also, results suggest elevated default option exercise in the wake of enactment of crisis-period loan modification programs.

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1. Introduction

Default on residential mortgages skyrocketed during the late-2000s, giving rise to widespread financial institution failure and global financial crisis. Among factors salient to mortgage failure, analysts have pointed to the importance of property value declines induced rising negative equity, unemployment and broader income shocks, lax underwriting including fraud, and expansive use of risky loan products, to name a few.[1] In this paper, we provide new evidence of increased ruthlessness of default option exercise as another (but yet to be fully explored) fundamental driver of crisis period defaults. In fact, we find shifts in default option exercise behavior were even more important to the run-up in defaults than w declines in home equity.

In research dating from the 1980s, mortgage default is modeled as borrower exercise of the put option (see literature reviews by Quercia and Stegman, 1992 and Kau and Keenan, 1995). Indeed, empirical findings have shown that negative equity, a proxy for the intrinsic value of the put option, is a major driver of default (see, for example, Giliberto and Ling, 1992, Quigley and Van Order, 1995, and Deng, Quigley and Van Order, 2000). Recent research, however, indicates that home equity must turn deeply negative before most borrowers exercise the default option (see, for example, Bhutta, Dokko and Shan, 2016). Those findings offer empirical support for a "non-ruthless option-exercise" theory of mortgage default (see, for example, Vandell, 1995; Ambrose, Buttimer and Capone, 1997). We extend this literature to show systematic variability in ruthlessness of default option exercise among a cross-section of MSAs and over the economic cycle.[2]

To empirically identify the dynamics of default option exercise, we apply microdata to estimate hazard models of mortgage default (defined as over 60-day delinquency), where the conditional probability of default is a function of the contemporaneous value of negative equity of the underlining property and numerous other factors. The estimated coefficient on negative equity

[1] The long list of references include but are not limited to Mayer, Pence and Sherlund, 2009, Demyanyk and Van Hemert, 2011; Mian and Sufi, 2009; Keys, et al, 2010; Agarwal et al, 2011, 2012, 2014, 2016; Piskorski, Seru, and Witkin, 2015; Rajan, Seru, and Vig, 2015; Cheng, Raina and Xiong, 2014; Gerardi, et al, 2008; Mian and Sufi, 2011; Mian, Sufi, and Trebbi, 2010, 2015; An, Deng and Gabriel, 2011; Taylor and Sherlund, 2013, Haughwout, et al, 2011, 2014; Li, White, and Zhu, 2011; Brueckner, Calem and Nakamura, 2012; Case, Shiller and Thompson, 2014; Rajan, Seru, and Vig, 2010, 2015; Corbae and Quintin, 2015; Cotter, Gabriel, and Roll, 2015; Ambrose, Conklin and Yoshida, 2015; Bayer, Ferreira and Ross, 2016, Keys, et al, 2016, etc.

[2] In related literature on corporate default, Duffie et al (2009) find evidence of dynamic variation in the role of common latent factors in predicting firm level default.

(below labelled the negative equity beta) is a measure of borrower ruthlessness (or propensity) to default in the presence of negative equity. Contrary to the existing mortgage default literature, we allow the negative equity beta to vary over time and place.

Recent research has further underscored the importance of income shocks as a default trigger (see, for example, Foote, Gerardi, and Willen, 2008; Elul et al, 2010; Campell and Cocco, 2015; and Gerardi, et al, 2015 for the double trigger argument).[3] Hence, our default model includes highly disaggregated zip code-level income controls. Also, our model includes a large number of other covariates including controls for incentive to refinance (to address for the competing risks in option exercise) as well as numerous borrower, loan, and locational characteristics.

We estimate our models using expansive micro data on loan performance during the 2006-2013 period.[4] Our primary datasets include monthly mortgage performance history for both private-label securitizations (PLS) and Freddie Mac conventional conforming loans. Results of rolling window local estimation of the hazard model show a marked run-up in the negative equity beta from 0.07 in 2007 to about 0.7 in 2012 (Figure 1), leading to substantially higher default probabilities for a given level of negative equity (Figure 2). Model simulation indicates that defaults would have been only one-third of their actual crisis period level, in the wake of the recorded house price implosion, had borrower propensity to default not turned up (Figure 3). These findings suggest that the rise in the negative equity beta during the crisis period was highly salient to the elevated default rate.

We also find substantial heterogeneity in the negative equity beta among sampled MSAs. Figure 3 shows dramatic cyclical movements in the negative equity beta among virtually all sampled metropolitan areas. However, the MSA-specific negative equity beta time-series differ both in slope and in turning point.

We then explore possible explanations of heterogeneity in borrower propensity to default. In so doing, we lay out a simple theoretical framework that illuminates the role of negative equity and other key variables in the borrower's decision to default. Our model builds on existing literature and assumes that borrowers have rational expectations and engage in default to maximize

[3] According to the double-trigger argument, negative equity is a necessary but not sufficient condition for mortgage default. That argument further stresses the importance of income shocks to default. Low (2014) presents evidence on positive equity and default.

[4] The current study focuses on the elevated pattern of default exercise during the GFC period. We have also estimated our default models with extended sampling period by including data prior to the crisis period. Our findings remain robust.

wealth (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). The model suggests that borrower propensity to default can vary over time due to factors such as changing borrower expectations on the path of the local economy, borrowers' subjective assessment of the conditional probability of foreclosure (versus workout), changing default transaction costs (including stigma effects), and the like. For example, pessimism about the future trajectory of house prices could make the borrower more sensitive to a negative equity position. Similarly, expectations of loan modification conditional on default could also lead to more ruthless option exercise.

We employ proxies for factors identified in theory to empirically assess drivers of observed variation in the negative equity beta. We find that MSA unemployment rate shocks, reflecting cyclical fluctuations in the local economy, are highly predictive of variation in the negative equity beta. Conditional on controls for the local business cycle, we find that borrower default propensities are sensitive to consumer distress, where our measure of distress is orthogonalized to current economic fundamentals. We also find evidence of a structural break in the negative equity beta time-series in 2009 which coincides with federal mortgage market intervention via the Home Affordable Modification Program (HAMP). These factors, together with MSA-fixed effects, explain almost two-thirds of the variation in the negative equity beta panel. Results further indicate that lagged HPI return is also highly predictive of the negative equity beta. Finally, while change in average income is an important predictor of default probability, it is not a significant driver of the variation in negative equity beta, consistent with our theoretical predictions.

We also seek to shed light on the structural break in default option exercise in 2009. A difference-in-differences analysis shows that those eligible for HAMP loan modification became significantly more sensitive to negative equity in the wake of program implementation, relative to the non-HAMP eligible control group. This finding is consistent with the notion that mortgage borrowers may be strategic and hence more likely to become delinquent when they expect lenders to modify defaulted loans (see, for example, Guiso, Sapienza and Zingales, 2013; Mayer, et al, 2014).[5]

[5] 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.

Our findings are robust to alternative model specifications and loan samples. As our primary sample is comprised of nonprime (subprime and Alt-A) loans, we re-estimate the model using Freddie Mac prime conforming loan data and confirm a similar pattern of negative equity beta variation. We assess the robustness of findings to alternative definition and functional form of negative equity (e.g., market vs. book value of negative equity in continuous, and categorical form). We also assess whether hazard model results are sensitive to size of the estimation rolling window (e.g., 2 vs 3 years). We further evaluate robustness in the negative equity beta among borrowers less likely to be liquidity constrained. In addition, we test specifications of the model that account for default burnout and age effects in both the negative equity beta and the baseline to the hazard model. Finally, we estimate the model using annual cohorts to assess whether changes in the mix of borrowers may have contributed to the observed variation in the negative equity beta. Results throughout indicate a similar countercyclical pattern of negative equity beta over the crisis period and beyond.

Our findings contribute to the literature in several important ways. First, results provide new insights into cyclical pattern of borrower decision to default and thus help our understanding of the GFC. Among relevant crisis-related analyses (see, for example, Mian and Sufi, 2009; Keys, et al, 2010; Agarwal et al, 2011, 2012, 2014, 2016; Demyanyk and Van Hemert, 2011; Nadauld, and Sherlund, 2013; Cheng, Raina, and Xiong, 2014; Piskorski, Seru, and Witkin, 2015; Rajan, Seru, and Vig, 2015; Elenev, Landvoigt, and Van Nieuwerburgh, 2016), temporal shifts in default behavior among mortgage borrowers have received only limited attention.[6] Here we show that changes in the propensity to exercise the mortgage default option were material to drive the crisis.

Second, our study adds to the growing literature on strategic default (see, for example, Riddiough and Wyatt, 1994a; Jagtiani and Lang, 2011; Guiso, Sapienza and Zingales, 2013; Mayer, et al, 2014). Mortgage default is a more than one-sided process and often involves strategic interaction among borrower and lender. We provide evidence that, in anticipation of policy-driven loan modifications, borrowers may be more willing to exercise the default option.

[6] Other studies include Gerardi, et al, 2008; Jaffee, et al, 2009; Mayer, Pence and Sherlund, 2009; Mian and Sufi, 2011; Mian, Sufi, and Trebbi, 2010, 2015; 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; Rajan, Seru, and Vig, 2010, 2015; Corbae, and Quintin, 2015; Cotter, Gabriel, and Roll, 2015; Ambrose, Conklin and Yoshida, 2015; Bayer, Ferreira, and Ross, 2016, Keys, et al, 2016, etc.

Third, our findings raise important issues of modeling and management of mortgage default risk in an ever-changing market environment. As evidenced in recent studies, statistical models may substantially underestimate default risk in the presence of economic fluctuations, policy intervention, and behavioral change (see, for example, An et al, 2012; Rajan, Seru, and Vig, 2015). Indeed, the assumption of a fixed and static negative equity beta may result in significant problems of default prediction and management (Frame, Gerardi and Willen, 2015). The time-varying coefficient hazard model may better characterize ongoing evolution in borrower default behavior so as to enhance risk management.

Finally, our study has important policy implications. While HAMP saved many defaulted borrowers from foreclosure (see, e.g., Agarwal et al, 2016), our findings suggest this program also may have had an unintended consequence of inducing some borrowers to enter into delinquency. 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 default option exercise among borrowers seeking a HAMP loan modification. Therefore, an effective policy/program should fully account for potential dynamic interactions from the market as reported in the current study.

The remainder of the paper is organized as follows: in the next section, we discuss our data; in section 3, based on hazard model estimates, we document the time-series and cross-sectional variations in the negative equity beta; in section 4, we explore factors that drive variations in the negative equity beta; and section 5 provides concluding remarks.

2. Data

2.1. Data sources

Our primary dataset consists of loan-level information obtained from BlackBox Logic (hereafter BBX). BBX aggregates data from mortgage servicing companies in the U.S. and conducts data standardization and cleaning. The BBX data file contains roughly 22 million non-agency (jumbo, Alt-A, and subprime) securitized mortgage loans, making it a comprehensive source of mortgage information.[7] BBX provides detailed information on borrower and loan characteristics at origination, including the borrower's FICO score, origination loan balance, note

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

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 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, property type, loan amount (in thousands of dollars), loan purpose, borrower-reported occupancy status, and in the case of originated loans whether the loan was sold in the secondary market.

Since there is no unique common identifier of a loan from these two databases, we use the following common variables to match loans common to the BBX and HMDA files[8]: loan purpose, occupancy status, property type, origination year, zip code (census tracts in the HMDA data are mapped to zip codes), and loan amount (in thousands). Our match ratio is about 75 percent and the characteristics of the matched loans are representative of the original BBX sample. Later, we find that estimation results are not sensitive to the addition/removal of HMDA variables in our data. However, for the sake of model completeness, we utilize the BBX-HMDA matched sample for the main analysis.

We then merge the loan-level data with other proxies for labor and housing market fundamentals as well as controls for macroeconomic conditions and sentiment. For example, to calculate negative equity for each loan in each quarter, we merge the loan event history with zip code-level house price index from CoreLogic. We also utilize the S&P/Case-Shiller MSA-level Home Price Index to calculate a time-varying house price volatility, which is then used to normalize our negative equity measure across MSAs. To calculate refinance incentive for each loan in each quarter, we merge mortgage interest rates from the Freddie Mac Primary Mortgage Market Survey to our loan event history. To obtain a measure of borrower income change from loan origination to each loan performance period, we merge the IRS adjusted gross income (AGI) data at the zip-code level to our loan event history. In addition, we supplement our mortgage data

[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.

with macroeconomic variables including the MSA-level unemployment rate from Bureau of Labor Statistics, Treasury bond rate from the Federal Reserve Board, consumer distress index from St. Louis Fed, and credit card default rate from the New York Fed Consumer Credit Panel. For purposes of robustness, we also estimate our models using loan-level data from Freddie Mac for conventional conforming mortgages. Additional information on data and variable construction is found later in the paper.

2.2. Sample and descriptive statistics

In our main analysis, we focus on first-lien, 15- and 30-year fixed-rate (FRM) subprime and Alt-A (hereafter non-prime) mortgage loans originated during 2003-2007 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] 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 cross-sectional 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.

Our sample contains 131,015 fixed-rate non-prime (subprime and Alt-A)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. That distribution reflects the rise and fall of the non-prime mortgage market. For example, 15,567 loans (about 12% of our loan sample) were originated in 2003 but the number of loan originations grew to 41,402 in 2006 (about 32% of our loan sample). A sharp decline in non-prime origination ensued with the onset of the crisis in 2007.

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, nearly 19 percent (24,724 loans) originate from Miami, followed by Los Angeles (16 percent), New York (15 percent). Dallas also comprises nearly 13 percent of the non-prime loan sample. Washington DC has the lowest share

[9] A series of filters is also applied: we exclude those loans with interest only periods; 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.

of loans at about 1 percent (1,425 loans). Altogether, the fixed-rate non-prime mortgage loans in our 10 MSA sample represent almost 24 percent of the national total of such mortgages.

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 nearly 46 percent of these loans experienced an over 60-day delinquency. Another 35 percent were prepaid. At the time of data collection (2014-Q1), about 19 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 1 Panel D, we report descriptive statistics of loan and borrower characteristics. The average origination loan amount is $214,233. Non-prime mortgage loans usually carry higher interest rates than prime loans. The average note rate is 7.22 percent, which is substantially higher than the average note rate on prime mortgages during our study period.[10] A quarter of the loans carry an interest rate of over 8 percent. The average borrower FICO score is 609 and the median FICO score is 620. While the average LTV is 73 percent, a relatively high 25 percent of loans have LTV in excess of 80 percent. In addition, about 15 percent of loans carry second liens. The average combined LTV is 74%. We also calculate an average 25 percent mortgage payment (principal and interest) to income ratio.

As discussed previously, we focus only on 15- and 30-year FRMs. In fact, 94 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 19 percent of originated mortgages were for home purchase. Cash-out refinance and rate/term refinance mortgages comprised 61 and 20 percent of the sample, respectively. Owner-occupied loans comprise 94 percent of our sample, whereas investment property loans constitute 6 percent.

Almost 34 percent of sampled loans are characterized by low or no documentation while roughly 64 percent of loans are characterized by full documentation. African American and Asian borrowers comprise 21 percent and 3 percent of our sample, respectively. In contrast to prime mortgages, a large proportion (almost 60 percent) of sampled non-prime loans carry prepayment penalties.

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[10] As reported in the Freddie Mac Primary Mortgage Market Survey, during 2003-2007, the average note rates of conventional prime 30-year FRM and 15-year FRM are 6.1 percent and 5.8 percent, respectively.

3. Rise in Mortgage Default Propensities

3.1. Default hazard models

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; Pennington-Cross, 2002; Demyanyk and Van Hemert, 2011; and An, et al, 2012). The hazard model is convenient primarily because it allows us to work with the 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 this definition of default is that lenders and servicers typically intervene in the default process only after 60-day delinquency; as such, the 60-day delinquency event reflects the borrower decision-making, as is the focus of this paper.

The literature typically assumes the hazard rate of default of a mortgage loan at period T since origination is of the form

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

Here $h_0(T)$ is the baseline hazard function, which depends only on the age (duration) T of the loan; and $Z'_{i,t}$ is a vector of covariates for loan i that includes all identifiable risk factors.[11] In the proportional hazard model, changes in covariates shift the hazard rate proportionally without otherwise affecting the duration pattern of default. Covariates include contemporaneous LTV (or negative equity), FICO score, payment (debt) to income ratio, refinance incentives (as prepayment is a competing risk to default), and a host of other loan, borrower, and locational characteristics.

In our analysis, we allow the coefficient of negative equity in the hazard model to be time-varying so as to focus on possible intertemporal variation in the sensitivity of borrower default probability to negative equity. Therefore, our model becomes a time-varying coefficient (partially linear) model of the form

$$h_i(T, Z'_{i,t}) = h_0(T)\exp(Z'_{i,t}\beta_t), \quad (2)$$

To estimate a time-varying coefficient hazard model, we adopt the rolling window local estimation approach from the statistics literature. The idea is that the time-varying coefficient model can be treated as locally linear, so we can assume the coefficients to be constant for each

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

short time window and apply the usual estimation method to obtain a local estimator.[12] In that regard, we form quarterly three-year rolling windows to construct our local estimation samples. As discussed below, we also assess robustness of results to the size of the rolling window.

The hazard model is estimated with loan event-history. We thus construct the quarterly event-history of each loan based on the performance history reported by BBX and merge 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. The market value of the property is calculated by adjusting property value at origination given subsequent zip code-level house price index (HPI) changes, while the market value of the loan is calculated based on the market prevailing mortgage interest rate and remaining mortgage payments at each quarter (see, for example, Deng, Quigley and Van Order, 2000)[13]. To account for cross-MSA differences in house price volatility, we calculate HPI volatility-adjusted negative equity for use in model estimation.

We employ zip code-level data on income growth to control for income shocks. That term is calculated based on IRS data on adjusted gross income (AGI). Our assumption is that borrower income growth moves in tandem with zip code-level income growth plus random noise. Further, it also seems reasonable to assume that the random noise component of individual income growth is independent of property value change and other variables in our model. Accordingly, this term should not bias estimates of other model coefficients. Also, as in Bhutta, Dokko and Shan (2016), we use county-level credit card delinquency rates as an alternative measure of income shocks.

We account for the competing risks of mortgage prepayment via a measure of the incentive to refinance (alternatively, one can view this as measure of risk associated with the distance to the mortgage prepayment). That measure is computed as the contemporaneous difference between the market value of the loan and the book value of a loan. The book value of the loan is the remaining mortgage balance (from the loan amortization schedule) whereas the market value of the loan is computed based on the remaining mortgage payments and the mortgage interest rate prevailing in the market. Sample statistics of the time-varying covariates are reported in Table 2.

Static covariates included in the hazard model include loan and borrower characteristics

[12] This can result in unsmoothed estimates. A more sophisticated method is the two-step procedure presented in Fan and Zhang (1999) and Fan and Zhang (2008) that will result in smoothed estimates.
[13] One might argue that borrowers do not calculate the market value of the loan in assessment of negative equity, but instead focus on remaining loan balance, otherwise known as the book value of the loan. In further tests, we confirm that results are robust to the book value definition of negative equity.

such as borrower FICO score, payment-to-income ratio, loan credit category (Alt-A vs. subprime), documentation type (full vs. low doc), loan type (30-year vs. 15-year), loan purpose, property type, occupancy status, log origination loan balance, prepayment penalty indicator, borrower race and gender, and the like. We also include MSA-fixed effects and vintage-fixed effects. MSA-fixed effects account for the possible impact of varying state foreclosure laws and residual MSA-specific characteristics on default probability, whereas vintage-fixed effects control for unobserved changes over time in underwriting standards. [14] To account for potential non-linearities, we also include square terms of such key variables as negative equity, income growth, FICO score, and payment-to-income ratios.

3.2. Negative equity beta time series

Prior to presentation of our rolling window estimates and to assure the reasonableness of model specification, we examine a pooled-sample baseline model. Estimates of the baseline model are reported in Table 3. As is evident, model coefficients conform to economic intuition and to findings in the existing literature (see, e.g. Deng, Quigley and Van Order, 2000; Deng and Gabriel, 2006). For example, negative equity is positively related to default risk. That relationship is non-linear as reflected by the significance of the negative equity square term. The refinance incentive term is negative and significant and is consistent with competing risks of mortgage prepayment and default. FICO score is negative and significant in determination of default probability, whereas the payment-to-income ratio is positive and significant. Alt-A loans are associated with lower default probabilities than subprime loans, all things equal; as would similarly be expected, 15-year fixed-rate mortgages (FRMs) are lower default risk than 30-year FRMs. Low/no doc loans, investment property loans, loans with over 80 percent LTV at origination, and larger denomination loans are all characterized by elevated default hazard. The coefficient on income growth is negative and significant suggesting that higher borrower income growth serves to reduce default probabilities. In addition, the relation is concave as evidenced in the sign and significance of the square term of income growth.

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

As discussed above, our focus is on the time variation in the negative equity beta. In Figure 1, we display rolling window estimates of the negative equity beta from equation (2). Given the presence of the square term in negative equity, the negative equity beta is calculated as the coefficient of the negative equity term plus two times the coefficient of the negative equity square term times the mean value of the negative equity term – the first-order partial derivative of the hazard rate with respect to negative equity.

We plot both the point estimate and the confidence band of the negative equity beta. Clearly evidenced are sizable and significant intertemporal variations in the estimated beta. In that regard, the negative equity beta rose gradually from about 0.05 in 2006 to over 0.1 in 2008. Subsequently, in the wake of housing and mortgage crisis, the negative equity beta ran up to about 0.4 in 2009 and then nearly 0.6 in 2010. After a slight decline in early 2011, it rose further during late 2011 to reach a peak of around 0.8 in mid-2012. Subsequent to that, a clear trending down in negative equity beta was evidenced; nonetheless, as recently as 2014-Q1, the estimated beta remained elevated at about 0.5. Note that samples of non-prime loans are limited in size in early and late years of the sample and the confidence band surrounding the estimates is larger during those periods. That notwithstanding, results indicate statistically significant differences over the estimation timeframe in the negative equity beta.

To provide further insights as to the economic significance of changes in the mean estimated beta, we plot in Figure 2 the impact of negative equity on default probability in 2007 and 2012. Interestingly, negative equity had a limited impact on default probability in 2007. A loan with 20 percent negative equity had only about a 5 percent additional chance of entering into default relative to a loan with 10 percent negative equity, and a loan with 30 percent negative equity had only about 11 percent higher risk than that with 10 percent negative equity. In marked contrast, by 2012 the impact of negative equity on loan default probability was sizable. In that year, a loan with 30 percent negative equity had over a 220 percent chance of entering into default as compared to a loan with 10 percent negative equity. In addition, a loan with 40 percent negative equity had over a 340 percent chance of entering into default as compared to a loan with 10 percent negative equity. Loans with negative equity in the range of 10 - 30 percent witnessed an increase in the default hazard ratio of 140 – 280 percent during the 2007 to 2012 period.

As is evident in Figure 1, the estimated movement over time in the negative equity beta appears to be strongly correlated with cyclical fluctuations in house prices and the broader economy. During pre-crisis boom years and in the context of strong housing market performance, the negative equity beta was small in magnitude. As boom turned to bust, the negative equity beta rose quickly. Finally, in the wake of the post-downturn expansion and as economic conditions improved, the negative equity beta again declined.

During the crisis period, not only were more borrowers characterized by negative equity, but also more borrowers chose to exercise the default option conditional on given level of negative equity. Hence the sharp run-up in defaults during the crisis period reflected declines in home equity compounded by a markedly elevated borrower propensity to default in the presence of negative equity. To illustrate the net effect of elevated borrower propensity to default that drives sharp upward movement in mortgage default during the crisis period, we conduct the following experiment: we apply the estimated negative equity beta associated with 2003-2008 loan performance event history data with a sample of 2003 vintage loans, to predict 2006-2011 loan performance of the 2006 vintage loans, assuming perfect foresight in house price movement. The dashed-line in Figure 3 shows the predicted cumulative default rates by loan age (quarters). The solid line in the chart depicts the actual cumulative default rate of the 20006 vintage loans. Over the 23-quarter horizon, even in the event of perfect foresight regarding house prices, the predicted default rate (using the pre-crisis observed borrower default propensity) is only about one-third of the actual default rate. In other words, had borrower propensity to default remained unchanged during the crisis period, defaults would have been substantially lower than those actually recorded.

To put this further into perspective, application of the observed default propensity of the 2006 vintage loans to a hypothetical flat house price trajectory yields a default prediction that is 46 percent below the actual default rate, compared to a 64 percent under-prediction using the negative equity beta from the pre-crisis period in the example discussed above. Together, these findings highlight the importance of increased ruthlessness of borrower default option exercise to elevated crisis period defaults as well as further underscore that changes in default behavior were more salient to crisis period defaults than were declines in home equity.

One might question whether the estimated increase in the negative equity beta is an artifact of the non-prime loan sample. To address that issue, we re-estimated our models using prime conventional conforming loans from Freddie Mac in place of our non-prime loan sample.[15] Results in Appendix Figure 1 indicate the time series pattern in the negative equity beta is robust to loan sample.

Among other robustness checks, we estimate the rolling window model using different window sizes (24 vs. 36 months). To address the concern of potential measurement error bias due to the noise from the HPI estimations, we further test whether the negative equity beta is sensitive to standard deviations of the point estimates of MSA-level HPI (a measure of noise in the HPI).[16] Next, we replace the continuous negative equity term with a categorical variable indicating whether the loan is characterized by negative equity or not in the current quarter, regardless of the magnitude of negative equity. The results are robust to those alternative model specifications.

3.3 MSA-level Negative Equity Beta Panel

We further evaluate spatial heterogeneity in the negative-equity beta time series across metropolitan markets. To do so, we stratify the sample by MSA and estimate the rolling window model. Note that estimation precision is reduced by the substantially smaller MSA samples.[17] To obtain a better picture of the spatial heterogeneity in the MSA-specific beta estimates, we plot the polynomial of the default option beta time-series for each of the top 5 MSAs in Figure 3. As is evident, most MSAs display significant cyclical movement in the negative equity beta over the boom, bust and crisis aftermath. For example, Los Angeles, Miami, Dallas and several other MSAs demonstrate a hump-shaped negative equity beta during 2006-2013 as borrower propensities to exercise the default option rose significantly during the crisis and declined thereafter.

Interestingly, we also observe variations in beta levels and turning points across MSAs. For example, the negative equity betas are substantially larger in Los Angeles and Miami than in New York and Dallas. In addition, while the default option beta estimates peaked in 2010 in both Los Angeles and Miami, it continued to rise through 2012 in Chicago and New York. Finally, we also observe substantially larger volatility in the estimated betas in certain MSAs, notably including Las Vegas, Miami and Los Angeles.

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[15] To promote credit risk transfer (CRT) deals, starting in 2014 Freddie Mac began releasing to the public detailed loan-level loss data on their first lien, full documentation, fixed-rate mortgage (FRM) loans originated between 1999 and 2014. We obtained these data directly from the Freddie Mac website.
[16] We thank Darrell Duffie for pointing this out.
[17] In addition, we do not have adequate observations to obtain sensible estimations for early 2006 and late 2013-early 2014, so we lost a few quarters of estimates during those periods.

4. What Drives Variations in Default Propensities?

4.1. A Theoretical Framework

As evidenced above, variations in negative equity beta are sizable both in the time- series and in the cross-section. Below, we explore some explanations of these variations. We start with a simple theoretical framework to inform the empirical analysis.

The 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; Schwartz and Torous, 1992; Ambrose, Buttimer and Capone, 1997). Recent literature has extended early literature in the context of a more general household utility/wealth maximization framework. In the broader model, mortgage borrowers exercise the default option to maximize utility/wealth, subject to liquidity constraints and other exogenous shocks (see, e.g., Campbell and Cocco, 2015; Corbae and Quintin, 2015).

As in the mortgage default literature, we characterize mortgage loans as debt contracts with a compound default (put) option, such that a borrower who does not default in a given period has the right to default in the future.[18] 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.

Building on Riddiough and Wyatt (1994b) and others, we allow for the possibility of a loan workout in the wake of default. Accordingly, if the borrower chooses to default, there are 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 and credit impairment (Cunningham and Hendershott, 1984, Foster and Van Order, 1985). There are also 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 workout 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

[18] In this simplified framework and given our interest in the drivers of default option exercise, we do not focus on mortgage prepayment. The model can also be extended to consider utility-maximization in the context of the competing risks of mortgage default and prepayment (see Deng, Quigley and Van Order, 2000, for a discussion).

$$B_t = p_t[-(H_t - M_t) - R_t - S_t - (1 + r_t)^{-1} E_t B_{t+1}] + (1 - p_t) V_t,$$

$$\text{where} \quad B_{t+1} = p_{t+1}[-(H_{t+1} - M_{t+1}) \cdots] \cdots \tag{3}$$

Equation (3) shows that the default benefit consists of two parts: the first part is 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; and 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

$$B_T = p_T[-(H_T - M_T) - R_T - S_T] + (1 - p_T) V_T, \tag{4}$$

as there's no remaining next period default option.

It has long been recognized that certain exogenous shocks such as loss of job could trigger 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 default resulting from income shocks in the context of a utility/wealth maximization problem. 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,

$$Y_t \geq P_t + D_t + C_t, \tag{5}$$

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 the 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 and psychic distress. Alternatively, the borrower can choose to default to avoid such transaction costs. We denote such transaction costs as W_t. Further we denote the probability that the borrower becomes insolvent as q_t. The ultimate benefit of default to the borrower at decision point t is then

$$G_t = (1 - q_t) B_t + q_t (W_t + B_t) = B_t + q_t W_t. \tag{6}$$

The default condition is $G_t \geq 0$.

Model solution requires information about the full dynamics of house prices, mortgage interest rates, transaction costs, borrower income, other debt payments, consumption, the conditional probability of foreclosure given loan default, and benefits of loan workout. While a closed-form solution is unlikely, we are able to make some inferences that inform the empirical analysis.

First, consider the probability of default. Per equation (3), a borrower benefit from default is the extinguishment of negative equity $(H_T - M_T)$. The probability of default then varies positively with that term. The probability of default also varies with the borrower's expectation of house prices and interest rates over the life of the loan, 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 magnitude of workout benefit, and borrower probability of insolvency.

Further, per above, the sensitivity of default probability to negative equity, which is the first-order partial derivative of default probability with respect to negative equity, should be a function of the borrower's expected conditional probability of foreclosure p_t. It should also be a function of borrower expectations of future house prices, and mortgage interest rates.[19] This is because B_t depends on $E_t B_{t+1}$, which varies with current H_t as well as expected changes in house prices and mortgage interest rates.[20]

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 vary with changing market expectations, the conditional probability of foreclosure (or workout), and other factors.

4.2. Panel data regression of MSA-level negative equity beta

In this section, informed by the above theoretical framework, we study underlying factors that drive variation in the estimated negative equity betas (sensitivity of default probability to negative equity). Recall that our rolling window hazard model estimates yield a panel of negative equity betas by MSA and by quarter. As discussed above, we hypothesize that potential drivers

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[19] Here we assume negative equity is independent of borrower insolvency probability, q_t, and transaction costs (a combination of R_t, S_t and W_t).

[20] 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.

of the negative equity beta include such factors as borrower changing market expectations, the future path of house prices, and the conditional probability of foreclosure.

We proxy for borrower market expectations using measures of the local business cycle and consumer sentiment. Both terms are available at the MSA-level. Following Korniotis and Kumar (2013), we use unemployment rate innovation as a measure of local business cycle. It is calculated as the current quarter unemployment rate divided by the average of the past four-quarters. Also, borrowers might use past evidence of house price appreciation to gauge future returns. For this reason, we include an alternative lagged house price return term.

We use a consumer distress index to proxy sentiment. The index comes from CredAbility and is a quarterly comprehensive measure of the average American household's financial condition. CredAbility 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. Given that this distress index in part reflects economic fundamentals, which might be already reflected by unemployment rate innovation, we first regress the CredAbility consumer distress index on unemployment rate innovations as well as time- and MSA-level fixed effects to obtain a distress index orthogonalized to fundamentals. We then use the orthogonalized distress index in our analysis.

There is no consensus on how to measure borrowers' subjective assessment of likelihood of loan modification (vs foreclosure) conditional on default. Our approach is to test for structural breaks in default option exercise coincident to enactment of major crisis-period loan modification programs, as existing literature suggests elevated borrower strategic default in the wake of such loan modification programs (see, e.g., Mayer, et al, 2014).

Note that our theory suggests that while borrower income shocks are an important driver of default probability, they should not directly affect the negative equity beta. However, to account for the possibility that our first-stage hazard model does not fully control for this factor, we include average income growth in our panel data regression as well.

The sample statistics of the above variables are included in Table 2. For example, the average unemployment rate innovation is 108%, indicating that the average local unemployment rate was rising over the life of sampled loans. The average consumer distress index is 74 on a scale of 100. A lower level of the index indicates more consumer distress.

We present results of our panel data regression in Table 4. The dependent variable is the by-MSA by-quarter estimate of the negative equity beta from the hazard model. In model 1, we include among explanatory terms the MSA unemployment rate innovation, the orthogonalized MSA consumer distress index and a time dummy. MSA unemployment rate innovation is positive and significant, indicating an elevated negative equity beta in the context of a weaker local economy. The orthogonalized MSA consumer distress index is negative and significant, suggesting elevated default option exercise in the context of higher levels of consumer distress. The time dummy is positive and significant, indicating a raised negative equity beta post 2009Q3. We tested a number of other breaking points but find post-2009Q3 provides the best fit of the data. Later in the paper we test whether this result is related to the borrower's changing view of the likelihood of receiving a loan workout in the wake of the enactment of a major mortgage modification program. The three variables combined explain about 44 percent of the variations in negative equity beta.

In model 2, we add MSA-fixed effects. Those fixed effects may reflect variation in the default legal environment across areas. In that regard, Ghent and Kudlyak (2011) find that borrowers in non-recourse states are more sensitive to negative equity. With MSA-fixed effects, model 2 explains about two-thirds of the variation in the negative equity beta. In model 3, we replace the MSA unemployment rate innovation and orthogonalized MSA distress index terms with proxies for house price expectations and income shocks. House price expectations are computed based on the Case-Shiller 20 MSA house price index returns whereas borrower income shocks are IRS zip code-level average adjusted-gross income aggregated to the MSA-level. Model 4 is identical to model 3 except for the addition of MSA-fixed effects. Results of models 3 and 4 show that lagged HPI return is significant and negative in explanation of the negative equity beta. To the extent lagged HPI return is a measure of borrower expectations, this result suggests that the negative equity betas are damped in the context of elevated expectations of house price returns. Consistent with our theory, while change in average AGI is a positive and significant factor in the first-stage hazard model for default probability, that same factor is insignificant in determination of the negative equity beta. In other words, borrower insolvency probability is a determinant of default probability but not necessarily an important factor in explaining borrower default propensities. The time dummy remains significant and positive.

Finally, in model 5 we include all five variables. Results there are consistent with those of the above models. In sum, empirical findings based on the panel data analysis are consistent with theory in that controls for the local economic cycle, sentiment and house price expectations explain much of the variation in the negative equity beta.

4.3 Hazard model with interaction terms

Literature on varying coefficient models suggests that if we know the determinants of time variation in the negative equity beta, we can simply include interaction terms between the covariate and those factors and estimate the model in linear form (see, Cai et al., 2008). 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. As the focus of this paper is the time-varying coefficient of negative equity, 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 house price return, business cycle, sentiment and other indicators that we discuss in the next section.

We now turn to estimation of the hazard model with interaction terms. 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. We start with the hypothesized drivers of the negative equity beta explored in section 4.2, namely unemployment rate innovations, orthogonalized MSA consumer distress index, and a time dummy coincident to implementation of the HAMP loan modification program.

Model estimates are reported in Table 5. While the regressions include a large number of loan, borrower, and locational controls, we focus in the table on the interaction terms. In the first column, results are based on the full sample. As is consistent with results in the panel data model, the estimated negative equity beta is higher for MSAs and time-periods with higher unemployment rate innovations. In other words, borrower sensitivity to negative equity varies with the economic cycle – borrowers are more sensitive to negative equity and are more likely to pull the trigger on default in bad times. Further, findings indicate that innovations in the unemployment rate are themselves positively associated with default probability. As is also consistent with results of panel estimation, low levels of orthogonalized MSA consumer sentiment are associated with higher likelihoods of loan default. We similarly find evidence of a structural break in default likelihood and behavior in 2009-Q3. All things equal, borrowers are more likely to default after the third quarter of 2009; further, borrowers become more sensitive to negative equity at that time.[21] As suggested above, that timing is coincident to implementation of a major loan modification program (HAMP) that likely affected borrower priors regarding receipt of a favorable loan modification conditional on loan default. We also test alternative versions of the local business cycle indicator including a state-level coincident indicator. Results are robust to that transformation of the business cycle indicator.

Note that zip code-level income growth is included among hazard model control terms. It is shown to be a significant driver of default probability. We further test whether borrower income constraint is associated with observed variations in the negative equity beta. To that end, we stratify the sample based on payment-to-income ratio and re-estimate the model using the bottom quartile of borrowers. These borrowers are least likely to have liquidity issues and hence are less sensitive to income shocks. Results in the second column of Table 5 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 unemployment rate innovations, orthogonalized MSA consumer distress index and the 2009Q3 time dummy.

In addition to analyzing subsamples based on borrower payment-to-income ratios, we also dynamically sort sampled loans based on neighborhood income growth. In each year, we sort sampled loans into four quartiles based on zip code income growth and then re-estimate the model separately for each quartile. We similarly hypothesize here that liquidity constraints should be least binding in the highest borrower income growth neighborhoods. Results are presented in Table 6. Results confirm the robustness of findings as regards variation in the negative equity beta with respect to various drivers even among the least liquidity constrained and highest income growth neighborhoods.

We conduct a series of additional robustness checks. In so doing, we replace zip code-level income growth by county-level credit card delinquency rates as well as augment our model

[21] 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.

specification to assess the effects of a "woodhead" [22] measure (missed default opportunities) and age effects in determination of the negative equity beta. Results in Appendix Tables 1 show our findings regarding drivers of beta changes are highly robust to those specifications.

To assure our results are not merely driven by specific sample of mortgage loans, we also re-run our analysis using alternative loan samples. Specifically, we re-estimate our models using only prime jumbo loans, and conventional conforming Freddie Mac loans, respectively. Results as displayed in Appendix Table 2 again show consistent results.

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 3, results are robust to the cohort specification, so as to underscore the primary findings of the paper.

4.4. HAMP Program Effects

In the wake of the housing crisis, numerous government mortgage modification programs were enacted with the aim of mitigating home foreclosure. Among the most notable was the federal Home Affordable Modification Program (HAMP), which was implemented in the first quarter of 2009. The HAMP program used federal subsidies to incentivize lenders to modify loans rather than foreclose on defaulted borrowers. In the spirit of the "Lucas Critique", we suspect that enactment of a major foreclosure abeyance program may have influenced the default behavior of mortgage borrowers, e.g., borrowers may have become more likely to default to the extent a loan modification was forthcoming.

The existing literature provides ample evidence on strategic default. Riddiough and Wyatt (1994) and Guiso, Sapienza and Zingales (2013) argue that a borrower's delinquency decision may depend on the anticipated lender response (for example, the likelihood of foreclosure conditional on delinquency). Mayer et al. (2014) provide evidence of increased borrower willingness to strategically default in response to a lender loan modification program. As discussed above, in Table 5 we report on estimation of elevated default probabilities post-2009-Q3. The structural

[22] See Deng and Quigley (2001) for a discussion.

break coincides with the timing of HAMP implementation. Further, results show a sizable and significantly elevated negative equity beta for the post-2009 period. Below we report on related corroborating difference-in-differences analysis.

For a loan to qualify for modification under the HAMP program, a number of criteria must be met. First, only owner-occupied loans were eligible for modification under HAMP. Second, the loan must have been originated prior to January 2009. Third, the remaining balance on the loan must be less than $729,500. Fourth, the borrower's debt-to-income ratio at time of modification was required to be in excess of 31 percent as the intent of the modification was to reduce borrowers monthly housing payments to no more than 31 percent of gross monthly income. Finally, there was a HAMP implementation window, which originally was set to be from March 2009 to December 2012 but later was extended through 2016. We utilize the above eligibility rules to conduct difference-in-differences (DID) analysis of changes in borrower default option exercise in the wake of the enactment of the HAMP program. Agarwal et al (2016) use this strategy to identify the impact of HAMP on loan renegotiations.[23]

Similar to Agarwal et al (2016), our DID control group is comprised of investor property loans that did not qualify for modification under HAMP whereas our treatment group includes owner-occupied loans which may be qualified for HAMP pending other conditions. We use the 2009-Q1 HAMP enactment as the treatment 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.[24] As long as one group of borrowers had a higher probability of receiving a HAMP modification than the other group based on *ex ante* borrower expectations, we are able to identify HAMP effects via our DID test.

Given well-known challenges in applying DID framework in the context of non-linear models such as the Cox hazard model (Card and Krueger, 1994, Ai and Norton, 2003 and Karaca-Mandic, Norton and Dowd, 2012), we instead conduct our DID analysis using a linear regression

[23] In contrast to Agarwal et al (2016) our analysis focuses on borrower delinquency rather than loan modification.
[24] Not all HAMP applications that met those five criteria were approved and some fell out of the program after the trial period.

modeling framework. Table 7 presents our DID regression results. The DID regression takes the form

$$Y = \beta_1 T + \beta_2 T * \text{After} + \beta_3 \text{After} + Z' \gamma, \quad (9)$$

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 dependent variable Y takes value of "1" if a loan defaults in a particular quarter and "0" otherwise. Note first in Appendix Figure 2 the parallel trends exhibited in the negative equity beta time-series among the treated (owner-occupied) and control (investor) loans pre-treatment. However, as shown in Table 7, post-2009-Q1 HAMP implementation, the treated owner-occupied loans exhibit a statistically elevated negative equity beta. These findings are consistent with the hypothesis that the federal program may have inadvertently resulted in elevated default propensities among borrowers in that group. In an alternative specification, we conduct a DID analysis where we utilize outstanding loan balance above and below the HAMP cutoff. The alternative specification yields similar results (see column 2 of Table 7).

We further conduct a placebo test of our difference-in-differences test, where we randomly choose a cutoff point prior to policy implementation to evaluate whether the DID regression results might simply reflect uncontrolled differences between our control and treatment groups. Results in Table 8 indicate lack of significance associated with the treatment group beta for a random period prior to the implementation of the HAMP program. In addition, in Appendix Table 4, we show the robustness of our HAMP test results in the context of a more limited test window.

5. Conclusion

In the wake of the late-2000s implosion in house values, mortgage default skyrocketed. While crisis period default commonly has been associated with sizable run-up in borrower negative equity, we show that outcome was precipitated as well by increased ruthlessness of default option exercise. Results of hazard model estimation 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. Findings indicate that the marked upturn in borrower default propensity was more important factor driving crisis period mortgage failure than the collapse in home equity that was focused of the conventional wisdom. Panel data analysis indicates that that much of the variation in default option exercise can be explained by the local business cycle, house price expectations, consumer distress, and federal policy innovations.

Our findings have implications for 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 also provides guidance on factors governing cross-section and time-series 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 borrowers via mortgage modification. Arguments against such programs point to borrower moral hazard, whereby anticipated bailout of distressed borrowers may encourage irresponsible financial behavior. Our findings supports the previous literature that federal foreclosure prevention and loan work-out programs may have inadvertently incented higher levels of delinquency, through additional channel of elevated default propensity, 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.

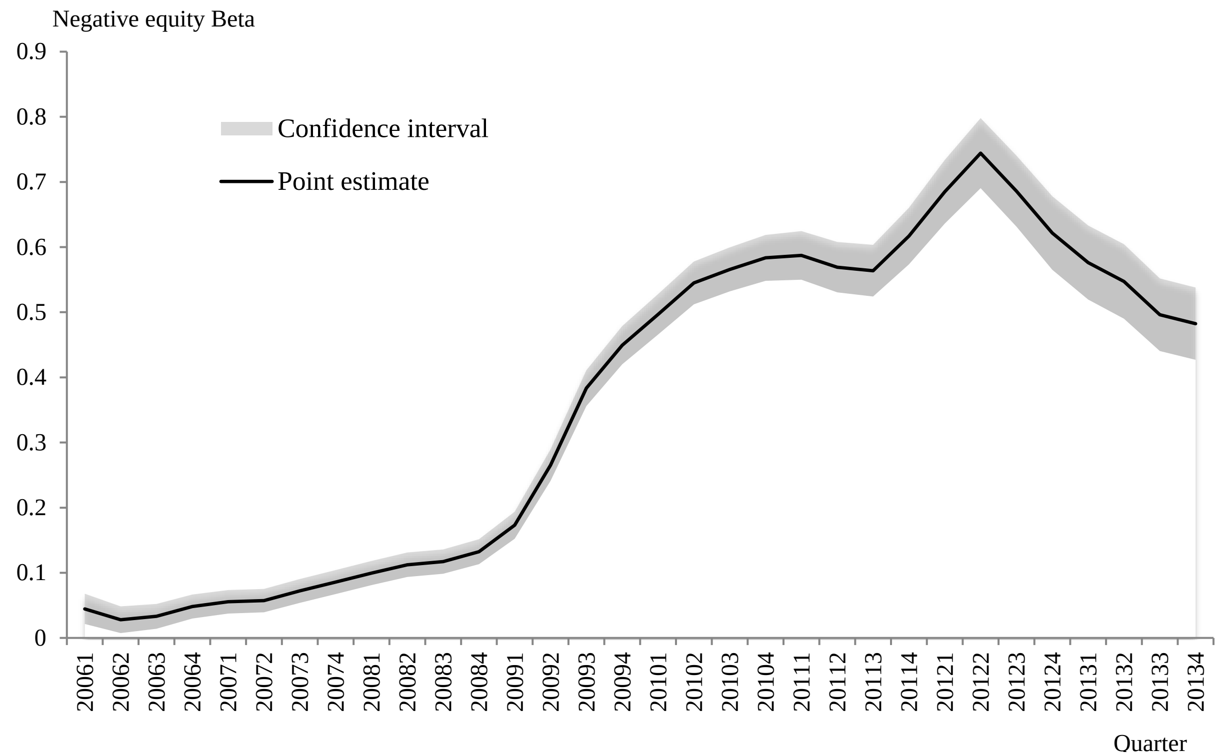


Figure 2 The Impact of Negative Equity on Mortgage Default Probability

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. Values of all other covariates are set at sample means.

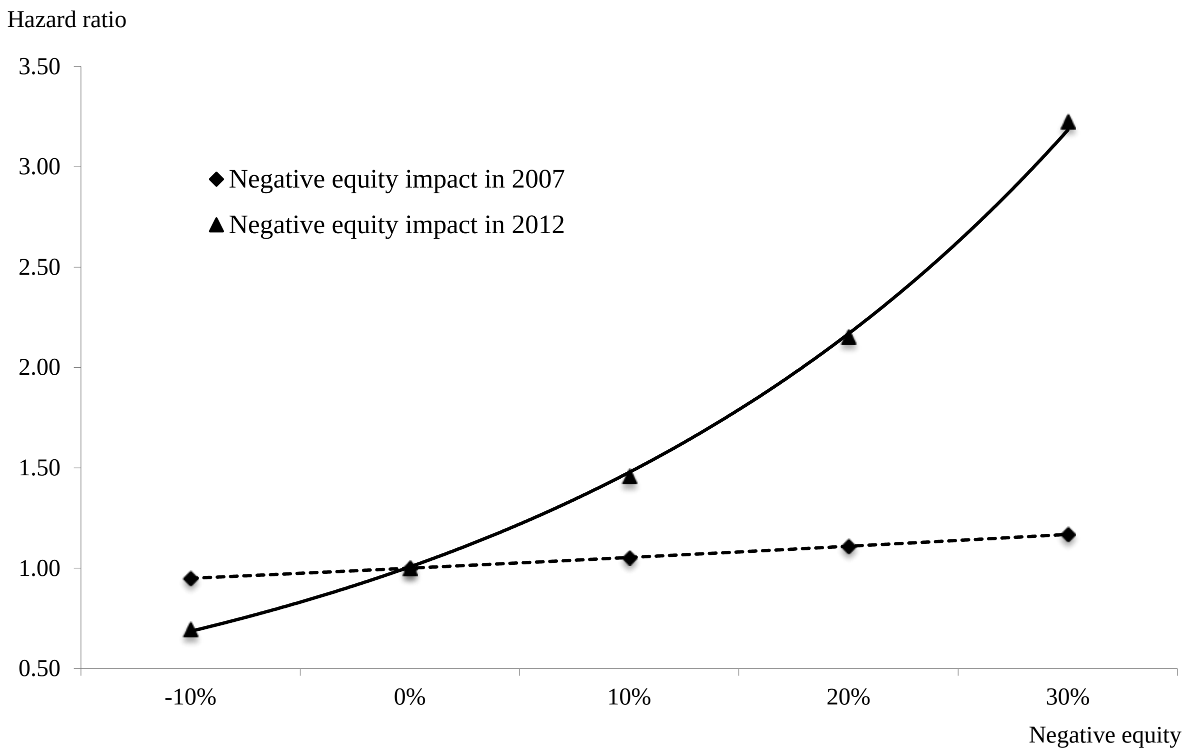


Figure 3 The Impact of Negative Equity on Default Prediction

Here we use negative equity beta estimated based on 2003-2008 performance information of the 2003 vintage loans (the wrong beta) to predict 2006-2011 performance of the 2006 vintage loans, assuming we have full foresight of house price movement. The dashed-line shows predicted cumulative default rates by loan age (quarters). As a comparison, the solid line in the chart shows the actual cumulative default rate of the 20006 vintage loans, while the dotted-line shows the prediction with beta estimated based on the actual 2006 vintage data (the correct beta). Over the 23-quarter horizon, the predicted default rate with the wrong beta is only about one third of the actual default rate.

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 estimated 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 changes.

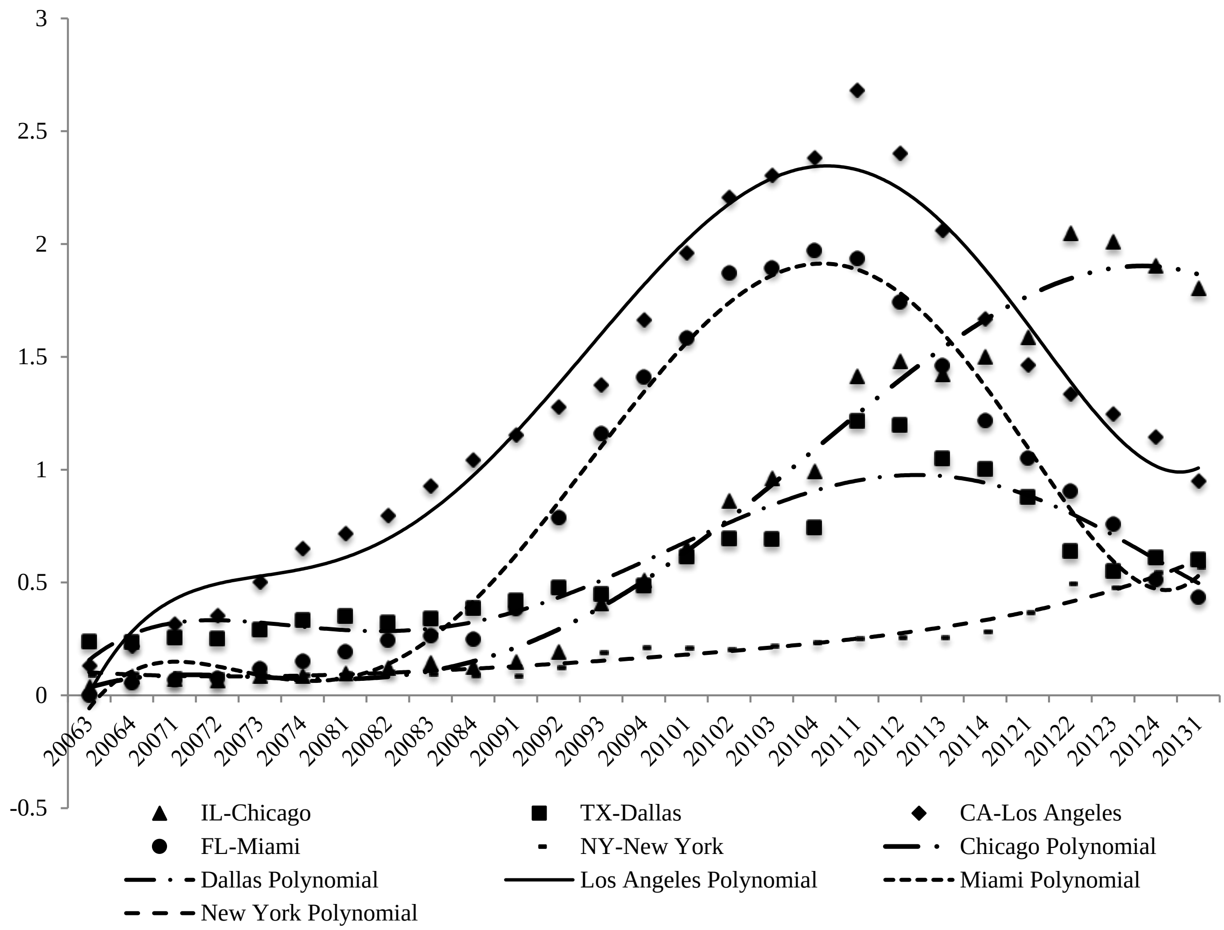


Table 1 Descriptive Statistics of Sampled Loans

This table shows the frequency distributions and means of the loan characteristics in our sample. All the loans are originated during the period 2003 – 2007 and are securitized by non-agency private-label security (PLS) issuers. 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 and 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 (about 13 percent of the sample). 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 PLS issuers during the period of 2003-2007 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. 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. 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 term 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 including home purchase, rate/term refinance and cash-out refinance. Occupancy status indicates whether the home was used as an investment, owner-occupied (primary residence), or second home. Prepayment penalty type is an indicator denoting that a fee will be charged to the borrower if she elects to make unscheduled principal payments. The data are from Blackbox Logic (BBX) based on servicer reports.

Panel A Loan Vintage Distribution

Origination Year	Frequency	Percent	Cumulative Percent
2003	15,567	11.88	11.88
2004	24,510	18.71	30.59
2005	34,983	26.70	57.29
2006	41,402	31.60	88.89
2007	14,553	11.11	100.00
Total		131,015	

Panel B Geographic Distribution

MSA Name	MSA Code	Frequency	Percent
Atlanta	12060	10,702	8.17
Boston	14460	6,028	4.60
Chicago	16980	12,805	9.77
Dallas	19100	16,708	12.75
Detroit	19820	8,185	6.25
Los Angeles	31100	20,379	15.55
Miami	33100	24,724	18.87
New York	35620	19,991	15.26
Phoenix	38060	10,068	7.68
Washington DC	47900	1,425	1.09
Total		131,015	
As a share of the national sample		23.65%	

Panel C Termination Type

Termination type	Frequency	Percent
Current	25,052	19.12
Prepay	46,065	35.16
Default	59,898	45.72
Total	131,015	

Panel D Loan and Borrower Characteristics

Variable	**Mean**	**Std. Dev.**	**1th Percentile**	**Median**	**99th Percentile**
Original loan amount	214,233	140,622	50,000	175,500	660,000
Note rate (%)	7.22	1.66	2.00	7.24	11.20
FICO score	609	43	350	620	678
Payment-to-income ratio	0.25	0.24	0.08	0.26	0.43
LTV (%)	73	16	23	78	100
Combined LTV (%)	74	17	24	79	100
Borrower household income ($000)	88	97	21	69	384
Alt-A loan	0.49	0.50	0	0	1
Full documentation	0.64	0.48	0	1	1
Low/no documentation	0.34	0.48	0	0	1
Reduced documentation	0.02	0.02	0	0	1
Owner-occupied property	0.94	0.24	0	1	1
Second/vacation home	0.01	0.07	0	0	0
Investment property	0.06	0.23	0	0	1
LTV greater than 80%	0.25	0.43	0	0	1
Borrower race: White	0.55	0.50	0	1	1
Borrower race: Asian	0.03	0.17	0	0	1
Borrower race: African American	0.21	0.41	0	0	1
Borrower race: Other	0.22	0.41	0	0	1
Female borrower	0.37	0.48	0	0	1
30-yearfixed-rate mortgage	0.94	0.24	0	1	1
15-yearfixed-rate mortgage	0.06	0.24	0	0	1
Single-family	0.82	0.38	0	1	1
Planned-unit-development (PUD)	0.09	0.29	0	0	1
Condo/Coop	0.09	0.28	0	0	1
Home purchase loan	0.19	0.39	0	0	1
Rate/term refinance	0.20	0.40	0	0	1
Cash out refinance	0.61	0.49	0	1	1
With prepayment penalty	0.60	0.49	0	1	1
Total number of loans			131,015		

Table 2 Summary Statistics of the Event History Sample

This table reports summary statistics of our event-history (loan-quarter) sample. It provides the mean, standard deviation, and the 1th and 99th percentiles of the key covariates in the event-history sample that are used in the hazard model. 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. Zip code-level income growth is calculated based on IRS adjusted-gross income (AGI) data. County-level credit card default rate is defined as the percentage of credit card borrowers with 60-plus day delinquency and calculated based on New York Fed Consumer Credit Panel data. Unemployment rate innovation is the current quarter unemployment rate divided by its four-quarter moving average and is based on Bureau of Labor Statistics (BLS) data. Consumer distress index is a quarterly comprehensive measure of the average American household's financial condition compiled by CredAbility and made available by St. Louis Fed.

Variable	Mean	Std. Dev.	1th Pctl.	Median	99th Pctl.
Negative equity (continuous variable)	-0.41	0.80	-3.46	-0.25	0.49
Negative equity dummy	0.26	0.44	0.00	0.00	1.00
Volatility adjusted negative equity	-31.86	73.94	-303.01	-12.93	18.12
Refinance incentive (%)	5.63	9.31	-6.13	3.52	23.69
Zip code income growth	0.03	0.08	-0.16	0.03	0.29
County credit card delinquency rate (%)	3.90	1.47	1.75	3.53	8.48
MSA unemployment rate innovation (%)	1.08	0.22	0.82	1.00	1.66
MSA consumer distress index	73.93	8.08	60.12	74.04	87.27
Percentage of loans that ever experienced negative equity			48.2%		
Total number of loan-quarters			2,929,075		

Table 3 MLE Estimates of the Baseline Default Model

This table presents the MLE estimates of the Cox proportional hazard model for default for the fixed-rate Alt-A and subprime mortgage loans in the ten largest 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. MSA- and vintage-fixed effects are not reported here, either, but they are available upon request. Variable definitions are discussed under Table 2. Parameter point estimates are reported with standard errors included in the parentheses, and ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)	Covariate	Estimate (S.E.)
Income growth	-0.037***	LTV at origination greater than 80%	0.131***
	(0.004)		(0.007)
Income growth squared	-0.002*	15-year FRM	-0.246***
	(0.001)		(0.016)
Negative equity	0.214***	Planned-unit development	-0.054***
	(0.009)		(0.011)
Negative equity squared	0.003***	Condominium	-0.049***
	(0.000)		(0.012)
Refinance incentive	-0.142*	Rate/term refinance	-0.291***
	(0.068)		(0.01)
Alt-A loan	-0.295***	Cash out refinance	-0.05***
	(0.009)		(0.009)
Low or no documentation	0.186***	With prepayment penalty clause	0.045*
	(0.007)		(0.02)
Investment property	0.179***	Unknown prepayment penalty clause	-0.014
	(0.014)		(0.02)
FICO score	-0.015**	Asian borrower	-0.040*
	(0.005)		(0.020)
FICO score squared	0.039***	African American borrower	0.061***
	(0.002)		(0.008)
Payment-to-Income (PTI) ratio	0.109***	Other non-white borrower	0.012
	(0.007)		(0.008)
PTI squared	-0.003***	Female borrower	-0.002
	(0.000)		(0.006)
Log balance	0.063***	MSA-fixed effect	Yes
	(0.005)	Vintage-fixed effect	Yes
N		2,929,075	
-2LogL		2,467,224	
AIC		2,467,300	

Table 4 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 dependent variable is the negative equity beta estimated from the Cox proportional hazard model for default (the first stage analysis) for each MSA in each quarter (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. Variables definitions are the same as in Tables 2 and 3. In addition, the HPI return is calculated based on the Case-Shiller MSA home price index; change in average AGI is based on zip code-level IRS data aggregated to the MSA-level. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Explanatory variable	Estimate (S.E.)				
	Model 1	Model 2	Model 3	Model 4	Model 5
MSA unemployment rate innovation	0.364***	0.132***			0.327*
	(0.036)	(0.028)			(0.145)
Orthogonalized MSA consumer distress index	-0.095***	-0.176***			-0.082***
	(0.015)	(0.026)			(0.011)
Post 2009Q3	0.852***	0.805***	1.254***	0.896***	0.916***
	(0.057)	(0.055)	(0.057)	(0.055)	(0.050)
Lagged HPI return			-6.171***	-3.001***	-1.979**
			(0.908)	(0.721)	(0.702)
Change in average AGI			-0.593	-0.439	-0.164
			(0.728)	(0.528)	(0.565)
MSA-fixed effect	No	Yes	No	Yes	Yes
N	287	287	287	287	287
Adjusted R-Square	0.436	0.657	0.296	0.659	0.717

Table 5 Default Option Exercise and Business Cycle, Sentiment and Structural Break

This table presents the MLE estimates of the Cox proportional hazard model for default described by equations 7 and 8. Orthogonalized MSA consumer distress index is the residual from a regression where MSA-level consumer distress index is regressed on the MSA-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. The low PTI subsample are loans with PTI in the lower quartile. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)	
	Full sample	Low PTI Subsample
Negative equity * MSA unemployment rate innovation	0.155*** (0.008)	0.109*** (0.012)
MSA unemployment rate innovation	0.144*** (0.005)	0.169*** (0.009)
Negative equity * Orthogonalized MSA consumer distress index	-0.096*** (0.008)	-0.070*** (0.012)
Orthogonalized MSA consumer distress index	-0.027*** (0.005)	-0.066*** (0.008)
Negative equity * Post 2009Q3	0.261*** (0.023)	0.158*** (0.033)
Post 2009Q3	0.088*** (0.016)	0.146*** (0.029)
Control variables	Income growth, income growth squared, negative equity, negative equity squared, refinance incentive, 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, payment-to-income ratio (PTI), PTI squared, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development (PUD) 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, and vintage-fixed effect.	
N	2,929,075	880,899
-2LogL	2,462,438	570,925
AIC	2,462,552	571,039

Table 6 Effects of Business Cycle, Sentiment, and Structural Break on Negative Equity Beta with Loan Portfolios Sorted by Income Growth

This table presents estimates of the Cox proportional hazard model described in equations 7 and 8 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 is calculated based on IRS AGI data. High income growth means the zip code income growth is in the 3rd quartile and highest income growth means the zip code income growth is in the upper quartile. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

	Estimate (S.E.)	
Covariate	High income growth	Highest income growth
Negative equity * MSA unemployment rate innovation	0.191*** (0.016)	0.111*** (0.012)
MSA unemployment rate innovation	0.134*** (0.011)	0.164*** (0.009)
Negative equity * Orthogonalized MSA consumer distress index	-0.083*** (0.017)	-0.023* (0.011)
Orthogonalized MSA consumer distress index	-0.018** (0.007)	-0.017** (0.007)
Negative equity * Post 2009Q3	0.284*** (0.055)	0.329*** (0.033)
Post 2009Q3	0.109** (0.034)	-0.081** (0.030)
Control variables	Income growth, income growth squared, negative equity, negative equity squared, refinance incentive, 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, payment-to-income ratio (PTI), PTI squared, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development (PUD) 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, and vintage-fixed effect.	
N	1,617,636	1,311,439
-2LogL	1,328,790	989,911
AIC	1,328,904	990,025

Table 7 Difference-in-Differences Tests of the HAMP Eligibility Effect

This table presents the difference-in-differences (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 here is a simple linear regression where the dependent variable Y takes value of "1" if a loan falls into default in a particular quarter and "0" otherwise. In the first test, loans in the 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. In the second test, loans 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. The time window of our loan performance records is from 2007Q1 to 2011Q1, among which 2009Q1 is when the HAMP starts to be implemented. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

	Treatment group vs. control group	
	Owner-occupied loans vs. investor loans	Outstanding balance under vs. over HAMP threshold
Treatment group beta	-0.004*** (0.001)	0.000 (0.000)
Treatment group beta * Post 2009Q1	0.004*** (0.001)	0.000*** (0.000)
Post 2009Q1	0.002** (0.001)	0.005*** (0.001)
Control variables	Income growth, income growth squared, negative equity, negative equity squared, refinance incentive, negative equity * MSA unemployment rate innovation, negative equity * orthogonalized MSA consumer distress index, 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, payment-to-income ratio (PTI), PTI squared, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development (PUD) 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, and vintage-fixed effect.	

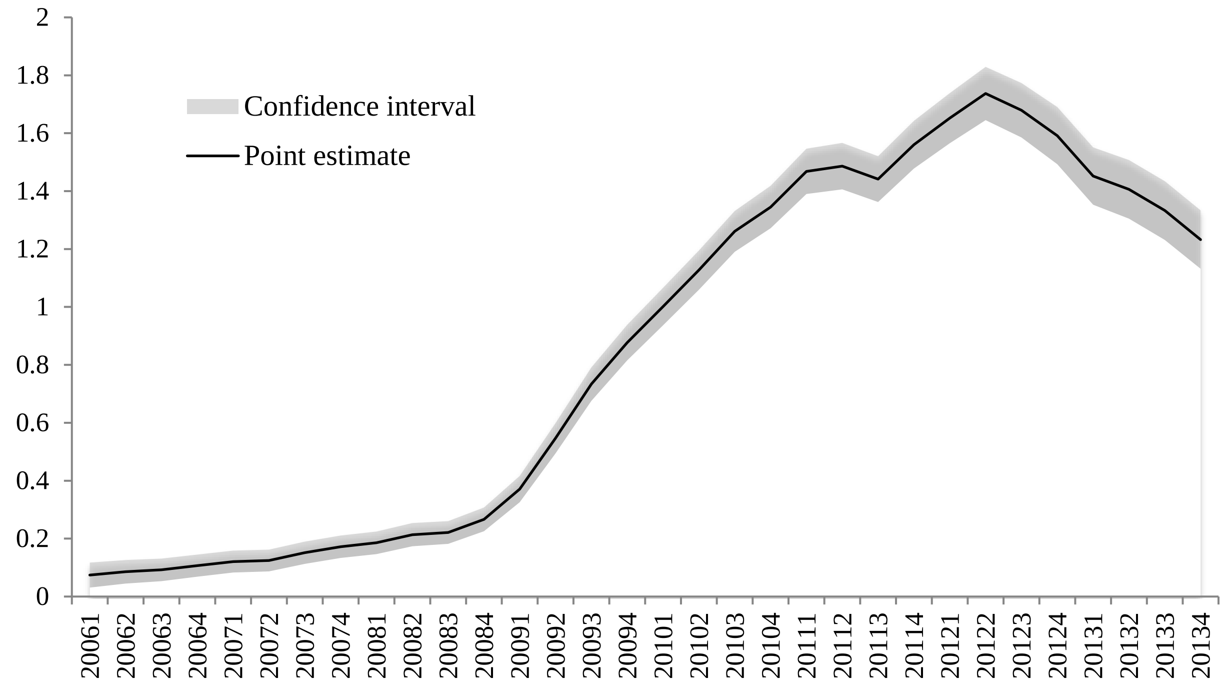
Table 8 Placebo Test of the Difference-in-Differences Test of the HAMP Eligibility Effect

This table presents results of a placebo test of the difference-in-differences (DID) test of the HAMP eligibility effect on borrower default option exercise. The test is in the same form as test 1 in Table 7, except that the test window is from 2006Q1 to 2010Q1 and we pick a random break point where there is no policy change. The treatment group are owner-occupied property loans and the control group are investment property loans. ***, **, and * indicate 0.1%, 1%, and 5% significance, respectively.

	Owner-occupied loans vs. investor loans
Treatment group beta	-0.003*** (0.001)
Treatment group beta * Post 2008Q1	-0.000 (0.001)
Post 2008Q1	0.008*** (0.001)
Control variables	Income growth, income growth squared, negative equity, negative equity squared, refinance incentive, negative equity * MSA unemployment rate innovation, negative equity * orthogonalized MSA consumer distress index, 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, payment-to-income ratio (PTI), PTI squared, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development (PUD) 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, and vintage-fixed effect.

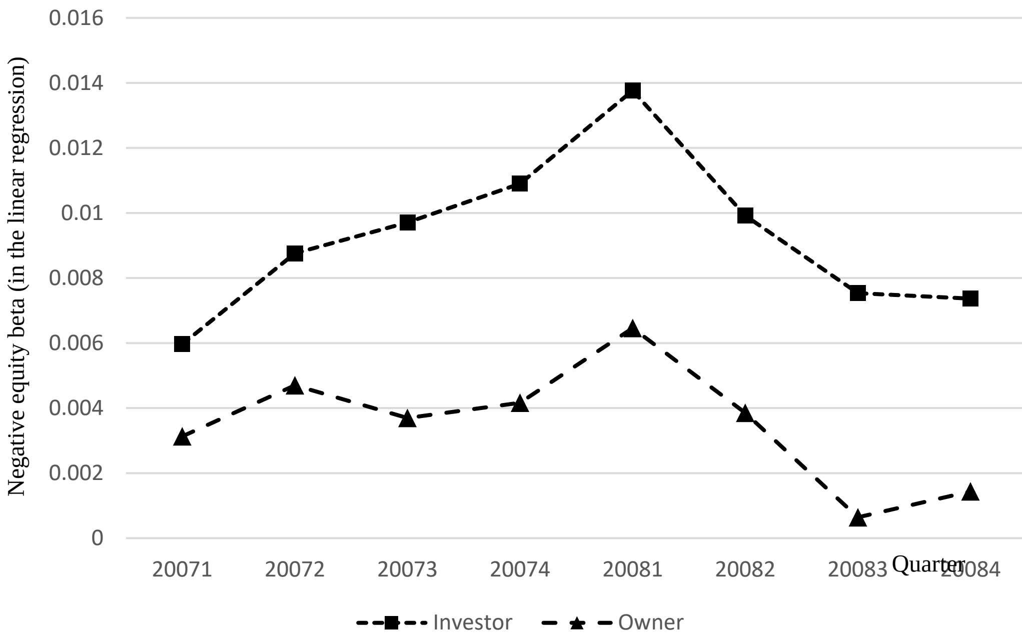
Appendix Figure 1 Rolling Window Estimates of Negative Equity Beta based on Freddie Mac Fixed-Rate Mortgage Loans

This figure shows the point estimates (the dark line) and the confidence interval (the shaded area) of negative equity beta in a hazard model based on Freddie Mac data. The estimation is based on three-year rolling window samples of fixed rate prime conventional conforming loans.



Appendix Figure 2 Parallel Trend Test for the Difference-in-Differences Test

This figure shows the linear regression negative equity beta of investor loans and owner loans, respectively, prior to HAMP. The difference between the two groups of loans was relatively stable prior to HAMP, as shown here.



Appendix Table 1 Alternative Hazard Model Specifications

This table presents results of alternative specifications of the Cox proportional hazard model for default for the Alt-A and subprime FRM loan sample for the 10 MSAs. Model 1 is the model in Table 5; in model 2, instead of using zip code level adjusted-gross income (AGI) growth, we use county-level credit card delinquency rate to control for income shock effect as in Bhutta, Dokko and Shan (2016); in model 3, we add "number of missed default opportunities" as an additional variable to control for the burn out effect; and finally in model 4, we add a loan age effect in negative equity. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively. Standard errors are not shown in this table but they are available upon request.

	Estimate			
	Current model	Alternative 1	Alternative 2	Alternative 3
Negative equity * MSA unemployment rate innovation	0.155***	0.150***	0.119***	0.196***
MSA unemployment rate innovation	0.144***	0.225***	0.188***	0.134***
Negative equity * Orthogonalized MSA consumer distress index	-0.096***	-0.097***	-0.074***	-0.086***
Orthogonalized MSA consumer distress index	-0.027***	-0.054***	-0.048***	-0.030***
Negative equity * Post 2009Q3	0.261***	0.258***	0.156***	0.586***
Post 2009Q3	0.088***	0.225***	0.221***	-0.025
Negative equity * "number of missed default opportunities"			-0.304***	
"Number of missed default opportunities"			0.545***	
Income growth	-0.024***		-0.015***	-0.026***
Income growth squared	-0.001		-0.001	-0.001*
Credit card delinquency rate		-0.137***		
Credit card delinquency rate squared		0.027***		
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 squared, refinance incentive, 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, payment-to-income ratio (PTI), PTI squared, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development (PUD) 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, and vintage-fixed effect.			

Appendix Table 2 Effects of Business Cycle, Sentiment, and Structural Break on Negative Equity Beta: Alternative Loan Samples

This table presents results of a Cox proportional hazard model using different loan samples. Model specification is the same as that in Table 5. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)		
	Current sample	PLS Jumbo	Freddie Mac
Negative equity * MSA unemployment rate innovation	0.099*** (0.010)	0.429*** (0.028)	0.320*** (0.017)
MSA unemployment rate innovation	0.128*** (0.006)	0.196*** (0.018)	0.068*** (0.010)
Negative equity * Orthogonalized MSA consumer distress index	-0.063*** (0.010)	-0.098*** (0.028)	-0.187*** (0.014)
Orthogonalized MSA consumer distress index	-0.034*** (0.006)	-0.017 (0.016)	-0.017* (0.008)
Negative equity * Post 2009Q3	0.273*** (0.029)	0.159* (0.064)	0.523*** (0.044)
Post 2009Q3	0.026 (0.021)	0.561*** (0.043)	0.267*** (0.026)
Control variables	Income growth, income growth squared, negative equity, negative equity squared, refinance incentive, 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, payment-to-income ratio (PTI), PTI squared, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development (PUD) 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, and vintage-fixed effect.		
N	1,508,195	790,697	4,675,542
-2LogL	1,359,948	310,820	1,190,920
AIC	1,360,058	310,920	1,191,017

Appendix Table 3 By-Vintage Hazard Model Results

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.) 2003	2005	2007
Negative equity * MSA unemployment rate innovation	0.062*** (0.018)	0.115*** (0.018)	0.018** (0.006)
MSA unemployment rate innovation	0.069*** (0.020)	0.207*** (0.017)	0.182*** (0.023)
Negative equity * Orthogonalized MSA consumer distress index	-0.067*** (0.023)	-0.116*** (0.018)	-0.013*** (0.002)
Orthogonalized MSA consumer distress index	-0.009 (.013)	-0.028** (0.009)	-0.070*** (0.013)
Negative equity * Post 2009Q3	0.193*** (0.061)	0.183*** (0.045)	0.065* (0.030)
Post 2009Q3	0.314*** (0.065)	0.462*** (0.045)	0.126* (0.060)
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	584,432	789,867	282,163
-2LogL	279,302	557,417	308,043
AIC	279,408	557,523	308,149

Appendix Table 4 Diff-in-Diff Test of the HAMP Eligibility Effect with a Narrower Test Window: Owner-Occupied vs. Investor Property Loans

This table presents the difference-in-differences (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 2010Q1, among which 2009Q1 is when the HAMP starts to be implemented. ***, ** and * indicate 0.1%, 1% and 5% significance, respectively.

Covariate	Estimate (S.E.)
Treatment group beta	-0.005*** (0.0001)
Treatment group beta * Post 2009Q1	0.003*** (0.001)
Post 2009Q1	0.002 (0.001)
Control variables	Income growth, income growth squared, negative equity, negative equity squared, refinance incentive, negative equity * MSA unemployment rate innovation, negative equity * orthogonalized MSA consumer distress index, 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, payment-to-income ratio (PTI), PTI squared, log loan balance, indicator of original LTV greater than 80%, 15-year FRM indicator, planned unit development (PUD) 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, and vintage-fixed effect.