Re-default Risk of Modified Mortgages*

Jian Chen
IFE Group and Johns Hopkins University, USA

Jin Xiang
IFE Group, USA

Tyler T. Yang
IFE Group, USA

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* Address correspondence to: Jian Chen, jian.chen@ifegroup.com or jian.chen@jhu.edu; Jin Xiang, jin.xiang@ifegroup.com; Tyler T. Yang, tyler.yang@ifegroup.com, IFE Group, 51 Monroe Street, Suite 1100, Rockville, MD.

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Abstract: During the recent housing recession and financial crisis, mortgage modification has been heavily promoted by government as a way to stabilize the housing and the national banking systems. Numerous programs, such as the Home Owners Preserving Equity (HOPE), Home Affordability Modification Program (HAMP), and Home Affordability Refinance Program (HARP), were introduced or enhanced to allow more aggressive modifications than traditionally observed prior to the crisis. Loan modification is believed to be a way to avoid foreclosure and help borrowers to keep their homes. However, the effectiveness of modification in preventing eventual foreclosure has not been quantified.

In this paper, we use FHA modified loans to analyze their re-default risk. We use loan-level data to trace the performance of loans with heavy modifications. We have three major empirical findings. First, the empirical model shows that modified loans tend to have much higher re-default risk than otherwise identical never-defaulted loans. Second, the re-default model shows that re-default hazard is less sensitive to traditional risk drivers, compared with non-modified loans. Third, the re-default risk declines initially with the magnitude of the payment reduction associated with the modification received. However, as the payment reduction becomes substantial, the re-default probability increases.

Our empirical results suggest payment reduction is most effective around 10% to 30% level, in order to reduce the re-default risk. The effect is relatively flat between 30% to 40% level. Payment reduction beyond 40% level turned to increase re-default risk, controlling for all observable variables. These findings have profound implications in how lenders may design optimal modification policies.

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Introduction

During the recent housing recession and financial crisis, mortgage modification has been heavily promoted by government as a way to stabilize the housing and the national banking systems. Numerous programs, such as the Home Owners Preserving Equity (HOPE), Home Affordability Modification Program (HAMP), and Home Affordability Refinance Program (HARP), were introduced or enhanced to allow more aggressive modifications than traditionally observed prior to the crisis. Loan modification is believed to providing benefits to the mortgage borrower, the lender, and the overall housing market in the following three aspects.

First, it helps borrowers to avoid foreclosure and keep their homes. Brevoort and Cooper (2013) shows that the average drop in the credit score during foreclosure could be 150-250 points, and the post-foreclosure credit recovery of the borrower could be lengthy and painful. For subprime borrowers, it takes about 5-7 years for their credit score to recover to the pre-foreclosure level. For prime borrowers, it could take 7-10 years to recover. The borrower groups associated with recent vintages are hurt so badly, and some of them may never recover from the trauma of foreclosure, in terms of credit profile. Thus foreclosure avoidance via loan modification definitely helps the distressed borrowers to keep a better shape in credit, and keep their houses as shelters.

Second, it provides the lender an alternative other than going through foreclosure and the eventual REO process. Loss given default rate is an important factor in determining mortgage default risk. It is largely driven by the local house price movement, initial financial leverage ratio, foreclosure costs, lawyer fees, maintenance costs, and the time length for the REO sale. The whole process could be very costly, especially during the housing downturn of 2006-2012. Qi and Yang (2009) reported the LGD rate could be as highly as 49.2% for the highest CLTV bucket for FHA loans during 1990-2003. Chen, Dai, and Yang (2013) reported for some states, such as MI, OH, the LGD rate of FHA loans could be as high as 80%-85% during the 2000-2012 period. Obviously with such high loss rate, even a loan modification with 50% principal reduction is still cost effective, if moral hazard is not considered.

Third, it reduces the shadow inventory of distressed homes in the foreclosure/REO pipeline. As we mentioned early, the foreclosure process could be lengthy and could take up to two, or even five years for some judicial states. As long as the foreclosure courts are backlogged with those loans which are in the pipeline, the continuing supply of additional housing units will make the housing market weak. Also this expectation will weaken the confidence of home builders as well. Removing those mortgage loans from the shadow inventory definitely help the housing market achieve a healthy recovery.

To March 2014, it is reported by the HAMP official web site, that nearly 2 million mortgage assistance actions, including 1.3 HAMP modifications have been performed.[1] This is much less

[1] http://www.makinghomeaffordable.gov

than the originally planned 7-8 million target. The median monthly payment reduction is $544, and homeowners have saved $25.5 billion since the HAMP modifications.

However, the effectiveness of modification in preventing eventual foreclosure has not been adequately quantified and appears to be not conclusive. A May 2012 Fox Business report has alleged that programs like HAMP modifications are helping only a few homeowners and have not been effective at dealing with the mortgage crisis.[2] The National Taxpayer Union has also argued that HAMP has been grossly ineffective.[3] Based on OCC's mortgage metric report for 2013 Q3, the re-default rate within 5 years is close to 70%.[4] The following statements are quoted from the report.

> "Servicers modified 3,288,717 mortgages from the beginning of 2008 through the end of the second quarter of 2013. At the end of the third quarter of 2013, 45.5 percent of these modifications were current or paid off. Another 6.3 percent were 30 to 59 days delinquent, and 11.1 percent were seriously delinquent. Another 5.1 percent were in the process of foreclosure, and 7.8 percent had completed the foreclosure process."[5]

In this paper, we use FHA modified loans to investigate the effectiveness of modification in preventing re-default. Loan-level data is used to trace the performance of loans with heavy modifications. The empirical results show that modified loans tend to have much higher re-default risk than otherwise identical never-defaulted loans. The re-default risk declines initially with the magnitude of the payment reduction associated with the modification received. However, as the payment reduction becomes substantial, the re-default probability increases. Our empirical results suggest payment reduction is most effective around 10% to 30% level, in order to reduce the re-default risk. The effect is relatively flat between 30% to 40% level. Payment reduction beyond 40% level turned to increase re-default risk, controlling for all observable variables. These findings should have profound implications for loan modification policy design, and change the conventional optimal modification strategy.

This paper is organized in the following structure. Section 1 offers an overview of the literature on mortgage default, and re-default of loan modifications. Section 2 briefly outlines the competing hazard risk model for mortgage termination, and the specification of multinomial logistic models. Then we describe the summary statistics of the data, and give some discussion on the model variable speciation in section 3. In section 4 we present the empirical model results. Lastly in section 5, we summarize the major findings and provide some hypotheses for the seemingly unintuitive result, and discuss the policy implication of our research.

[2] http://www.foxbusiness.com/industries/2012/05/02/mortgage-programs-target-many-help-few/
[3] http://www.ntu.org/news-and-issues/government-reform/hamp-terminate.html
[4] http://www.occ.gov/publications/publications-by-type/other-publications-reports/index-mortgage-metrics.html
[5] See Appendix for the detailed status of mortgages modified.

1. Literature Review

In this paper, we focus on the effectiveness of loan modification in preventing re-default. Therefore, in this section, we review the literature on mortgage default models and also the literature on re-default of loan modifications, providing a background upon which our paper are developed.

1.1. Literature Review of Residential Mortgage Default

There has been abundant literature on mortgage default, even before the subprime meltdown followed by the global financial crisis. They can be broadly categorized into two types: option-based (or "structural") default models and hazard-based (or "reduced-form") default models.

The option-based default models follow the Merton (1974) seminal work, and formulate mortgage default as a put option, which may be exercised when the option is in-the-money, i.e., the collateral value is lower than the mortgage value, and the borrower can realize monetary gain by selling the property at a higher price (the mortgage value). Kau et al. (1992, 1993) build option-based pricing models for Fixed Rate Mortgages (FRMs) and Adjustable Rate Mortgages (ARMs). Titman and Torous (1989) build similar models for commercial mortgages. However, some empirical works (Forster and Van Order 1984, 1985) suggest that mortgage borrowers do not default as efficiently as the option theory suggest.

In order to accommodate these empirical findings, Crawford and Rosenblatt (1995) extend the option-based default model to include transaction cost, which can be interpreted as loss of credit opportunities in the future, and some non-monetary factors, such as stigma associated with foreclosure record. Kau, Keenan, and Kim (1993) build contingent claim valuation models with both transaction costs and "suboptimal" exercising, and calculated default probabilities of mortgage loans. Kau, Keenan, and Kim (1994) also argue that even without transaction cost, the borrower would not default immediately when the collateral value drops below the mortgage value, due to time value of the option.

Vandell (1995) conducted a comprehensive survey on these option-based models, and still find the predicted mortgage default rate is much higher than the default rate actually observed, even after including transaction cost, and sub-optimality. Buist and Yang (1996) characterize how stochastic household income partly determines a household's choice of rental or mortgage contracts through time. Yang, Buist, and Megbolugbe (1998) extend the normal two-factor (interest rate and house price) contingent claim model to three-factor model to include the stochastic income factor, which both affect the borrower's borrowing capacity to refinance and the ability to pay existing mortgage payment obligation.

Even with all these adjustments, option-based default models are still not widely used by industry practitioners, mainly because of three reasons. First, it is very time-consuming to solve the American option pricing problem with multiple factors. Second, it is hard to calibrate the default zone empirically with microeconomic data. Third, it is difficult to capture the real dynamics of random drivers and their correlations in an arbitrage free framework.

Due to the above limits, the other type of mortgage default model, i.e., hazard-based model, has gained a lot of popularity recently, especially with the influx of large amount of default data after the subprime crisis. The option-based model tries to solve for the boundary values of the state variables (such as interest rate, house price, income level) and identify the option exercise zone. Instead of solving for the optimal (or suboptimal) exercise boundary, the hazard-based model assumes that the mortgage could default (or prepay) at any time after origination, conditional on that it has not prepaid or defaulted yet. The hazard function in this model is generally defined as the product of a baseline hazard and a function of time-varying covariates, such as the Cox proportional hazard model. These covariates could include variables upon which the option value depends, such as probability of negative equity, refinance incentive, etc. However, they are not limited to those option related variables, and can include any other important factors, when deemed necessary or empirically sound, such as credit score, seasonal dummies, etc. The hazard-based model can be estimated relatively straight-forward and fit reasonable mortgage prepayment and default behaviors empirically. Also it does not need to explicitly address the so-called "sub-optimality" under the pure option-based model framework.

Several early empirical studies have applied the Cox proportional hazard model to evaluate mortgage default or prepayment risk (such as Green and Shoven, 1986; Schwartz and Torous, 1989; Quigley and Van Order, 1990, 1995). However, these models generally address the prepayment and default separately, as if they were independent terminations. We know that these two termination events are mutually exclusive, thus making them competing hazard. Also factors driving one event generally deter the other. For example, borrowers with high credit score are more likely to prepay, and less likely to default. Mortgage with higher loan-to-value ratio are more likely to default, and less likely to prepay. Thus these two events are highly inter-dependent.

In a series of papers, Deng, Quigley, and Van Order (1996, 2000) and Deng (1997) attempt to simultaneously estimate the prepayment and default risk of residential mortgages from micro level data. After that, the competing hazard risk model has been widely accepted as the standard modeling approach to estimate the prepayment and default behavior of residential mortgages, and many researchers have added contribution in this lieu of literature, mainly on finding new explanatory variables or re-examining the traditional credit risk factors. For example, Keys et al. (2010) find securitization level during the subprime boom period increases the default hazard risk; Foote et al. (2010) find affordability level at origination not a significant default indicator, while expectation of future house price appreciation is significant; Gerardi, Goette, and Meier (2010) find low financial literacy level definitely highly correlated with higher default risk; Krainer and Laderman (2011) suggest that tightening mortgage underwriting guidelines may have contributed to low prepayments and high delinquency; Fuster and Willen (2013) try to incorporate payment size into the hazard function.

In this paper, we follow the standard literature to use the most recent competing hazard risk model in estimating the default and prepay risk. Since we focus on loan modification and re-default, we review papers that specifically address the re-default risk of loan modification in the next section.

1.2. Literature Review of Residential Mortgage Modification Re-default

Haughwout, Okah, and Tracy (2009) is one of the first papers to conduct research on subprime modification, which proceeds the government initiated HAMP program. They find that the re-default rate declines with the magnitude of the reduction in the monthly payment, and it declines relatively more with principal forgiveness, compared to interest rate reduction.

Voicu et al. (2012) estimate a hazard-based framework to compare the performance of HAMP vs. non-HAMP modifications, and find HAMP mods are more successful than non-HAMP mods. They also find payment reduction as the main determinant for mod re-default.

McCoy et al. (2012) examine the performance of new private-label mortgage loan modifications after 2009. They find these more recent private-label loan modifications have a lower overall re-default rate, compared to similar modifications made in pre-2009 years. They also report that having a fixed rate mortgage, higher credit score, lower initial mortgage note rate all contribute to a lower re-default rate. Mortgage type, loan purpose, and documentation level all affect the success rate. They confirm that payment reduction via principal forgiveness is most effective, compared to arrears capitalization and rate reduction.

A payment reduction related research is conducted by Tracy and Wright (2012). They did not attempt to estimate the re-default rate for modified loans. Instead, they estimated a competing risk model to estimate the sensitivity of default risk to downward adjustments of borrowers' monthly mortgage payments for a large sample of prime adjustable-rate mortgages. They found payment reduction a significant driver in reducing the default risk.

However, none of these previous researches identified the increasing re-default rate, associated with excessive payment reduction. We believe our paper is the first to identify this phenomenon.

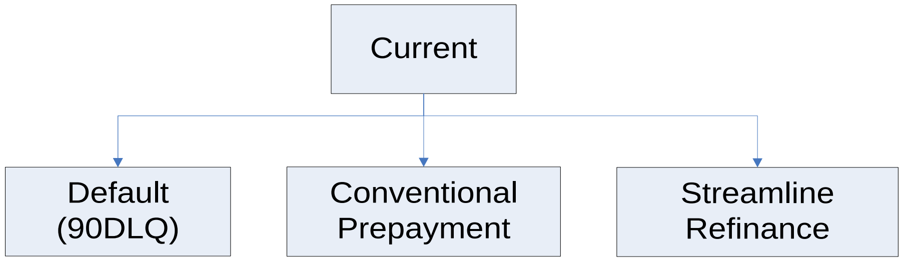
2. A Competing Hazard Risk Model for Post-Modification Performance

In this section, we briefly introduce the competing hazard risk model framework used in this paper and the specification of our multinomial logistic models.

2.1 A Competing Hazard Risk Model for Mortgage Default

Our model framework is given by the following chart.

Figure 1: Competing Hazard for Current FHA Loans



Following the standard practice of modeling mortgage termination, we establish the competing hazard risk model framework with the following three source of termination.

Default: this event is defined as becoming 90 days delinquent from "current" status. Technically a mortgage is not terminated at this stage. It can go back to current, be modified, be prepaid, go to foreclosure or short sale. However, we are mainly interested in the borrower-driven events such as 90DLQ. The following events are largely driven by both the borrower and the lender, and heavily influenced by policy interventions and operational constraints, such as foreclosure moratorium, modification initiative, foreclosure lag, servicing capacity, backlog in foreclosure court, etc. Thus we only model the competing hazard for loans in "current" status, which could have self-cured from previous defaults, or have been modified in the past. The performance of defaulted loans will be another topic.

Conventional Prepayment: this event is defined as the borrower pays off the mortgage via a property sale transaction, or refinance into a conventional mortgage, generally a GSE loan. FHA loans have an annual mortgage insurance premium (MIP), which generally result in higher effective coupon rate (nominal mortgage note rate plus MIP). When house price appreciates and/or loan amortizes, and the current LTV reaches 80%, FHA borrowers can refinance to GSE loans without paying the insurance premium. During the subprime boom period of 2004-2007, it is widely speculated that many FHA loans refinanced into subprime. But after that subprime meltdown, most of the conventional prepayments are believed to take the GSE refinance opportunities, especially as FHA increases its MIP dramatically.

Streamline Refinance: this event is defined as the borrower refinance into another FHA via the streamline refinance program. This program allows the current FHA borrowers to take advantage of lower interest rate, and exempt them from the traditional underwriting process, i.e., property appraisal and credit profile check are not required.

The reason for us to separate total prepayment into conventional prepayment and streamline refinance is based on the following observations.

First, conventional prepayment and streamline refinance are driven by different events. Conventional prepayment includes both housing turnover and rate refinance, while streamline refinance only include rate refinance.

Second, conventional prepayment and streamline refinance have difference refinance rates. During a conventional refinance, the borrower is comparing the GSE mortgage rate with her effective coupon rate. For a borrower considering streamline refinance opportunity, she is comparing the new effective coupon rate (new FHA mortgage rate plus new MIP) with her existing effective coupon rate.

Third, conventional prepayment and streamline refinance are driven by different agency behaviors. Both the GSEs and FHA have raised their fees after the financial crisis, yet at different level and different dates. The GSEs have sharply raised their delivery fees and guaranty fees after the conservatorship in 2008. FHA raised their upfront MIP in 2008, and then raised annual MIP in 2010, 2011, 2012, and 2013. In 2013, FHA also changed the minimum MIP schedule and revoked the annual MIP expiration threshold at CLTV 78%. FHA also has special treatments for streamline refinance loans, based on their prior mortgage endorsement date.

All these differences have made it extremely hard to combine the conventional prepayment and streamline refinance into one hazard function.

2.2. Specification of Multinomial Logistic Models

As summarized above, the competing hazard model framework attempt to model loan behaviors in current status. For loans currently at the start of the quarter, the competing risks are prepayment, transition to default status, or remaining current, as was shown above in Exhibit 1. The number of competing risks includes three possible types: remaining current, default, streamline refinance (SR), and other prepayment (PRE). This gives rise to four possible transition probabilities requiring estimation.

We specified multinomial logistic models of quarterly conditional probabilities for transitions from current to prepayment, default, or remaining current. The corresponding mathematical expressions for the conditional probabilities over the time interval from t to $t+1$ for loans starting in current status in a quarter t to conventional prepayment, streamline refinance, default, remain current, respectively, in the subsequent quarter $t + 1$ are given by:

$$\pi_{PRE}^{CUR}(t) = \frac{e^{\alpha_{PRE}^{CUR} + X_{PRE}^{CUR}(t)\beta_{PRE}^{CUR}}}{1 + e^{\alpha_{PRE}^{CUR} + X_{PRE}^{CUR}(t)\beta_{PRE}^{CUR}} + e^{\alpha_{SR}^{CUR} + X_{SR}^{CUR}(t)\beta_{SR}^{CUR}} + e^{\alpha_{DEF}^{CUR} + X_{DEF}^{CUR}(t)\beta_{DEF}^{CUR}}} \tag{1a}$$

$$\pi_{SR}^{CUR}(t) = \frac{e^{\alpha_{SR}^{CUR} + X_{SR}^{CUR}(t)\beta_{SR}^{CUR}}}{1 + e^{\alpha_{PRE}^{CUR} + X_{PRE}^{CUR}(t)\beta_{PRE}^{CUR}} + e^{\alpha_{SR}^{CUR} + X_{SR}^{CUR}(t)\beta_{SR}^{CUR}} + e^{\alpha_{DEF}^{CUR} + X_{DEF}^{CUR}(t)\beta_{DEF}^{CUR}}} \tag{1b}$$

$$\pi_{DEF}^{CUR}(t) = \frac{e^{\alpha_{DEF}^{CUR} + X_{DEF}^{CUR}(t)\beta_{DEF}^{CUR}}}{1 + e^{\alpha_{PRE}^{CUR} + X_{PRE}^{CUR}(t)\beta_{PRE}^{CUR}} + e^{\alpha_{SR}^{CUR} + X_{SR}^{CUR}(t)\beta_{SR}^{CUR}} + e^{\alpha_{DEF}^{CUR} + X_{DEF}^{CUR}(t)\beta_{DEF}^{CUR}}} \tag{1c}$$

$$\pi_{CUR}^{CUR}(t) = \frac{1}{1 + e^{\alpha_{PRE}^{CUR} + X_{PRE}^{CUR}(t)\beta_{PRE}^{CUR}} + e^{\alpha_{SR}^{CUR} + X_{SR}^{CUR}(t)\beta_{SR}^{CUR}} + e^{\alpha_{DEF}^{CUR} + X_{DEF}^{CUR}(t)\beta_{DEF}^{CUR}}} \tag{1d}$$

We apply the approach developed by Begg and Gray (1984), in which we estimate separate binomial logistic models for each possible transition type and then recombine the estimates to derive the multinomial logistic probabilities. Begg and Gray (1984) applied Bayes Law for conditional probabilities to demonstrate that the values of parameters α_f^i and β_f^i estimated from separate binomial logistic (BNL) models are parametrically equivalent to those for the corresponding multinomial logistic (MNL) model once appropriate calculations are performed. Assume that the conditional probabilities for current-to-prepay and current-to-default transitions for separate BNL models for loans in current status at the start of quarter t are given, respectively, by:

$$\Pi_{PRE}^{CUR}(t) = \frac{e^{\alpha_{PRE}^{CUR} + X_{PRE}^{CUR}(t)\beta_{PRE}^{CUR}}}{1 + e^{\alpha_{PRE}^{CUR} + X_{PRE}^{CUR}(t)\beta_{PRE}^{CUR}}} \tag{2a}$$

$$\Pi_{SR}^{CUR}(t) = \frac{e^{\alpha_{SR}^{CUR} + X_{SR}^{CUR}(t)\beta_{SR}^{CUR}}}{1 + e^{\alpha_{SR}^{CUR} + X_{SR}^{CUR}(t)\beta_{SR}^{CUR}}} \tag{2b}$$

$$\Pi_{DEF}^{CUR}(t) = \frac{e^{\alpha_{DEF}^{CUR} + X_{DEF}^{CUR}(t)\beta_{DEF}^{CUR}}}{1 + e^{\alpha_{DEF}^{CUR} + X_{DEF}^{CUR}(t)\beta_{DEF}^{CUR}}} \tag{2c}$$

where we have used upper-case Π to indicate the binomial logistic probability and distinguish it from the lower-case π that was used above to denote the multinomial logistic probabilities. Estimation of the binomial logistic (BNL) probabilities in (2a) - (2c) produces estimates of parameters α_f^i and β_f^i that can be substituted directly into equations (1a) - (1c) to derive the corresponding multinomial logistic (MNL) probabilities.

3. Data, Variable and Summary Statistics

In this section, we introduce our sampling method and explain how we construct the model variables, including control variables. Lastly, we provide summary statistics on the sample.

3.1 Choice-Based Sampling Approach

The entire population of loan-level data and loan modification data from the FHA single-family data warehouse were extracted for this analysis. We focus on the fixed-rate 30-year fully underwritten purchase and refinance loans. This produced a population of over 22 million single-family loans originated between 1975 through the second quarter of 2013. Among these loans, historical status transition records during 1996 and later years were reconstructed to estimate the loan status transition models. Our model estimation dataset did not include pre-1996 data due to the limited availability of reliable 90-day default episode data and major change in FHA underwriting policies in 1996. The resulting dataset was used to generate loan-level transition event histories until the end of the observed data period.

In credit risk modeling, a choice-based sample is commonly used for large populations with relatively rare events of interest. We used a two-stage choice-based sampling process for estimating the transition equations where the sampling rates are determined by the terminal status of each loan and its status at each period.

This sampling approach enhances the efficiency of model estimation, and is supported by the literature. Manski and Lerman (1977)'s *Econometrica* paper "The Estimation of Choice Probabilities from Choice Based Samples" is one of the first papers to address the topic of choice-based samples. Before that, sampling was mainly used on independent variables, instead of on dependent variables. Because the parameters of a probabilistic choice model are estimated conditional on the independent variables, the sampling technique generally does not produce bias. Manski and Lerman prove that for a general probabilistic choice model, when the choice-based samples are weighted correspondingly, the MLE estimator is consistent and converges to the un-sampled estimator. Scott and Wild (1986) discuss the response-based sample in a logistic model framework, and found that although the weighted estimators might be less efficient, the sampling produces unbiased parameter estimates of the logistic coefficients. Xie and Manski (1988, 1989) argue that although under the logistic model, the random sampling and response-based sampling maximum likelihood estimators coincide for all parameters except the intercept, modelers should avoid assuming the logistic model form and analyzing the response-based samples without adjusting the sample weights. The weighted maximum likelihood method estimates a constrained best predictor of the binary response.

Two-stage choice-based sampling

First step, over sample the bad loans, where a bad loan is defined as a loan that has ever been 90-day delinquent:

a. Loan-level sampling rate of good loans = 10%
b. Loan-level sampling rate of bad loans = 100%

Second step, over sample in the bad quarters, where a bad quarter is defined as the quarter that a loan becomes a first-time 90-day delinquent and all subsequent performance quarters:

c. Quarterly loan-level sampling rate of non-default quarters = 10%
d. Quarterly loan-level sampling rate of default and subsequent quarters = 100%

With this two-stage sampling process, we calculate the following sampling probability matrix that shows the ultimate sampling probability for loan-quarter combinations. The corresponding weights we used are the reciprocal of the probabilities of selection.

Table 1. Choice-based Sampling Probability Matrix

Sampling Rate	Good Loan	Bad Loan
Good Quarter	10%	10%
Bad Quarter	N/A	100%

We used loans originated from 1996 through 2012Q3 to estimate the status transition models starting in current that transition to other statuses, corresponding to the loan cohorts for which complete data were available on new 90-day default episodes. These data were used to generate quarterly loan-level event histories to the end of the sampling period or when the loan claimed, fully prepaid or matured.

3.2 Model Variables

In this section, we first discuss the major model variables, then the control variables.

3.2.1 Major model variables

Prior Loan Modification Indicator

We separated the loans which were cured by themselves or by loan modification and for the latter we introduced a prior loan modification indicator (Prior_mod). The prior loan modification indicator is equal to 1 after the flag of loan modification cure is turned on, and remains at 1 until the termination or payoff of the loan. For example, if a loan receives a loan modification and is cured from default in its 20th quarter, the prior loan modification indicator is equal to 1 and remains 1 starting from the 21st quarter.

Loan Modification Payment Change

The purpose of loan modification is to change one or more of the terms of a loan. This allows the loan to be reinstated, and results in a payment the borrower can afford. Therefore, the percentage change of monthly payment resulting from a loan modification (Payment_rdct) will affect the borrower's capacity to service the loan, and hence impact the future transition of the loan.

Since the financial crisis and the crash of the U.S. housing market, loan modification has been widely used to reduce foreclosures. At the beginning of the financial crisis, most loan modifications were in the form of forbearance, resulting in monthly payment increases. In the subsequent years, modifications of the terms such as interest rate and amortization schedule became the most frequent types of modification. Within all the major types of loan modifications, forbearance is the only type which would result in monthly payment increases. As mentioned above, most of the forbearances occurred at the beginning of the financial crisis and the number of forbearances became insignificant since 2010. Since forbearance is not expected to be a major modification type in the future time horizon, we floor the percentage of monthly payment change to zero so that the monthly payment change resulting from forbearance will not impact the estimation and forecast of the model.

The details of the loan modification payment change are not retrievable for some of the modified loans. In such a case, we created an indicator specifying this missing information (Payment_rdct_mis).

Borrower Credit Scores

Borrower credit scores is an important predictor of claim and prepayment behavior. FHA has relatively complete data on borrower FICO scores for loans originated since May 2004. In addition, FHA retroactively obtained borrower credit history information for selected samples of FHA loan applications submitted as far back as 1992.

Debt-to-Income (DTI) Ratio

The DTI ratio measures the ratio of monthly debt payment to before-tax total household income at origination. There are two ratios available: the front-end ratio, which counts only the mortgage-related housing cost, i.e., PITI (principal, interest, tax and insurance); and the back-end ratio, which includes payments for all other regular monthly debt, including car loans, student loans, and credit cards. We use the front-end ratio to capture the debt burden effect for the borrower, because it is better documented and measured more accurately than the back-end ratio.

Current Loan-to-Value (CLTV) Ratio

This variable is calculated as the origination Loan-to-Value (OLTV), divided by the appreciation factor since origination (i.e., inflating-or deflating-the denominator, the house price), adjusted for amortization. Empirical results show that the mortgage default rate is very sensitive to the CLTV ratio, when the property value moves into the negative equity range (at a CLTV near to or greater than 100%).

Loan-to-Value Ratio

The initial LTV is recorded in FHA's data warehouse. For fully underwritten mortgage products and streamline refinance loans with required appraisals these LTV values are used directly to compute the CLTV.

Relative Loan Size

This variable is proxied by the mortgage origination amount, divided by the average loan origination amount in the same state for the same fiscal year. Empirical results show this variable is very significant in prepayment-related termination. This is consistent with option theory, since loans with higher loan size could achieve higher monetary savings, given the same relative mortgage spread.

Spread at Origination/SATO

SATO is measured as the spread between the mortgage note rate, C, and the prevailing mortgage rate, R, at the time of origination. It is widely regarded as the lender surcharge for additional borrower risk characteristics, which are not captured by standard underwriting hard data such as FICO score, OLTV, DTI ratio, documentation level, etc. A high SATO loan is generally more risky, compared to a similar loan with a low SATO. Some researchers also argue that a high SATO is an indicator of predatory lending, which also tends to increase credit risk.

$$SATO = C - R \tag{3}$$

Number of Quarters Since the End of Last Default Episode

We use the number of quarters since the end of the latest default episode (CX_TIME) for transitions in the current status. The CX_TIME is set to zero at the origination of each loan until the end of its first default episode. It becomes 1 after the end of the default episode, and keeps increasing quarterly until the start of next default. For example, if a loan experiences a second default episode, CX_TIME continues to increase until the start of the second default episode, and it is set to 0 during the second default episode. After the end of the second default episode, it is reset to 1 and continues to accumulate until the next default.

Mortgage Premium (Refinance Incentive)

In this paper, we use the percentage difference between the monthly payment of a potential refinance $PMT_1(t)$ relative to the current payment $PMT_0(t)$ as the refinance incentive,

$$Refi\_incentive(t) = 100 * \frac{PMT_0(t) - PMT_1(t)}{PMT_0(t)}. \tag{4}$$

This variable is an approximation to the call option value of the mortgage given by the difference between the present value of the “anticipated” future stream of mortgage payments discounted at the current market rate of interest and the present value of the mortgage evaluated at the current note rate. Additional details are given in Deng, Quigley, and Van Order (2000) and Calhoun and Deng (2002).

For the transition into the FHA streamline refinance mortgage, we use as the refinancing option for a FHA mortgage, by definition. For all other transitions we use the payment from a market mortgage, assumed to be a GSE mortgage.

Also, we added the annual FHA mortgage insurance premium (MIP) to the mortgage rate, in both the current FHA loan and the potential new FHA loan (for SR), as follows:

$$effect\_coupon\_rate(t) = C(t) + annual\ MIP(t), \tag{5}$$

where $C(t)$ is the coupon rate for extant FHA loans.

For the effective GSE refinancing rate, we want to add the effective refinancing points to the contract rate, which translates the one-time points to an equivalent interest rate spread over time. FHFA publishes both the contract rate and this effective rate, and we calculated the spread difference and project it in our analysis. Therefore, we define the effective refinancing cost *avg_refi_cost* as the spread between the FRM30 effective rate and the contract rate provided in the FHFA survey:

$$GSE\_refi\_rate(t) = R(t) + avg\_refi\_cost\ , \tag{6}$$

Assuming refinancing costs are the same for both the GSE and FHA refinances, the effective rate for refinancing into an FHA loan is then built onto this GSE refinancing rate, by adding the average FHA to GSE spread and the new annual MIP:

$$FHA\_refi\_rate(t) = GSE\_refi\_rate(t) + avg\_FHA\_GSE\_sprd + annual\_MIP, \tag{7}$$

The payment on the current FHA loan is $PMT_0(t)$. Using the above effective refinance rates, we compute "effective" monthly mortgage payments for the current and the prospective new refinancing loans $PMT_1(t)$, which have a prefix denoting whether they are the GSE or FHA loan options. The refinance incentive for a GSE refinancing loan is:

$$GSE\_Refi\_incentive(t) = 100 * \frac{PMT_0(t) - GSE\_PMT_1(t)}{PMT_0(t)}. \tag{8}$$

The GSE refinance incentive variable is used in transitions other than current-to-SR. The refinance incentive for a loan refinanced from FHA in the transition current-to-SR is:

$$FHA\_Refi\_incentive(t) = 100 * \frac{PMT_0(t) - FHA\_PMT_1(t)}{PMT_0(t)}. \tag{9}$$

Burnout Factor

A burnout factor is included to identify borrowers who have foregone opportunities to refinance. It is measured as the accumulation of the positive spreads between the coupon rate and new refinance mortgage rate throughout the life of loan. The burnout factor is included to account for individual differences in propensity to prepay, often characterized as unobserved heterogeneity. In addition, unobservable differences in borrower equity at the loan level may give rise to heterogeneity that can impact both prepayment and default rates.

Credit Burnout

Similarly, credit burnout effect is that borrowers who have forgone a default option and showed resilience by making uninterrupted payments in the past are less likely to default in the future. We use the cumulative number of quarters that a property has been "underwater" to proxy this effect.

Purchase-Only HPI

In the calculation of CLTV, we use the Purchase-Only (PO) Home Price Index (HPI) published by FHFHA. The PO Index is based on repeat sales at market prices and does not use any appraised values. As such, it provides a more reliable measure of housing market conditions. Evidence cited below has found appraisal bias, albeit not from all appraisers. We want a house price series that accurately estimates CLTVs and thus what defaulted properties would sell for.

There is documented evidence of bias in residential appraisals so that the PO Index is a more accurate representation of market values. Chinloy, Cho and Megbolugbe (1997) compared the purchase prices against appraisals and found a two percent upward bias. In addition they found that appraisal prices exceed the purchase prices in 60 percent of the cases. They postulated that the existence of a moral hazard incentive to complete the deal might be the reason for the bias. More recent papers provide additional empirical support for the existence of appraisal bias, i.e., Agarwal, Ben-David and Yao (2012), Tzioumis (2013), and Zhu and Pace (2012). Another reason for using the PO HPI is that in recent years, industry practices are leaning toward the PO HPI. The most commonly used indices, such as Case-Shiller Home Price Index and CoreLogic HPI, are all constructed based on a purchase-only methodology. Since FHFA released their PO HPI at the MSA level this year, it is consistent with general industry practices to use the PO HPI, and is a major reason we were able to use it this year for the first time.

Home Price Volatility

Option theory predicts that the put (default) option value increases when the volatility of the collateral increases, everything else equal. Empirical results show the marginal effect of home price volatility on default behavior is generally positive, which is consistent with option theory. An easier way to interpret this phenomenon is that the home price volatility measures our uncertainty in calculating the updated property value; higher volatility would introduce more error on both positive and negative sides. However, the loss introduced on the negative side is not compensated by the gain on the positive side, due to the asymmetric nature of mortgage credit risk.

The home price volatility (sigma_parm_a) is the same as the measurement of parameters "*a*" calculated in the Probability of Negative Equity, which indicates uncertainty with regard to the dispersion of individual house price appreciation rates around the market average, represented by the local-level HPI. The parameter "*a*" is estimated by FHFA when applying the three-stage weighted-repeat-sales methodology advanced by Case and Shiller (1987, 1989).

Home Price Appreciation

The home price enters the model via two variables, each of which has a different interpretation. Home price appreciation since origination (at the metro/non-metro area level) determines the CLTV ratio, which is used to measure the current equity in the property. Short-term house price appreciation, which proxies for people's expectation of future house price movements, is also used. The rationale for this variable is that borrowers make their decisions not only on the realized historical information, but also on their expectation about future house price appreciation. Short-term home price appreciation, HPA2y(t), is calculated as the projected house price index one year ahead, HPI(t+4), divided by historical house price index one year ago, HPI(t-4), measured at both the national level and at the Metropolitan Statistical Area (MSA) level, HPI(i):

$$HPA2Y(t,i) = \frac{HPI(t+4,i)}{HPI(t-4,i)}. \tag{10}$$

When historical observations are used to estimate the transition equations, actual four-quarter-ahead observations are used to measure this variable. For simulations along future HPA/interest rate paths, the same measurement is made, using the projected HPAs four-quarters ahead.

The variable hpa2y_n = min(0, hpa2y) differentiates the response when the anticipated HPA is negative compared to positive.

Unemployment Rate

There is ample literature that indicates job loss, or loss of income, is one of the major trigger events for mortgage default. The natural choice of macroeconomic variables to capture this effect is the unemployment rate. However, during the period of 1994-2008, when the U.S. economy grew at a steady rate and only experienced a minor recession, the variation in the unemployment rate was extremely small, which makes it difficult to demonstrate that it is a significant factor: the national unemployment rate in that period was almost always between 4% and 6%. That is part of the reason why previous attempts to use this variable showed it as not statistically significant. After 2008, the unemployment rate rose rapidly, and consequently we have found that this variable is both statistically and economically significant in the borrower's default behavior.

We use two types of unemployment rates: the short-term unemployment rate change, *Delta_UE(t)*, and a relative unemployment rate, *Relative_UE(t)*. The short-term unemployment rate change is measured as the change in the unemployment rate level between last quarter and the level three quarters ago, which indicates the direction of change in unemployment. The relative unemployment rate is measured as the ratio between the unemployment rate level in last quarter, *UE(t-1)*, and the moving average over the last 10 years, *UE_10yr_avg(t)*, which indicates the current inventory of unemployment. For example, although the quarterly change in the unemployment rate did not vary much after year 2008, the relative unemployment rate continued to climb due to the recession. The formulas for computing these two measures are:

$$Delta\_UE(t) = UE(t-1) - UE(t-3), \tag{11}$$

$$Relative\_UE(t) = \frac{UE(t-1)}{UE\_10yr\_avg(t)}. \tag{12}$$

3.2.2 Control variables

Yield Curve Slope

Expectations about future interest rates and differences in short-term and long-term borrowing rates associated with the slope of the Treasury yield curve influence the choice between ARM and FRM loans and the timing of refinancing. We used the spread of the 10-year Constant

Maturity Treasury (CMT) yield over the 1-year CMT yield to measure the slope of the Treasury yield curve.

FHA Score Indicator

FHA adopted a number of changes in 2005 with potential impacts on underwriting, including implementation of its TOTAL scorecard. So this dummy variable is defined as unity if the loan was originated after 2004, zero otherwise.

Seasonality Indicators

The season of an event observation quarter is defined as the season of the year corresponding to the calendar quarter, where season 1 = Winter (January, February, March), 2 = Spring (April, May, June), 3 = Summer (July, August, September), and 4 = Fall (October, November, December). All categorical (0-1 dummy) variables take on the value of 1 for the specified quarter; and one of the categories is omitted as the reference category.

3.3 Summary Statistics

Table 2 describes the distribution of payment reduction for modified loans. This is the key variable that we focus on in this paper. Each column presents the sample dispersion of the payment reduction variable under corresponding transition. In order to investigate the changing effect of payment reduction on re-default, prepay and streamline refinance probability, we construct 6 dummies based on the continuous payment reduction variable. Although the way of constructing the 6 dummies sounds arbitrary, from table 2 we can see that there are enough observations for each dummy to generate reliable estimation results.

Table 2. Distribution of the Modification Payment Reduction

		Number of Observations Under Each Transition		
	Payment reduction (%)	Current to Default	Current to Prepay	Current to Streamline Refinance
Payment_rdct_d1	0 < - 10 %	121,275	105,145	105,029
Payment_rdct_d2	10% - 20%	102,085	92,106	92,010
Payment_rdct_d3	20% - 30%	36,284	32,979	32,942
Payment_rdct_d4	30% - 40%	15,322	13,941	13,929
Payment_rdct_d5	40% - 50%	3,799	3,291	3,287
Payment_rdct_d6	50% and above	2,772	2,241	2,239

Table 3 presents the summary statistics for model variables in the current to default transition. After the two-stage choice-based sampling, there are 10,642,828 observations in total. The top panel describes the loan characteristic variables, i.e., the loan to value ratio (LTV) and credit score information. The second panel provides information on macro-economic variables, such as housing price appreciation, unemployment rate and the 10 year and 1 year constant maturity Treasury bond (CMT) yield curve. Major model and control variables are listed in the third panel.

The summary statistics presented in table 3 show that all those variables have reasonable dispersion.

Table 3. Summary Statistics for Model Variables in Current to Default Transition

	Description	MIN	MAX	MEAN	STD
	Loan Characteristic Variables				
N	Total observations	10,642,828	10,642,828	10,642,828	10,642,828
LTV	Loan to value ratio	50	110	94.82	6.25
credit_score	Credit score	300	850	596.16	43.16
	Macro-economic Variables				
hpa2y_n	Housing price appreciation national level	-50.56	0.00	-2.95	6.01
delta_ue	Unemployment rate change in last two quarters	-14.50	12.05	0.14	0.81
ycslope	Yield curve slope measured as difference of 10 year CMT to 1 year CMT rates	-0.36	3.35	1.73	1.16
	Major and Control Variables				
loansize	Relative loan size	4.29	475.83	93.41	33.06
sato	Spread at origination	-5.42	3.45	0.21	0.60
ratio_tmp_tei	Front-end ratio	0.10	100.00	24.80	7.90
LTV_current	Current LTV	0.11	2.45	0.76	0.20
age	Mortgage age function	0	66	20.16	14.16
burnout	Burnout factor. Cumulative amount of quarterly positive refinance incentives	0	65.1	18.33	19.69
c_burnout	Credit burnout factor. Prior cumulative number of quarters default option is underwater	0	14	0.58	2.16
cx_time	Number of quarters since end of last default episode	0	64	5.40	7.85
GSE_refi_inc	GSE refinance incentive	-70.29	43.12	14.01	8.30

In section 4, we provide two subsample estimations for the current to default transition. The first subsample is with all loans that have zero payment reduction, and the second subsample is with loans that have positive payment reduction. Table 4 shows the summary statistics for these two subsamples.

Table 4. Summary Statistics for Subsample Estimations in Current to Default Transition

	Loans without positive principal reduction				Loans with positive principal reduction			
	MIN	MAX	MEAN	STD	MIN	MAX	MEAN	STD
	Loan Characteristic Variables							
N	10,361,268	10,361,268	10,361,268	10,361,268	281,537	281,537	281,537	281,537
LTV	50	110	94.87	6.21	50	109.85	93.15	7.40
credit_score	300	850	596.11	43.09	300	850	597.95	45.66
	Macro-economic Variables							
hpa2y_n	-50.56	0.00	-2.94	6.04	-50.56	0.00	-3.27	4.67
delta_ue	-14.50	12.05	0.15	0.81	-3.65	8.64	-0.18	0.72
ycslope	-0.36	3.35	1.71	1.17	-0.36	3.35	2.43	0.56
	Major and Control Variables							
loansize	4.29	475.83	93.18	32.94	12.03	356.65	101.61	36.02
Sato	-5.42	3.45	0.21	0.61	-4.05	3.11	0.30	0.45

ratio_tmp_tei	0.10	100.00	24.70	7.90	0.10	100.00	26.80	8.20
LTV_current	0.11	2.45	0.76	0.20	0.16	2.41	0.88	0.23
age	0	66	19.99	14.15	4	66	24.77	13.82
burnout	0	65.1	18.12	19.65	0	65.1	26.21	19.53
c_burnout	0	14	0.52	2.04	0	14	2.62	4.43
cx_time	0	64	5.44	7.94	1	23	3.73	2.67
GSE_refi_inc	-70.29	43.12	13.82	8.28	-38.16	40.25	21.27	5.36

4. Empirical Model Results

In this section, we present and discuss our empirical findings. Table 5 shows the estimation results when the continuous payment reduction variable is used in the regression. The coefficient of payment_rdct is negative. However, figure 2, which plots the actual and predicted default likelihood at each payment reduction value, shows that the effect of payment reduction to default is not monotonic as we first thought. The figure shows that actual default likelihood decreases with the payment reduction but then increases after some point. With very large payment reduction, we can see that the default likelihood decrease again. Nevertheless, figure 2 shows that the effect of payment reduction to default likelihood may not be monotone, and using discontinuous payment reduction variable might be a good choice to capture this non-monotone effect, i.e., use payment reduction dummies.

Table 5. Estimation Results of Current to Default Transition with Continuous Payment Reduction Variable

	Coefficient	Wald chi2	P-value
Intercept	-0.2717	319.63	<.0001
age	0.0194	19586.60	<.0001
burnout	-0.0097	8829.75	<.0001
c_burnout	0.0358	6711.32	<.0001
credit_score	-0.0095	309370.16	<.0001
credit_score_000	-0.1898	1739.77	<.0001
credit_score_999	-0.6433	81892.19	<.0001
cx_time	0.0322	35954.77	<.0001
delta_ue	0.1411	18695.87	<.0001
dti000	-0.0185	5.30	0.02
FHA_score	-0.1768	4216.07	<.0001
GSE_refi_inc	0.0441	65965.24	<.0001
hpa2y_n	-0.0102	5250.29	<.0001
Payment_rdct_mis	-0.3154	1849.62	<.0001
Prior_mod	1.5749	58542.13	<.0001
loansize	0.0007	994.96	<.0001
LTV	0.0003	6.31	0.01
LTV_current	0.8079	10330.46	<.0001
Payment_rdct	-2.5621	2346.62	<.0001
ratio_tmp_tei	0.0207	53389.45	<.0001
Sato	0.1719	7499.86	<.0001
season_fall	0.2754	16783.18	<.0001
season_spring	-0.0460	408.26	<.0001
season_summer	0.1782	6479.83	<.0001

ycslope	-0.0005	0.30	0.58

Figure 2: Actual and Predicted Default Probability at each Payment Reduction Level

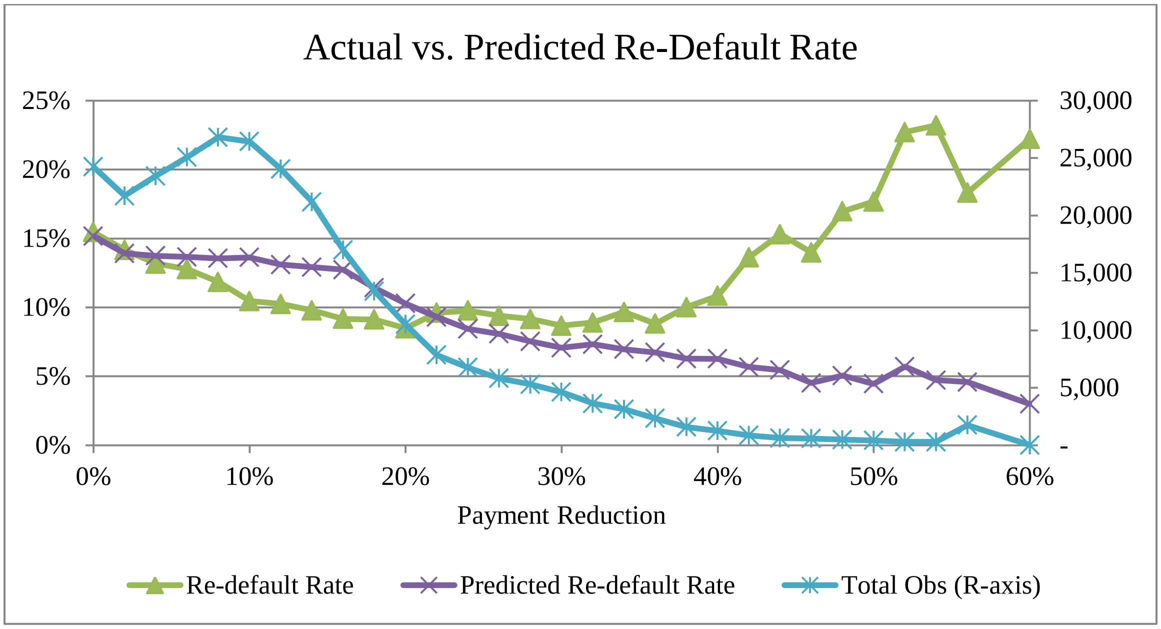


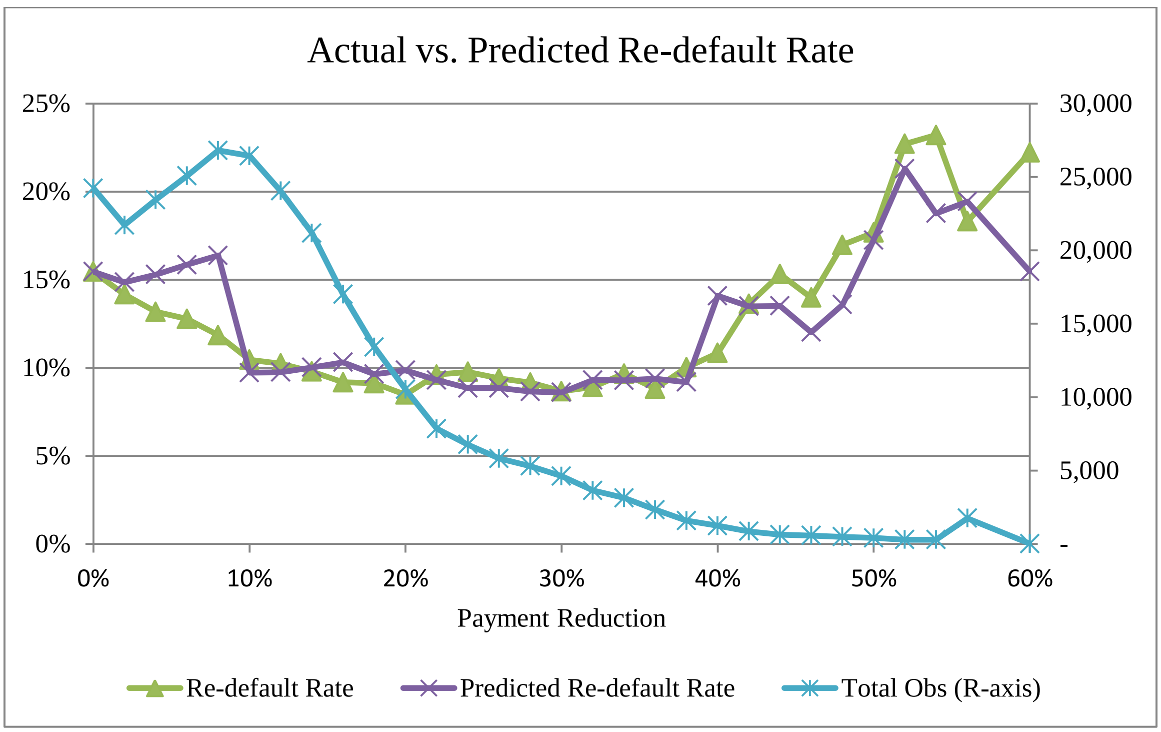
Table 6 presents the estimation results for the current to default transition, where we use payment reduction dummies instead of the continuous payment reduction variable. Interestingly, with moderate payment reduction, the default likelihood decreases. However, when payment reduction increases or with positive incremental in payment reduction, the magnitude change in default likelihood is positive. In other words, with more payment reduction, the default likelihood increases. The above conclusion is inferred from the evidence that the coefficients of payment reduction dummy are increasing. In addition, the coefficient of prior_mod is positive, implying that everything else equal, the loan with payment modification is more likely to default. The prior_mod is a dummy variable with value one if the loan has been modified. Figure 3 shows that payment reduction dummies capture the non-monotone effect of the payment reduction to default likelihood.

Table 6. Estimation Results of Current to Default Transition with Dummy Payment Reduction Variables

	Coefficient	Wald chi2	P-value
Intercept	-0.2673	309.21	<.0001
age	0.0194	19472.45	<.0001
burnout	-0.0097	8855.95	<.0001
c_burnout	0.0361	6822.50	<.0001
credit_score	-0.0095	309655.84	<.0001
credit_score_000	-0.1900	1743.41	<.0001
credit_score_999	-0.6433	81911.07	<.0001
cx_time	0.0323	36103.62	<.0001

delta_ue	0.1411	18673.54	<.0001
dti000	-0.0186	5.34	0.02
FHA_score	-0.1768	4212.31	<.0001
GSE_refi_inc	0.0442	66170.75	<.0001
hpa2y_n	-0.0102	5235.79	<.0001
Payment_rdct_mis	-0.3184	2141.05	<.0001
Prior_mod	1.5777	69246.28	<.0001
loansize	0.0007	1019.37	<.0001
LTV	0.0003	5.77	0.02
LTV_current	0.8073	10311.24	<.0001
Payment_rdct_d2	-0.6890	3167.61	<.0001
Payment_rdct_d3	-0.5892	915.87	<.0001
Payment_rdct_d4	-0.5754	387.36	<.0001
Payment_rdct_d5	-0.1162	5.60	0.02
Payment_rdct_d6	0.2471	24.26	<.0001
ratio_tmp_tei	0.0207	53320.20	<.0001
Sato	0.1720	7507.91	<.0001
season_fall	0.2754	16780.63	<.0001
season_spring	-0.0460	407.59	<.0001
season_summer	0.1782	6479.58	<.0001
ycslope	-0.0007	0.62	0.43

Figure 3: Actual and Predicted Default Probability at each Payment Reduction



The left panel of table 7 exhibits the regression results on subsample which includes all loans with zero payment reduction, and the right panel of table 7 presents the results on all loans with positive payment reduction. Table 7 shows that the traditional credit risk variables, such as credit score, negative equity level, debt-to-income ratio, etc., have weaker effect on the modified loans, compared with loans which have not been modified.

Table 7. The Estimation Results of Current to Default Transition under Different Sub-Sample

	Loans with no positive payment reduction			Loans with positive payment reduction		
Variable	Coefficient	Wald chi2	P-value	Coefficient	Wald chi2	P-value
Intercept	-0.1889	151.94	<.0001	-1.0176	58.37	<.0001
age	0.0192	18712.99	<.0001	0.0001	0.01	0.93
burnout	-0.0098	8860.17	<.0001	0.0028	10.50	0.00
c_burnout	0.0397	7848.02	<.0001	0.0035	2.64	0.10
credit_score	-0.0097	312491.78	<.0001	-0.0025	309.28	<.0001
credit_score_000	-0.1959	1823.41	<.0001	0.0177	0.25	0.62
credit_score_999	-0.6511	83028.89	<.0001	-0.0263	1.45	0.23
cx_time	0.0331	37802.77	<.0001	-0.0757	763.15	<.0001
delta_ue	0.1408	18350.74	<.0001	0.0925	103.20	<.0001
dti000	-0.0184	5.18	0.02	-0.1224	2.25	0.13
FHA_score	-0.1786	4236.46	<.0001	-0.0056	0.04	0.85
GSE_refi_inc	0.0444	65831.51	<.0001	0.0101	20.06	<.0001
hpa2y_n	-0.0099	4901.55	<.0001	-0.0093	42.64	<.0001
Payment_rdct_mis	-0.4903	3180.45	<.0001			
Prior_mod	1.7432	47272.20	<.0001			
loansize	0.0008	1058.75	<.0001	0.0001	0.34	0.56
LTV	0.0002	3.21	0.07	0.0024	6.50	0.01
LTV_current	0.8083	10060.73	<.0001	0.3184	35.40	<.0001
Payment_rdct_d2				-0.4037	808.94	<.0001
Payment_rdct_d3				-0.5102	534.83	<.0001
Payment_rdct_d4				-0.5326	283.02	<.0001
Payment_rdct_d5				-0.0928	3.51	0.06
Payment_rdct_d6				0.3356	45.72	<.0001
ratio_tmp_tei	0.0209	53612.97	<.0001	0.0075	94.73	<.0001
Sato	0.1719	7396.46	<.0001	0.0546	8.76	0.00
season_fall	0.2755	16513.77	<.0001	0.2607	230.49	<.0001
season_spring	-0.0434	356.58	<.0001	-0.1764	100.67	<.0001
season_summer	0.1785	6390.78	<.0001	0.1188	45.13	<.0001
ycslope	-0.0025	7.37	0.01	-0.0671	21.94	<.0001

The coefficients of prior_mod in table 6 and the left panel of table 7 are positive. The results in table 6 is based on samples pooling with zero and positive payment reduction, and the sample for the left panel in table 7 is on zero payment reduction loans. There are two groups of loans with zero payment reduction. The first group is with no loan modification, which is a dominant group. The second group is with negative loan payment reduction, which is a very small group. As we discussed in section 3.2, the loans with negative payment reduction are mostly forbearance, which is not expected to be a major modification type in the future time horizon, so we floor the percentage of monthly payment change to zero. However, the first group has prior_mod equal 0, while the second group has Prior_mod equal 1. Therefore, the positive coefficient of prior_mod in table 7 implies that all loans with negative payment reduction are more likely to default than identical non-modified loans.

In order to see whether loans with positive payment reduction are more likely to default compare to identical non-modified loans, we design the following regression. The regression sample is based on loans with positive payment reduction and loans without loan modification. Therefore, the prior_mod is turned on if the loan has positive payment reduction, and it is zero for the rest of loans. Table 8 presents the results for this regression. As we can see, the coefficient of prior_mod is positive, which clearly suggests that loans with positive loan modification is more likely to default comparing to identical loans with no modification.

The coefficients for the payment reduction dummy in table 8 increase and then reverse at a high payment reduction level. This evidence supports the fact observed in figure 2 that the actual default likelihood decrease with payment reduction at a decreasing speed at first, increase after some point, and then decline again at very high payment reduction.

Table 8. The Estimation Results of Current to Default Transition with Sub-Sample

	Coefficient	Wald chi2	P-value
Intercept	-0.1603	69670644.70	<.0001
age	0.0194	376738180.00	<.0001
burnout	-0.0090	84900364.90	<.0001
c_burnout	0.0377	26850720.70	<.0001
credit_score	-0.0097	92691800000.00	<.0001
credit_score_000	-0.2169	4082843.74	<.0001
credit_score_999	-0.6936	590165275.00	<.0001
cx_time	0.0422	152117423.00	<.0001
delta_ue	0.1394	43321170.50	<.0001
dti000	-0.0095	2253.41	<.0001
FHA_score	-0.1940	37182864.10	<.0001
GSE_refi_inc	0.0438	1286043969.00	<.0001
hpa2y_n	-0.0095	13224755.10	<.0001
Prior_mod	1.3275	80737155.70	<.0001
loansize	0.0008	16310284.70	<.0001
LTV	-0.0006	8352876.90	<.0001
LTV_current	0.9029	1660814852.00	<.0001
Payment_rdct_d2	-0.4263	2798712.45	<.0001
Payment_rdct_d3	-0.3031	478591.21	<.0001
Payment_rdct_d4	-0.2825	174847.04	<.0001
Payment_rdct_d5	0.0906	5782.67	<.0001
Payment_rdct_d6	-14.1846	112.44	<.0001
ratio_tmp_tei	0.0213	911409613.00	<.0001
Sato	0.1720	27638802.10	<.0001
season_fall	0.2687	57492994.80	<.0001
season_spring	-0.0434	1141567.93	<.0001
season_summer	0.1745	20664445.70	<.0001
ycslope	-0.0008	8899.58	<.0001

5. Policy Implication

In this section, we provide some discussion on our empirical results, and then move to the potential policy implication of our findings under two optimal modification strategies: first, optimal modification with monotonous Re-Default rate; second, optimal modification with mon-monotonous Re-Default rate.

5.1 Discussion of the Empirical Results

Based on the empirical model results, we come up with the following findings. First, modified mortgages re-default at a much higher rate, and the re-default rate is still driven by many traditional credit risk variables, such as credit score, negative equity level, etc.; second, the traditional credit risk variables have weaker effect on the modified loans, compared with loans which have not been modified; third, re-default rates are sensitive to payment reduction, but the relationship is not monotonous, which suggests some latent credit risk variable might be responsible for this phenomenon.

The explanation for finding 1 is very intuitive. Modified loans have defaulted at least once and then cured by payment reduction. Therefore, those loans, which have default experience, are more likely to default than identical non-default loans.

The intuition for finding 2 is relatively straight-forward. Empirically, the following credit risk attributes are generally considered to be predictive for mortgage default. First, borrower characteristics, such as credit score, income level, income stability, other debt obligations, debt-to-income ratio, reasons for financial distress, etc. Second, collateral characteristics, such as housing price, amount of (negative) equity in the house, local housing market dynamics, local housing market volatility, etc. Third, mortgage loan characteristics, i.e., rate reset if ARM, Payment shock if ARM.

Some of the credit attributes can be accurately measured and they are very useful in predicting mortgage default. Credit score is generally required at the time of mortgage underwriting, which measures the borrower's probability to become seriously delinquent on any of her credit lines within the next 18 months. [6] Although it is not designed to measure the default probability for mortgage loans, it is highly predictive in predicting mortgage default. Debt-to-income ratio is another commonly used origination variable, which measures the borrower's ability to pay. Higher debt-to-income ratio means lower disposable income, hence higher default rate.

However, at the time of modification, the borrower generally would have been deeply in delinquency. If the mortgage payment did not change in the past, such as in the case of fixed rate and normal amortization mortgage, the borrower mostly experience some forms of income reduction, such as unemployment/ underemployment, and/or financial distress from other life

[6] http://www.savvyoncredit.com/credit-score-measure/

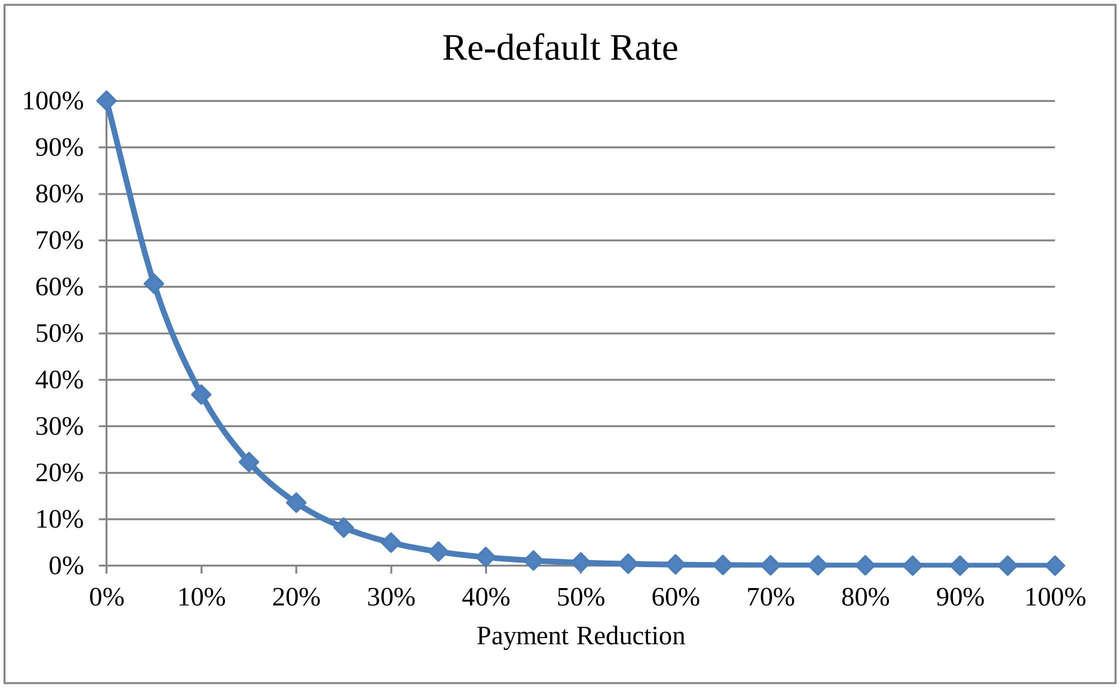
events, such as divorce, illness, etc. For adjustable rate mortgage, IO mortgage, or negative amortization mortgage, the payment could be adjusted upward, sometime significantly. Under this situation, even the borrower does not face income loss, or other financial distress, her ability to pay could be severely impaired, due to the incoming mortgage payment.

Although we generally observe many of these characteristics at the time of mortgage underwriting/origination, and can use them in common default model, some of them could be outdated and no longer indicative for the borrower's credit risk at the time of mortgage modification. For example, the credit score at time of origination is not very helpful for re-default prediction, since the borrower would have become seriously delinquent at that time, and the credit score would have been seriously impaired. Also, the origination debt-to-income ratio could be no longer valid since the borrower could have experienced income loss. Therefore, those traditional credit risk variables have weaker effect on the modified loans, compared with loans which have not been modified

The explanation for finding item 3 is a little bit tricky. The general belief for mortgage modification performance is that the re-default rate generally monotonously decreases as the payment reduction increases. Intuitively this makes a lot of sense since the more payment reduction, the less impact it will have on the borrower's residual income, and the lower the default risk for the loan modification.

Modification is generally justified when there is "imminent" default, which is to say, the borrower will surely default if there is no modification. Mathematically, it basically means the re-default rate will be 100% if there is 0% payment reduction. In the opposite case, if the payment reduction is 100%, i.e., the borrower is exempt from making any payments post-modification, the re-default rate will be 0%. Thus the conventional wisdom tells us that re-default rate should be a monotonous function, with regarding to payment reduction, and the relationship should look like the following.

Figure 4: Stylized Re-default Rate vs. Payment Reduction



However, one major assumption we made about the monotonous relationship between re-default rate and payment reduction is that all everything else equal.

Some of the variables we cannot directly observe, even at the time of origination, such as the income volatility. The income volatility contributes to default probability similarly as the asset probability contributes to default probability in traditional structural credit risk model. For example, in Merton (1974)'s seminal paper on defautable bond pricing in the option pricing framework, default occurs when the asset value drops below the liability at time of bond maturity. And the probability of default is driven by the following three factors. The first factor is firm's financial leverage. Higher leverage indicates the firm could lose its equity position easily, and increases the default probability. The second one is risk free rate. Higher risk free rate means higher drift term for the asset value in a risk-free world, and reduces the default probability. The third factor is asset volatility. Higher asset volatility widens the asset return distribution, and increases the default probability.

For consumer credit modeling, the asset level (collateral price) is still an important factor in determining default, since it measures the borrower's willingness to pay. However, consumers generally do not default immediately after the asset value (house price) drops below the mortgage balance, due to various reasons, such as attachment to the property, shelter needs, concerns about foreclosure records, etc. It is commonly believed the borrower would likely to default when both the following two conditions are met, unable to pay and unwilling to pay.

The collateral value drives the borrower's willingness to pay. When the borrower has positive equity in the house, even when she faces income loss and become unable to make the routine mortgage payment, she can still sell the house and avoid default. The income level drives the borrower's ability to pay. When the borrower has adequate disposable income to pay, even when the house is under water, she may choose to continue to keep the mortgage current. There have been many recent discussions on strategic default, defined as the borrower is able to pay, but choose not to, purely because of the negative equity position. However, if we look at the big picture, overall majority of the mortgage borrowers with negative equity are still making their payments. When the borrower is both unwilling **AND** unable to pay, default will occur. Thus, very similar to higher asset volatility drives up default probability, higher income volatility also drives up the default probability.

When we exam the common practice of loan modification, it generally follows the waterfall of rate reduction, term extension and principal forbearance/forgiveness.

According to Fannie Mae, the rule of thumb loan modification guideline is to limit the new debt-to-income ratio at 31%.[7] Thus the loan modification agent will first try to lower the mortgage rate to reduce the borrower's new debt-to-income ratio to that level. The borrower will need to go through income verification to prove that they did not lie about their new level of income. The rate reduction generally has a floor rate of 2%. If the debt-to-income ratio cannot be lowered to the target level even after excessive rate reduction, the modification agent will try to extend the mortgage term. However, the mortgage term cannot be extended for more than 40 years, and the benefit of payment reduction from a 30-year mortgage to a 40-year mortgage is limited. If both rate reduction and term extension cannot do the trick, the modification agent will consider principal forbearance and/or forgiveness. Both principal forbearance and forgiveness will put aside some principal for which part the borrower doesn't need to make principal and interest payment. It works as if the principal of the mortgage has been reduced. This approach theoretically can lower the mortgage payment, and hence the debt-to-income ratio to any level. The differ between principal forbearance and principal forgiveness is that the former approach still attaches the principal forborn as a second lien, which becomes due when the house is sold and there is residual revenue after the first lien mortgage is paid off, while the latter approach writes off the forgiven principal completely.

Under such strict constraint on debt-to-income ratio, we can reasonably assume that higher payment reduction implies higher income loss, thus higher income volatility. And this could very likely create the U-shaped re-default rate of modified mortgage loans.

5.2 Optimal Modification of Monotonous Re-Default Rate

From the lender's perspective, 0% re-default rate is not the "optimality" criteria. The lender's subjective is to maximize the present value of the loan modification. Ignoring discounting and re-default timing, the PV of a modified loan can be written as below, following the standard defaultable bond pricing formula. *LGD* is the loss given default rate, and is measured by the

[7] http://www.makinghomeaffordable.gov/tools/payment-reduction/Pages/default.aspx

$$PV = PD * (1 - LGD) * UPB_M + (1 - PD) * UPB_M$$

Where PD is the probability of default, and we can write it as a function of payment reduction:

$$PD = f(PR)$$

UPB_M is the *UPB* after modification, it can be written as a function of payment reduction as well, assuming the payment is reduced via principal forgiveness:

$$UPB_M = UPB_D(1 - PR)$$

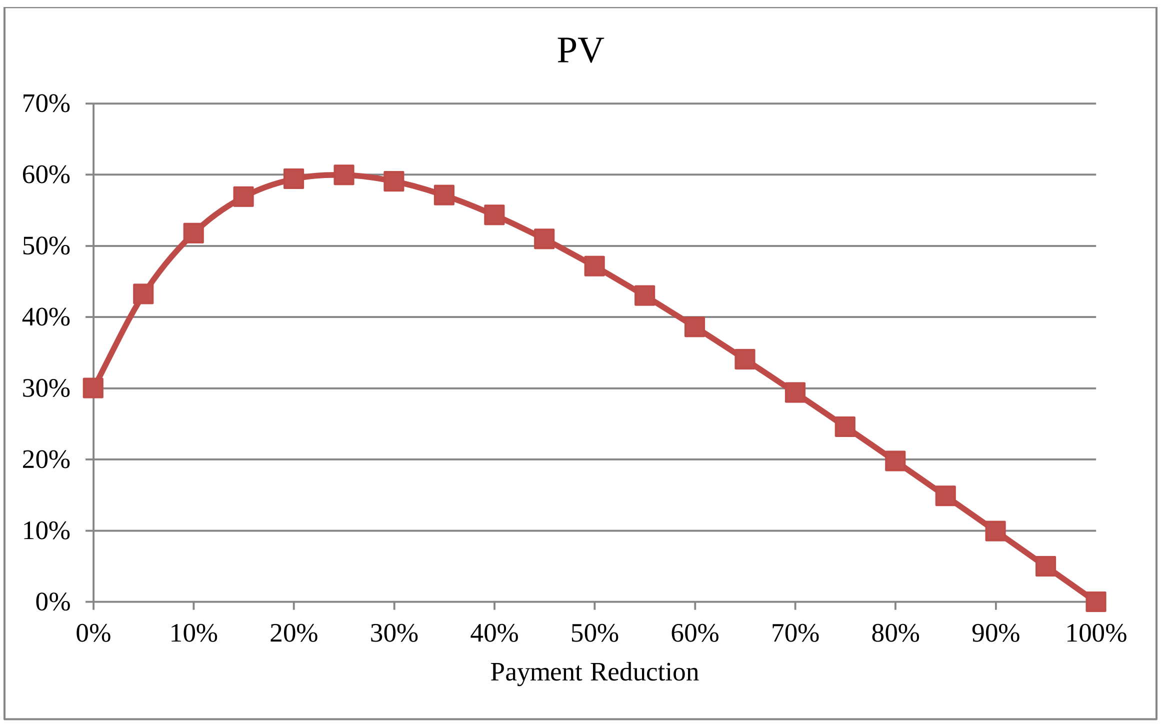
Where UPB_D is the *UPB* at the time of default.

Thus the PV can be written as:

$$PV = f(PR) * (1 - LGD) * UPB_D(1 - PR) + \big(1 - f(PR)\big) * UPB_D * (1 - PR)$$
$$= UPB_D(1 - PR) * (1 - f(PR) * LGD)$$

Obviously, when payment reduction is 100%, the PV is zero; when payment reduction is 0%, and re-default rate is 100%, the PV is $UPB_D * (1 - LGD)$, thus purely determined by *LGD*. The following chart shows the stylized PV, as a function of payment reduction.

Figure 5: Stylized Present Value vs. Payment Reduction



In order to find the optimal modification strategy, or payment reduction level, we need to take the first order derivative of the above formula, with regard to variable *PR*. When the first order derivative equals zero, we will find the optimal modification strategy which maximize the lender's PV from the loan modification.

$$\frac{dPV}{dPR} = UPB_D(-1) * (1 - f(PR) * LGD) + UPB_D(1 - PR) * \left(-\frac{\partial f(PR)}{\partial PR} * LGD\right) = 0$$

And the optimality condition follows as below:

$$(1 - f(PR) * LGD) = (1 - PR) * \left(-\frac{\partial f(PR)}{\partial PR} * LGD\right)$$

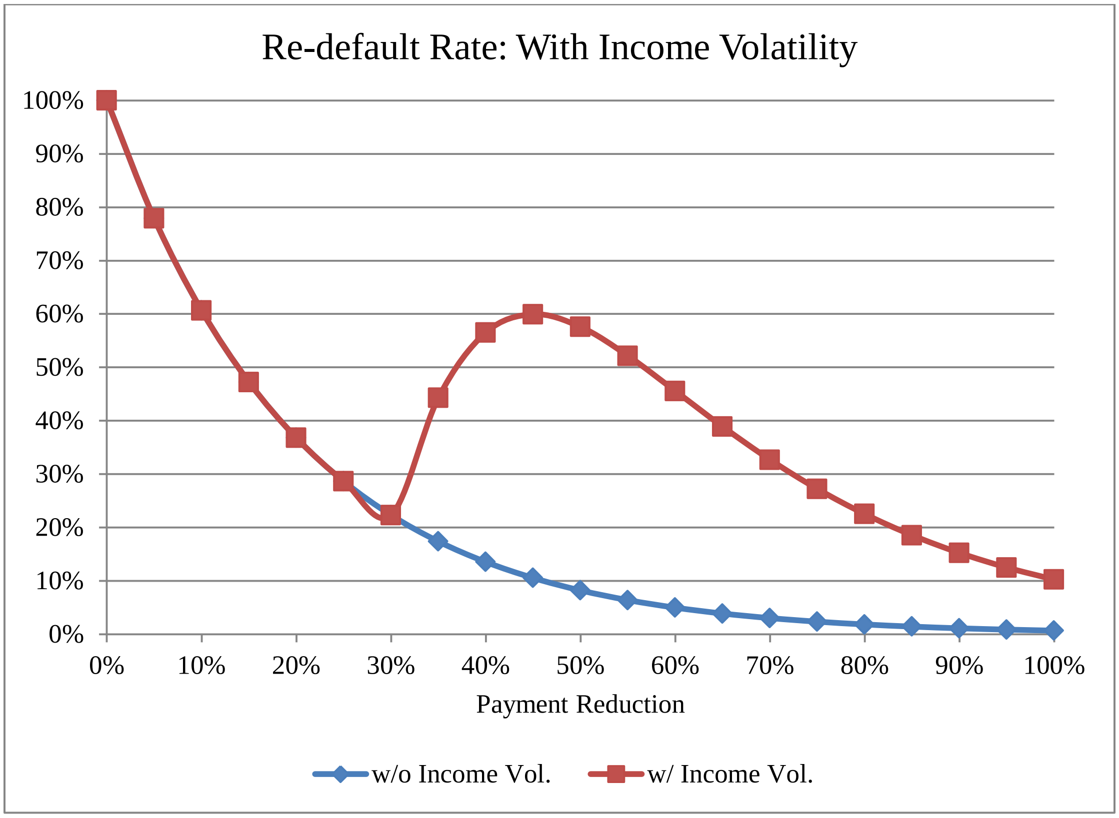
Assuming *f(PR)* is a monotonous decreasing function results in the following three conclusions, as demonstrated in Exhibit 2:

1. PV is a concave function of *PR*, and;
2. There exists a single optimal point, where PV is maximized by the *PR* satisfying the above optimality condition;
3. At the optimal point, the change of PV is relative mild with regarding to *PR*, which means even the optimality is violated in a small range, the difference from optimal PV is not huge.

5.3 Optimal Mortgage Modification with Non-Monotonous Re-Default Rate

If we introduce the payment reduction magnitude as a proxy for income volatility, the additional benefit of marginal payment reduction might be offset by the increased income volatility, as demonstrated in the following stylized example of re-default rate with income volatility.

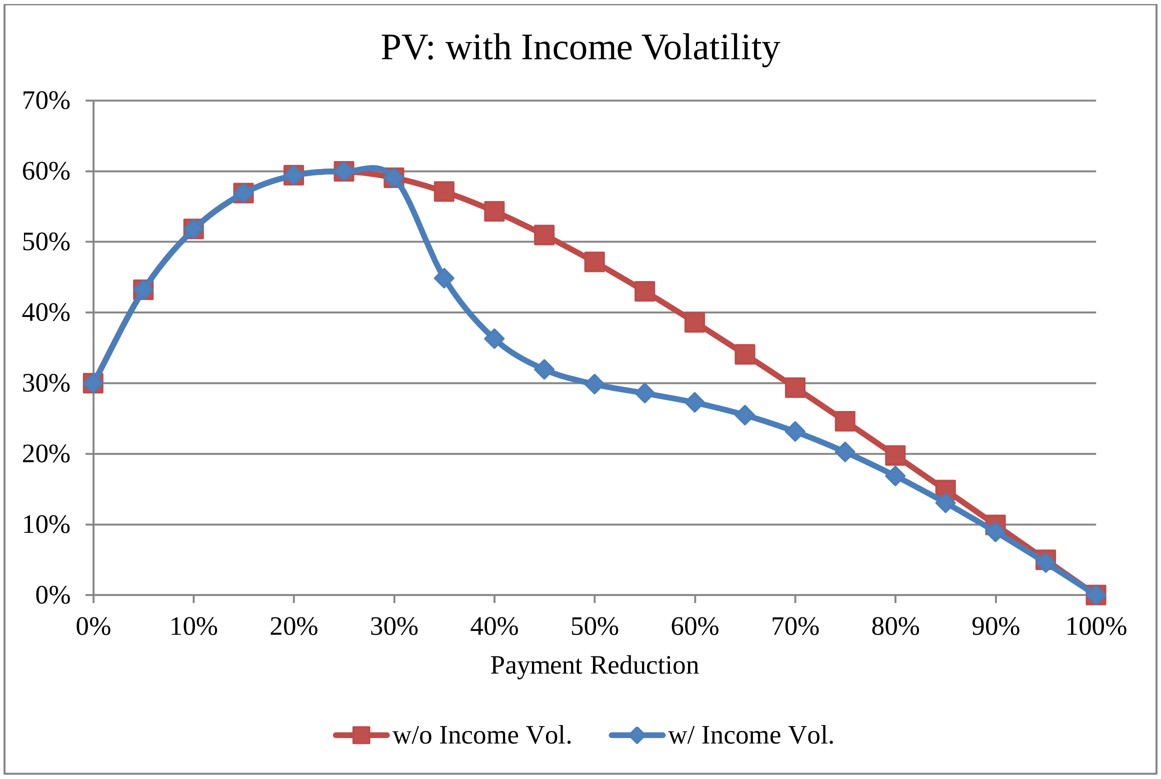
Figure 6: Stylized Re-default Rate with Income Volatility



Following the logic to derive the optimal modification strategy in 5.2, we plot the PV as a function of payment reduction, with income volatility as in Figure 7. Under this new assumption, it can be seen that

1. PV is NO LONGER a concave function of *PR*, and;
2. There still exists a single optimal point, which may not overlap with the optimal point under the optimality condition without income volatility;
3. At the optimal point, the change of PV is relative sensitive with regarding to *PR*, which means even the optimality is violated in a small range, the difference from optimal PV could be significant.

Figure 7: Stylized PV with Income Volatility



6. Conclusion and Future Research

In this paper, we use FHA modified loans to investigate the effectiveness of modification in preventing re-default. Loan-level data is used to trace the performance of loans with heavy modifications. The empirical results show that modified loans tend to have much higher re-default risk than otherwise identical never-defaulted loans. Also the loan modification re-default rate is less sensitive to traditional credit risk drivers, compared to never-modified loans. The re-default risk declines initially with the magnitude of the payment reduction associated with the modification received. However, as the payment reduction becomes substantial, the re-default probability increases.

The last finding is the first time such phenomenon being identified. It not only changes our intuition about the relationship between re-default rate and payment reduction, but also makes us to re-think what the best way to modify distressed residential mortgages is.

We plan to further explore the impact of income volatility on mortgage default behavior. Yang, Buist, and Megbolugbe (1996) has built the theoretical framework and incorporated borrower income as a random driver for mortgage termination. Yet it has not included empirical data to support the results. Diaz-Serrano (2005) finds that borrowers with higher income volatility may not be able to accumulate precautionary savings to meet mortgage payments when shocks in income occur. However, it is using national level macroeconomic data, which is very likely affected by other latent macro factors. We will try to establish a plausible theoretical framework with income volatility explicitly imbedded, and locate microeconomic level indicator for income volatility to support the theory empirically.

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Appendix

Table A1. Status of Mortgages Modified in 2008-2Q2013

	Total	Current	30-59 Days Delinquent	Seriously Delinquent	Foreclosures in Process	Completed Foreclosures	Paid Off	No Longer in the Portfolio*
2008	443,294	21.1%	4.3%	9.2%	5.4%	16.7%	4.5%	38.9%
2009	593,884	31.2%	5.3%	11.5%	6.2%	12.7%	4.1%	28.9%
2010	955,422	40.0%	5.9%	11.0%	5.5%	8.2%	3.1%	26.2%
2011	569,553	47.4%	6.6%	12.3%	5.5%	4.0%	2.4%	21.7%
2012	479,820	61.5%	8.0%	12.3%	3.9%	0.9%	1.2%	12.2%
2013	246,744	70.4%	8.9%	9.4%	1.2%	0.1%	0.5%	9.5%
Total	3,288,717	42.6%	6.3%	11.1%	5.1%	7.8%	2.9%	24.3%
HAMP Modification Performance Compared With Other Modifications**								
Other Modifications	1,774,830	46.2%	7.3%	13.3%	5.5%	6.3%	2.8%	18.6%
HAMP Modifications	732,747	53.8%	5.4%	7.2%	3.3%	3.4%	1.7%	25.3%
Modifications That Reduced Payments by 10 Percent or More								
	2,083,687	48.7%	6.3%	9.6%	4.1%	5.2%	2.1%	23.9%
Modifications That Reduced Payments by Less Than 10 Percent								
	1,205,030	31.9%	6.2%	13.8%	6.7%	12.1%	4.2%	25.0%

*Processing constraints prevented some servicers from reporting the reason for removal from the portfolio.
**Modifications used to compare with HAMP modifications include only modifications implemented from the third quarter of 2009 through the second quarter of 2013.
Source: http://www.occ.gov/publications/publications-by-type/other-publications-reports/index-mortgage-metrics.html