Liquidity constraints, home equity and residential mortgage losses*

Hung Xuan Do[a,b†], Daniel Rösch[c], Harald Scheule[b]

[a]*School of Economics and Finance, Massey University, New Zealand*

[b]*Finance Discipline Group, UTS Business School, University of Technology, Sydney*

[c]*Department of Statistics and Risk Management, Faculty of Economics, University of Regensburg*

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† Corresponding author.

Email addresses: h.do@massey.ac.nz (Hung Xuan Do), daniel.roesch@ur.de (Daniel Rösch), harald.scheule@uts.edu.au (Harald Scheule).

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ABSTRACT

This paper analyses how mortgage borrower liquidity constraints and home equity drive the realized loss rates given default using loan-level data. We define defaulted loans with zero loss as cures and those with non-zero loss as non-cures. We find economically that borrower liquidity constraints and positive equity explain cure, while negative equity explains non-zero loss. The findings provide an important economic-rationale for a separation of the cure and loss processes in mortgage loss models and their applications such as loan pricing and bank capital regulation. The results have great relevance for the multi-trillion dollar mortgage industry for a more efficient capital allocation, better mortgage pricing and more forward-looking loan loss provisioning.

Keywords Cure • Loss Given Default • Liquidity Constraints • Home Equity • Mortgage • Resolution • Selection.

JEL Classification G21 • G28 • C19

1. Motivation

Residential mortgage loans are by far the most important asset class on bank balance sheets. Data released by the Federal Reserve Bank shows that all US commercial banks held real estate loans equivalent to $3.7 trillion in 2008 and $3.9 trillion in 2018. Mortgage credit risk is closely related to house prices and was considered to be a low risk prior to the Global Financial Crisis (GFC). Given default, mortgage loans often cure and result in zero loss rates given default (LGD). Commercial banks estimate probabilities of default (PDs) and LGDs for loan loss provisioning, regulatory capital requirements and loan pricing.

The GFC and subsequent literature have shown that borrowers may default in response to (i) liquidity constraints, (ii) negative equity, or a combination of both. For example, Elul et al. (2010) and Demyanyk et al. (2011) consider credit card utilization rates to proxy for liquidity constraints of borrowers and find that mortgage default is driven by both liquidity constraints and negative home equity. Foote et al. (2008) and Bhutta et al. (2010) document the impact of negative equity on mortgage default for the US. Gerardi et al. (2018) employ data from the Panel Study of Income Dynamics to analyse the impact of household level income and housing equity shocks on mortgage default and find both factors play significant roles in explaining mortgage default decisions. In addition to this strand of the literature, Campbell and Cocco (2015) introduce a dynamic model that explains the mechanism through which the loan-to-value (related to home equity) and loan-to-income (related to liquidity constraints) ratios affect mortgage default.

Whilst the distinction between liquidity constraints and home equity has been analysed in the context of default prediction, the consequences on bank risk and losses from defaults, namely LGDs has not been considered. The majority of existing research focuses on unsecured credit exposures such as corporate and credit card loans without dissecting liquidity and negative equity processes. Examples are Chava et al. (2011), and Jankowitsch et al. (2014).

In terms of residential mortgage loans, the empirical LGD distribution generally has a bimodal shape with a high peak at zero. Figure 1 shows that nearly 30% of the total LGD observations are zero-LGDs. That is, a significant fraction of defaulted loans does not generate losses. This is due to either (i) a bank's strategies in dealing with the defaulted loans such as loan modification or outright forgiveness of scheduled payments; or (ii) the property value after foreclosure exceeding the value of the outstanding loan and associated resolution (i.e., workout) costs. We follow Do et al. (2018) to define defaulted loans with zero-LGD as cure loans and those with non-zero LGD as non-cure loans.[1] We hypothesize that default events which result in cures are more associated with the liquidity constraints of borrowers and those not cured with negative equity.

[Figure 1 about here]

We investigate the hypothesis by employing the methodological spirit of Yao et al. (2017) and Do et al. (2018), which suggest modeling cure and non-cure loans differently. We modify the Heckman selection model (see Heckman, 1979) so that the dynamics of cure and non-cure loans are captured in two stages. The first stage aims to model the probability of cure and the second stage devises the magnitude of the non-zero LGD. Both stages are estimated jointly and Figure 2 illustrates this approach. This methodology has the merit of separately tracking the processes of cure and non-zero LGD. We find that mortgage defaults experiencing liquidity constraints and/or positive equity have a greater likelihood of resulting in cure events while mortgage defaults with negative equity have a greater likelihood of resulting in non-zero LGDs. The findings imply that negative equity was more causal than borrower liquidity constraints to the losses realized during the GFC, which differs from the liquidity constraints experienced by banks. Mortgage borrower liquidity is related to the probability of cure in a v-shape fashion.

[1] In this paper, we use the two terms non-zero LGD loan (zero LGD loan) and non-cured loan (cured loan) interchangeably.

The findings provide a strong economic-rationale for observed LGDs, the separation of the cure and loss processes in residential mortgage loss models and applications such as loan pricing, forward-looking loan loss provisioning and bank capital regulation. The expected loss rate given default under this approach is calculated as (1-Probability of Cure)×(Non-zero LGD), which may replace the current singular treatment in bank calculations that averages over the cure and non-zero loss process. This will improve banks' efficiency in capital utilization because capital costs of the expected losses will be meaningfully lower if a portion of defaulted loans in a bank's residential mortgage portfolio can be adequately linked with a high cure probability. A separation of the two processes allows for a better identification and lower cross-subsidization between loans.

[Figure 2 about here]

Negative equity and liquidity constraints are overlapping with a number of external factors. For example, liqudity constraints reflect the length of delinquency, moratorium on foreclosures and scandals in the mortgage market. The literature on loss rate modeling includes a number of contributions. Qi and Yang (2009) and Zhang et al. (2010) analyse factors driving loss severities including the economy at loan origination and the economy during a loan's life. Andersson and Mayock (2014) model Florida mortgage LGDs and control for the fact that loss severities are only observed post default. Related to this, Campbell et al. (2011) show that house prices related to foreclosure are lower than the market prices. Clauretie & Daneshvary (2009) analyse different sales choices by the lender and find a trade-off effect between lowest price discounts and marketing costs. Clauretie and Herzog (1990) and Collins et al. (2011) analyse the impact of state foreclosure policies on loan losses and modifications. Ambrose and Capone (1996) provide a cost-benefit analysis for foreclosure alternatives. Cordell and Lambie-Hanson (2016) document greater foreclosure timelines post GFC and Cordell et al. (2015) analyse the implied costs. Le and Pennington-Cross. (2018) decompose losses into property

sales and holding costs. Park and Bank (2014) analyse the impact of seniority and the macro economy on loss rates for Korean mortgages.

The remainder of this paper is organized as follows. Section 2 describes the data source and construction of variables. We provide the preliminary analyses in Section 3. Section 4 develops an econometrics framework for modeling LGDs which follows a two-step-selection mechanism for cure and non-cure loans. Section 5 discusses empirical results and Section 6 concludes the paper.

2. Data and construction of variables

2.1 Data

Our sample is provided by International Financial Research, which collects subprime loan level origination and performance data for the US non-agency residential mortgage-backed securities. The data is published to meet the information requirements of investors in these securities provided by the servicing agents. Similar data has been used in other studies such as Rajan et al. (2015). The data has similar properties to prime mortgages in terms of risk drivers but has higher default and loss rates. Agarwal et al. (2012) confirm that subprime loans are not exposed to adverse selection.[2]

We focus on single-family first lien loans and aggregate monthly intervals to quarterly intervals observed from 2005:Q2 to 2015:Q1. The complete dataset contains information on the loan (e.g., loan issuer, actual loan balance at origination and observation time, scheduled loan balance at the end of each period, loan age, interest rate and loan type), on the property (e.g., property location, property value at origination, owner occupancy), and on the borrower (e.g., FICO score at origination).

[2] In the study of Agarwal et al. (2012), adverse selection bias is broadly defined as the subjective decision of lenders to retain some specific types of loans (e.g., loans with high quality) in their portfolio while selling others to investors (e.g., loans with lower quality).

Further, the data includes information about (i) the initial loss as the cost of repossession and write-off of any accrued interest not received based on a current valuation by the servicer (loss on liquidated property) and (ii) subsequent losses, which are adjustments for the actual sale if the sale is below the mortgage amount less the initial recovery cost (loss on previously liquidated loans). Initial losses are recorded if a deficient valuation or a debt service reduction (i.e., loan modification) is noted. Losses include "out-of-pocket" expenses of servicers such as expenses spent on preserving the collateral property (maintenance costs), legal fees and other foreclosure related expenses (see Levitin, 2010). After delinquency and before liquidation, servicers continue to advance payments and the interest on such advances is not included in our loss definition.[3] We include both original and the subsequent losses in the calculations of losses given default.

We define the default event as loan foreclosure and exclude defaulted loans that have not yet been resolved (unresolved loans, hereafter).[4] We consider a defaulted loan as resolved if the servicer has excluded the loan from its portfolio and no further losses accrue to investors. Further, observations with missing values in variables are omitted and we finally record 509,408 defaulted loans that are resolved, which peaked during the crisis period (see Table 1).[5]

[3] The procedures to calculate investor losses are detailed in the Residential Mortgage-Backed Security (RMBS) prospectus and the pooling and servicing agreement. Cordell et al. (2008) show that servicers have a liability to act in the best interest (i.e., maximising value) of investors.

[4] Clauretie and Daneshvary (2009) show that mortgage foreclosure may result in various outcomes: third party sales, deed in lieu (transfer of title to lender), real-estate owned (lender owns the property after it fails to sell) or short sale (sale by homeowner with consent of lender). The data used in our paper is reported by loan servicers and we do not observe the channel that led to the loan loss.

[5] We follow Bekaert et al. (2014) to define the start of the subprime mortgage crisis as 7 August 2007, due to the initial fall of equity markets and the first intervention of central banks to provide liquidity to financial markets. The end of the GFC is defined as 29 May 2009 with reference to the National Bureau of Economic and Research.

2.2 Cure and non-zero loss given default

LGD represents the economic loss at default and it is common to discount workout cash flows to the time of default and compute the aggregate loss rate given default. We define the LGD of a loan as the present value of losses, divided by the current outstanding loan balance (current balance, hereafter) at default. We follow Qi and Yang (2009) and other contributions to discount losses to the time of default using the one-year LIBOR at default plus a spread of 3% for systematic risk. This discount rate is in line with Scheule & Jortzik (2017).[6] Hence, the LGD of loan *i* defaulted at time t_d is calculated as:

$$LGD_{i,t_d} = \frac{1}{Current\ Balance_{i,t_d}} \times \sum_{t=t_d}^{T} \frac{Losses_{i,t}}{(1+r)^{t-t_d}} \tag{1}$$

where *r* is the discount rate.

Our data contains information about the losses resulting from loan defaults until the first quarter of 2015. Most non-zero losses realize within 3 years of the default events.

Loans which have recently defaulted (e.g., 2014) have low resolution times (e.g., one year) and low LGDs. On the other hand, long resolution times imply greater losses that may in parts be explained by property neglect as documented by Lambie-Hanson (2015) and Harding et al. (2009). As a result, the mean LGD decreases towards the end of the observation period. This resolution bias is intrinsic to all workout information and we control for it by the time from default to the last observation of the entire sample (i.e., 2015:Q1) (DefaultToEOO). Note that DefaultToEOO is by design orthogonal from default.

[6] Realised losses are generally lagging the real economy. The study shows that LGDs imply beta coefficients for North America of approximately 50%. Applying a market risk premium of 6% translates into a risk premium of 3%.

Following Eq. (1), we define cure as zero LGD and non-cure as non-zero LGD, respectively. We summarize the cure rate and average LGDs per origination and observation year in Table 1. Consistent with Demyanyk and Hemert (2011), the majority of default loans are originated in years immediately prior to the GFC. Further, both average LGD (including zero-LGD) and average non-zero LGD (excluding zero LGD) peak for these vintages. This behaviour is opposite to the cure rate, which experiences troughs (equivalently, peaks with non-cure rate) during these years.

[Table 1 about here]

The trend of non-zero LGDs is inverse to the cure rate (or equivalently, is in harmony with the non-cure rate). These movements suggest a negative relation between cure rates and non-zero LGDs at *their mean level*. Comparing the average LGD and average non-zero LGD, we observe a time varying gap between them, which is mainly due to the changing behaviour of the cure rate. This indicates different dynamics between cure and non-cure loans and motivates us to analyse zero and non-zero LGDs in separation.

2.3 Test variables

In this section, we describe how we construct the test variables (i) borrower liquidity constraint and (ii) home equity. The full set of the explanatory variables is summarized in Table 2.

[Table 2 about here]

2.3.1 Borrower liquidity constraint

Mortgage performance data generally does not include information on borrower income, income changes or usages of liquidity facilities such as credit cards. We proxy borrower liquidity constraints by observed accumulated arrears. A borrower experiences a liquidity constraint if he or she cannot meet the loan repayment obligations. As a result, the actual current loan balance (current balance) is greater than the scheduled loan balance (scheduled balance). A larger gap between the actual balance and the scheduled balance reflects a higher level of borrower liquidity constraint. We calculate the liquidity constraint measure for borrower *i* at time *t* (denoted as LC_{it}) as follows: [7]

$$LC_{it} = \frac{Current\ Balance_{it} - Scheduled\ Balance_{it}}{Scheduled\ Balance_{it}} \times 100\% \qquad (2)$$

Note that we define default as foreclosure and our sample only includes foreclosed loans. In case of a foreclosure, accumulated arrears are observed if (i) the borrower is unable to make scheduled mortgage payments (i.e., liquidity constraint) or (ii) the borrower is able but strategically unwilling to make scheduled mortgage payments. The second case is generally due to negative equity, which has been documented in previous studies (e.g., Mian and Sufi, 2009; Gerardi et al., 2018). To control for strategic default we exclude all foreclosed loans with negative equity in a robustness test by the partitioned sample analysis shown in Table 9 and Figure 8.

According to the construction of the *LC* variable, there are two economically meaningful cases: (i) the borrower meets scheduled payments ($LC_{it} = 0$) or makes curtailment payments for the

[7] We set LC_{it} to zero if the current balance and scheduled balance are both zero, indicating that the borrower has repaid the loan in full and does not experience a liquidity constraint. We consider LC_{it} as a missing value (and exclude from analyses) if the scheduled balance equals zero but the current balance is positive. This has no further implications on the results as this filter rule only applies for six defaulted loans.

loan ($LC_{it} < 0$);[8] and (ii) the borrower does not meet scheduled payments and experiences a liquidity constraint ($LC_{it} > 0$). To control for potential outliers, we winsorize the *LC* values at the 5th and the 95th percentile.

2.3.2 Home equity

We employ the current loan-to-value ratio (*CLTV*) to measure home equity:

$$Home\ equity = 1 - CLTV \tag{3}$$

Home equity has a maximum value of one and is negative if the current value of the property drops below the current loan balance (i.e., *CLTV* is greater than one) and positive if the property value is equal or greater than the outstanding loan balance (i.e., *CLTV* is lower than one).

Similar to the *LC* variable, we also include splines for *Home equity* as summarized in Table 2 to allow for non-linear relations with regard to the probability of cure and the non-zero LGD models. We control for potential outliers by winsorizing *Home equity* values at the 5th and the 95th percentile.

As the information on the current value of the property is unavailable, we employ the House Price Index (HPI) for 401 Metropolitan Statistical Areas (MSAs) provided by the Federal Housing Finance Agency (FHFA) to calculate *CLTV*.[9] We first map the zip code of the property to the MSA of the HPI by using mapping data provided by the US Department of

[8] In either of these situations, the borrower does not experience a liquidity constraint. Curtailments refer to the cases where borrowers make extra principal loan repayments for their mortgages, and therefore, current balances are less than scheduled balances (see for example, Amromin et al., 2007; Adelman et al., 2010).

[9] We also perform a robustness check below using Zillow HPI as well as the 3-digit and 5-digit Zip Code FHFA HPI at the zip code level and obtain consistent results. This is consistent with Glennon et al. (2018) who find that the FHFA HPI index is comparable to other commercial HPI measures such as the Case-Shiller MSA index, and the Black Knight index (at the zip code , MSA , and state level).

Housing and Urban Development (HUD).[10] We then calculate the *CLTV* of loan *i* at observation time *t* as:

$$CLTV_{it} = \frac{Current\ Balance_{it}}{Current\ Appraisal\ Value_{it}} \tag{4}$$

where the current appraisal value is approximated by the HPI of the MSA *m* for loan *i*:

$$Current\ Appraisal\ Value_{it} = Original\ Appraisal\ value_{it_0} \times \frac{HPI_{mt}}{HPI_{mt_0}} \tag{5}$$

2.3.3 Non-linear effects

Further, we include spline terms for home equity and liquidity constraint as summarized in Table 2 to capture potential non-linear relations between the borrower liquidity constraint and probability of cure or non-zero LGD. The spline term at each knot (threshold) is constructed as:

$$\text{spline (variable, knot)} = \begin{cases} 0, & \text{if variable} < \text{knot} \\ \text{variable} - \text{knot}, & \text{if variable} \geq \text{knot} \end{cases}$$

The splines capture the additional effect in excess of the variable's effect for values above the knot level and the combined effect is equal to the sum of the variable and all spline effects.

The application of spline terms is motivated by the empirical evidence of a non-linear relation between the test variables and the components of LGD shown in Figure 3 and Figure 4. An advantage of the spline terms over some other techniques such as dummy coding for variable categories is the modeling of a continuous relations. A number of studies have

[10] We exclude loans with missing zip codes.

employed spline terms in credit risk modeling (see for example, Calem and LaCour-Little, 2004; Dirick et al., 2016; Kelly and O'Toole, 2018).

2.4 Control variables

We employ several variables common in the literature to explain the dynamics of the probability of cure and non-zero LGD including loan characteristics, borrower characteristics, property characteristics and economic conditions.[11]

Although there have been few studies focusing on residential mortgage LGD, a variety of determinants of loss severities have been examined. For example, a number of loan characteristics including loan age, size, type, and purpose have been investigated (see, Clauretie and Herzog, 1990; Lekkas et al., 1993; Pennington-Cross, 2003; Qi and Yang, 2009; Zhang et al., 2010). Property characteristics including owner occupancy, property types, (e.g., single family, condominium and manufactured house) and state foreclosure laws (judicial process, statutory right of redemption, deficiency judgment) are examined in Clauretie and Herzog (1990), Pennington-Cross (2003), Qi and Yang (2009), and Zhang et al. (2010). Economic conditions including housing market conditions, unemployment rate, real economic growth and median income are considered in Clauretie and Herzog (1990), Qi and Yang (2009), and Zhang et al. (2010). However, we observe that no study to date considers the FICO score as a driver of mortgage LGDs. This might be due to a common belief that FICO score is predictive for default and not predictive for LGD. We run a preliminary test on the relation between FICO and LGDs using Ordinary Least Square (OLS) regressions with clustered

[11] We do not include the loan age in our set of control variables because of the collinearity between loan age and the *DefaultToEOO* (a variable that we use to control the resolution bias), which results from standard maturities (in particular 30 years) applied to most of the analysed mortgage contracts. For state foreclosure laws, we do not include judicial process (*JP*) in the cure equation but the non-zero LGD equation. This helps to differentiate sets of covariates used in the two equations of our two-step selection approach (see Section 4) to avoid an identification problem for the selection model.

standard errors and find an unexpected result that higher FICO scores (i.e., higher credit quality borrower) are associated with higher LGDs.[12] We demonstrate below that this result is reasonable in a two-step selection model for cure and non-cure loans.

We summarize the definition and the source of these control variables in Table 2 and explain the empirical results for all control variables in Section 5.3.

3. Descriptive analysis

In this section, we provide a descriptive analysis for the relations between the probability of cure or non-zero LGD and the explanatory variables. Note that we only analyse default observations.

For categorical control variables, we report the relative frequency (%) of the discrete control variables for defaulted, cure and non-cure loans in Table 3. We observe a higher (lower) relative frequency of ARM (Owner Occupied) loans for non-cure loans than for cure loans. This is in line with our expectation that ARM (Owner Occupied) loans contain higher (lower) risk than fixed rate (investment) mortgage loans. Further, it is likely that defaulted loans originating from states that apply statutory right of redemption or prohibit deficiency judgement are less likely to be cured. These are inferred from a lower relative frequency of cure loans originated in states that prohibit deficiency judgement or apply statutory right of redemption compared to non-cure loans.

[Table 3 about here]

[12] To conserve space, we do not provide estimated results of these preliminary models. Details are available upon request.

We summarize the descriptive statistics of the main test variables and continuous control variables as well as their pairwise correlations in Table 4 and 5.

[Table 4 and 5 about here]

The pairwise correlations in Table 5 show that the relation between the continuous control variables and non-zero LGDs follow economic intuition.

Cure loans generally have a higher credit quality, home equity, house price appreciation and real GDP growth than non-cure loans. These statistics are in line with the positive correlations between these control variables and the cure rate. Furthermore, cure loans have a lower current interest rate and loan size, which is consistent with negative correlations between these variables and the cure rate as observed in Table 5.

Exceptions are liquidity constraint, FICO score and the unemployment rate, which do not follow that common behaviour. We discuss the FICO score, unemployment results and liquidity constraint below. The FICO score represents the credit quality of a borrower, whereby a higher FICO score implies a lower credit risk. Table 4 shows that the FICO score has a lower mean for cure loans compared to non-cure loans. These statistics are also consistent with a negative correlation between the FICO score and the cure rate that we observe in Table 5. In fact, this unique characteristic of the FICO score in cure loan can be explained by the common behaviour of borrowers trying to maintain their credit quality and is discussed in more detail in Section 5.3.

We observe that the unemployment rate has a higher mean in cure loans in comparison to non-cure loans. This adverse behaviour of the unemployment rate towards cure might be due to an increase in the unemployment rate and may reflect a higher likelihood of experiencing a liquidity constraint, as a loss of job implies a constraint on the mortgage serviceability and hence borrower liquidity. The liquidity constraint of the borrowers should be positively related

to cure loans. The pairwise correlations between cure rate, borrower liquidity constraint and unemployment rate are positive. The correlation between cure rate and borrower liquidity constraint is greater than the correlation between cure rate and unemployment rate.

Regarding the key test variables (i.e., borrower liquidity constraint and home equity), we find that their central measures are both significantly higher for cure loans than for non-cure loans (see Table 4). The positive correlation between these variables and the cure rate in Table 5 confirms that the borrower liquidity constraint and positive home equity are more associated with cure than non-cure events.

These relations may not be linear and thresholds may exist. That is, the sensitivity of cure rate changes if liquidity constraints and home equity cross the zero thresholds. In terms of home equity, the zero threshold distinguishes whether the equity position is positive or negative. Regarding the borrower liquidity constraint, zero is the threshold that differentiates whether the borrower makes curtailments for the loan or experiences liquidity constraint. We visualize the relations between borrower liquidity constraints, home equity and cure rate in Figure 3 and 4, respectively. We identify that thresholds of 0, 0.04, 0.08 and 0.52 of the borrower liquidity constraint are critical points where the relation changes. The thresholds of -0.2, 0, 0.1 and 0.2 of home equity (equivalent with *CLTVs* of 1.2, 1, 0.9 and 0.8, respectively) were chosen in line with the literature (e.g., Qi and Yang, 2009; Gerardi et al., 2018).

[Figure 3 and 4 about here]

Figure 3 shows that the relation between cure rate and borrower liquidity constraint follows an asymmetric v-shape with a long right-tail and a trough around 0.04%. Figure 4 displays an asymmetric tilde (~) – shape relation between home equity and the cure rate with a very high right-tail. These behaviours are confirmed by the relative frequency of cure and

non-cure rate by borrower liquidity constraint and home equity categories as shown in Table 6.

In summary, we observe from Table 3 as well as Figure 3 and 4 that the borrower liquidity constraint and positive home equity are associated with cure loans, whereas the negative home equity is more related to non-cure loans. These are also consistent with the pairwise correlations between cure rate, non-zero LGD, liquidity constraint and home equity observed in Table 2, which shows significantly positive correlations between liquidity constraint, home equity and cure rate and significantly negative correlations between home equity and non-zero LGD.

[Table 6 about here]

Borrower liquidity constraint is positively correlated with home equity, due to a time-delayed reflection between unemployment and borrower liquidity constraints. Normally, one would expect low unemployment rates and high home equity during an economic upturn as well as high unemployment rates and low home equity during an economic downturn. A negative correlation between borrower liquidity constraint and home equity is expected as the unemployment rate may lead to liquidity constraints (e.g., the loss of income may result in the inability to service a loan). Figure 5 shows that the dynamics of the unemployment rate and home equity support these expectations. However, we observe that the impact of the unemployment rate on the borrower liquidity constraint is lagged by one year (i.e., time-delayed reflection). Job losses do not translate into liquidity constraints in a contemporary fashion and the impact is lagged by approximately one year. This is reasonable as borrowers may rely on other sources of funding for some time after becoming unemployed. Besides, lenders may also support the borrowers to rectify the loan in this period by modification of payment terms or forgiveness of scheduled payments.

[Figure 5 about here]

We check the effect of the time-delayed reflection by looking at the correlation of a lag of four with the unemployment rate and home equity. We find that the correlation between the average borrower liquidity constraint and lag four of the average unemployment rate (home equity) is about 70% (-56%). This time-delayed reflection explains the positive contemporary correlation between borrower liquidity constraint and home equity that we observe in Table 5.

We inspect the sensitivity of the relation between a borrower liquidity constraint and LGD (including cure and non-zero LGD) against the time-delayed reflection effect by looking at the scatter plots between their time averages (see Figure 6). The overall positive association between borrower liquidity constraint and the cure rate is robust regardless of the time-delayed reflection effect. However, we observe a moderate negative association between the borrower liquidity constraint and the non-zero LGD, which becomes almost insignificant when we use a lag of four for the non-zero LGD. This indicates that the negative contemporaneous association between borrower liquidity constraint and non-zero LGD is not economically meaningful. This confirms that the association is due to the coincidental movements between the borrower liquidity constraint and home equity caused by the time-delayed reflection effect.

[Figure 6 about here]

4. Modeling framework

To address the bimodal nature of the LGD distribution, we follow the suggestion of Do et al. (2018) to capture the cure and non-cure loans in different modeling stages.[13]We modify the Heckman selection model to a two-step selection mechanism of the observed loss severities that conditions on the selecting non-cure event and considers censoring of non-zero LGD. The

[13] Our model differs as we condition on foreclosure.

two-step modeling includes: (i) the probability of cure for default events; and (ii) the non-zero LGD for defaults and non-cures. This selection mechanism is visually shown in Figure 2. We apply censored regression models for the non-zero LGD in the second stage as LGD is bounded by zero and one. Hence, our model includes two equations that can be summarized as follows:

(4.1) Probability of Cure (PC)

$$C_{it}^{*} = X'_{i,t-1}\beta + u_{it} \qquad u_{it} \sim N(0,1) \qquad (6)$$

$$C_{it} = \begin{cases} 1 & if\ C_{it}^{*} > 0 \\ 0 & if\ C_{it}^{*} \leq 0 \end{cases},$$

In our PC model (4.1), the cure variable, C_{it}, is a binary variable indicating whether the defaulted loan is cured ($C_{it} = 1$) or non-cured ($C_{it} = 0$), which is characterized by the outcome of the underlying latent process $C_{it}^{*} > 0$ or $C_{it}^{*} \leq 0$. $X_{i,t-1}$ is a vector of all cross-sectional and time-varying variables observed in the previous quarter that explains the PC, β is the vector of parameters and the error term u_{it} is assumed to follow a standard normal distribution.

(4.2) Non-zero LGD

$$L_{it}^{*} = Z'_{i,t-1}\alpha + \varepsilon_{it} \qquad \varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^{2}) \qquad (7)$$

$$L_{it} = \begin{cases} 1 & if \quad L_{it}^{*} \geq 1 \\ L_{it}^{*} & if \quad 0 < L_{it}^{*} < 1 \end{cases},$$

Following the selection mechanism shown in Figure 2, the magnitude of non-zero loss severity for loan *i* at time *t*, L_{it}, is only observed if loan *i* which defaults at time *t* is not cured (i.e., $C_{it} = 0$). In that case, the non-zero loss severity L_{it} is observed and follows a censored linear relation characterized by the underlying latent process L_{it}^{*} as shown in Eq. (4.2), where, $Z_{i,t-1}$ is a vector of all time-varying determinants of the LGD observed in the previous quarter and α is the associated parameter vector. We assume a normal distribution with zero mean and σ_{ε}^{2} variance for the error term ε_{it}. We find that the empirical distribution of the error term, ε_{it}, is

very close to normal, with skewness and excess kurtosis close to zero (e.g., -0.355 and 0.345 for our main model, respectively).[14]

Since these two linear equations are included in one closed system, the vector of error terms is assumed to follow a multivariate normal distribution:

$$\begin{pmatrix} u_{it} \\ \varepsilon_{it} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{u\varepsilon}\sigma_{\varepsilon} \\ \rho_{u\varepsilon}\sigma_{\varepsilon} & \sigma_{\varepsilon} \end{pmatrix}\right] \tag{8}$$

where $\rho_{u\varepsilon}$ denotes the correlation between the two error terms, u_{it} and ε_{it}.

We estimate the model using Maximum Likelihood estimation and we provide a derivation of the likelihood function in Appendix A. In addition, we ensure the robustness of our approach by comparing its forecasting performance with the popular OLS method used by many banks. We present the comparison results in Appendix B.

[14] We have also tested non-linear transformation models with clustered standard errors (such as logit and probit) for non-zero LGD and find consistent results. Details are available on request.

5. Empirical results

We examine the relations between borrower liquidity constraint/home equity and LGD by estimating the model with and without control variables for the full sample. As a robustness check, we separately investigate the crisis periods (i.e., from Q3:2007 to Q2:2009) as well as partitioned samples, for liquidity constraints and/or negative equity in the quarter before default.[15] We analyse four sub-samples, including (i) defaulted loans with negative equity in the previous quarter (Pure NE sample), (ii) defaulted loans with both liquidity constraints and negative equity in the previous quarter (LC and NE sample), (iii) defaulted loans with either liquidity constraints or negative equity in the previous quarter (No LC and NE sample), and lastly, (iv) defaulted loans with liquidity constraints in the previous quarter (Pure LC sample).

5.1 Borrower liquidity constraints

This section analyses the relation between borrower liquidity constraints and LGD (including probability of cure and non-zero LGD). We present the estimated results for the probability of cure and non-zero LGD equation in Table 7 and Table 8 and graph their relations in Figure 7 for the estimated parameters to gain further insight into how borrower liquidity constraint relates to the probability of cure and non-zero LGD.

[Table 7 and 8 about here]

Probability of cure

We find a significant non-linear effect of borrower liquidity constraint on the probability of cure. The estimated parameters at every spline knot (threshold) are all statistically significant at the 1% level (see Table 7), indicating that the effect of borrower

[15] To address the concern that most of the defaults occur in the crisis subsample, we also perform a robustness check with the after-crisis subsample which covers from 2009:Q3 to 2015:Q1. Our main results remain consistent. Details are available upon request.

liquidity constraint on the probability of cure changes significantly at these thresholds. This supports our choices of thresholds and further confirms a non-linear relation between borrower liquidity constraint and the probability of cure. Figure 7 consistently shows an asymmetric v-shape relation with an increasingly long right-tail and a trough at 0.04%. This pattern is robust for different models and sample periods under consideration.

[Figure 7 about here]

We observe a decreasing left-tail of the v-shape relation (until the borrower liquidity constraint is equal to zero), which is consistent with the economic intuition that the probability of cure is expected to be higher with greater curtailments. Furthermore, we observe that a sudden drop in the probability of cure (about 10% after controlling for other effects) associated with an increase of borrower liquidity constraint from 0 to 0.04% may be attributed to technical defaults. In the context of residential mortgage loans, technical defaults may arise from a failure to pay property taxes or homeowner's insurance premiums as described by Moulton et al. (2015). Following this research, technical defaults are not failures in loan repayment, and hence the borrower liquidity constraints associated with these defaults are by definition non-positive. Further, it is more likely that the value of property does not fall below the outstanding loan balance for technical defaults.[16] Hence, we observe a higher level of the probability of cure for borrowers with non-positive liquidity constraints relative to the positive ones as shown in Figure 7.

It is worth noting that the difference in the levels of probability of cure is also subject to the housing cycle, which has an impact on the likelihood that the technical defaults are accompanied with negative equity. For example, we may expect more technical defaults experiencing negative equity during the subprime mortgage crisis due to decreasing house

[16] This is consistent with our observation that approximately 61% of defaulted loans that did not experience positive borrower liquidity constraints did not have negative equity.

prices. Our robustness check for the crisis period demonstrates this point as a smaller drop of the probability of cure compared to the full sample estimation when borrower liquidity constraints occur (see Figure 7).

The moderate increase of the v-shape relation on the long right-tail between borrower liquidity constraint and probability of cure supports our hypothesis. Borrower liquidity constraints are more associated with cure than non-cure loans. This result is robust regardless of the employed model specifications and sample periods. A positive association between cure loans and borrower liquidity constraints is further supported by our empirical estimation using partitioned samples as shown in Table 9. The right-tail of the v-shape relation is captured for the LC and NE sample and the Pure LC sample. All the estimates of knots are statistically significant and show a similar pattern for the full sample and crisis sub-samples. For a better visualization, we graph the relation between borrower liquidity constraints and probability of cure in each partitioned sample's estimation in Figure 8. We observe a larger shift in their positive association in the Pure LC sample than in the LC and NE sample, which supports the point that cured loans are more associated with the borrower liquidity constraints. In addition, findings for the Pure LC sample confirm the robustness of our results after controlling for strategic defaults. It is worth noting that strategic defaults are particularly related to negative equity mortgages (see Mian and Sufi, 2009; Gerardi et al., 2018).

[Table 9 and Figure 8 about here]

Non-zero LGD

We observe an increase in the level of non-zero LGD when borrower liquidity constraints occur (see Figure 7). This is consistent with technical defaults that we have discussed earlier. We expect a lower level of losses of loan foreclosures caused by technical defaults, which is equivalent with non-positive borrower liquidity constraints, compared to loan

foreclosures with negative equity. Borrower liquidity constraints are negatively related to the non-zero LGD until the threshold 0.52%. That is, a higher positive borrower liquidity constraint is associated with a lower non-zero LGD. In terms of magnitude, we find that this overall trend is mostly driven by the defaulted loans that experience liquidity constraints but not negative equity in the previous quarter (see Figure 8). However, the decreasing trend is statistically insignificant after controlling for other effects (including home equity, see Pure LC sample column in Table 9). This can be explained by the time-delayed reflection of borrower liquidity constraints as we discussed in Section 3. This negative association may be due to an instantaneous co-movement between borrower liquidity constraints and home equity.

5.2 Home equity

In this section, we analyse the relation between home equity and LGD (including probability of cure and non-zero LGD). The estimated results for the probability of cure and non-zero LGD equations are presented in Table 7 and Table 8. Further, we analyze how home equity is related to the probability of cure and non-zero LGD by plotting their relations in Figure 9 on the basis of estimated parameters shown in Table 7 and Table 8.

Probability of cure

We consistently find a non-linear relation between home equity and the probability of cure with a continuously increasing trend. The estimated parameters at the knots -0.2, -0.1, 0 and 0.2 are statistically significant at the 1% significance level (see Table 7), indicating that the relation changes statistically at these points. This supports our choice of thresholds and it is also consistent with the literature (e.g., Qi and Yang, 2009; Gerardi et al., 2018). Overall, we observe an asymmetric tilde (~) – shape relation between home equity and the probability of cure with a flat relation in the middle (see Figure 9). We find that this pattern is robust for different model specifications and sample periods examined.

[Figure 9 about here]

Looking at the home equity on the negative and positive sides, we find that an increase in equity elevates the probability of cure while an increase in negative equity lowers the probability of cure significantly. These results imply that positive equity is a driver of cure loans and negative equity is a driver of non-cure loans. This follows economic intuition as positive (negative) equity indicates that the property value is above (below) the outstanding loan balance. Hence, the outstanding loan balance and resolution costs are (not) likely to be covered by the sale of the property for the case of positive (negative) equity. These results also hold for all partitioned samples as shown in Table 9.

Non-zero LGD

We find a decreasing trend of the relation between home equity and the non-zero LGD throughout when home equity increases (see Figure 9). The result indicates a robust negative relation between the two variables, that is, higher home equity leads to a lower non-zero LGD. This is consistent with previous literature for the residential mortgage loans (e.g., Pennington-Cross, 2003; and Qi and Yang, 2009). Greater home equity leads to a higher recovery rate (i.e., 1-LGD) and, therefore, lower non-zero LGD. This relation between home equity and non-zero LGD is not linear as the rate of changes of non-zero LGD is not constant for changes in home equity. This is shown by statistically significant estimates for all knots of home equity at the 1% significance level in Table 8 and visible in Figure 9. We find that the non-linear behaviour of the relation between home equity and non-zero LGD is much smoother than between home equity and the probability of cure. Overall, this pattern of the home equity/non-zero LGD relation is robust for different model specifications and sample periods.

In addition, the significantly decreasing trend of home equity/non-zero LGD relation also implies that a higher level of negative equity leads to a higher non-zero LGD.

5.3 Control variables

Probability of cure

Table 7 shows interesting results regarding the controls of the cure equation. A foreclosed loan associated with a higher FICO score is less likely to be cured. It is shown that higher FICO scores tend to be steadier over time (see FICO, 2008), which implies higher FICO borrowers have put more endeavour into fulfilling their loan repayment obligations. Borrowers may face a significant relative increase in credit costs if their credit risk lowers and this effect can last for more than ten years (see Han and Li, 2011). Generally, when high FICO customers confront liquidity constraints (e.g., temporary unemployment, divorce or demotion) and miss a loan repayment, it is likely that they will try to rectify the loans at an early stage of delinquency, only giving up and allowing the loans to be foreclosed if it is no longer worthwhile maintaining their obligations and FICO profiles. This is likely to happen if they experience negative equity alongside the liquidity constraints, or in other words, their property value drops below the outstanding loan amount, which finally leads to the losses being less likely to be fully recovered.

The other control variables show significant impacts on the probability of cure, which are consistent with economic intuition. We find that defaulted loans associated with higher risk (e.g., adjustable rate mortgages) are less likely to be cured, whereas those with lower risk (e.g., owner occupied loans) are more likely to be cured. Loan size has a significant concave effect on the probability of cure for the entire sample estimation, but the effect is statistically insignificant during the crisis period. This might be due to declining house prices during the GFC regardless of the house value at origination and hence, the loan size.[17] The current interest rate and state unemployment rate have a negative effect on the probability of cure while the

[17] At origination, the loan size dynamics are strongly consistent with the house value since the majority of mortgage loans are originated with a loan-to-value ratio of 80%.

house price appreciation and real GDP growth rate have a positive impact. A rise in the current interest rate or unemployment rate may decrease borrower ability to repay the loan. An increase in the house price appreciation or real GDP growth rate may improve this ability.

We find that the states prohibiting deficiency judgement and/or allowing for a statutory right of redemption have experienced a lower probability of cure for defaulted loans. A prohibition of deficiency judgement does not allow the lenders to collect the gap from borrowers if the repossession of a forced sale property cannot fully cover the outstanding loan balance and associated resolution costs. Besides, the statutory right of redemption can prolong the foreclosure and liquidation process and may result in significant extra costs.

Non-zero LGD

The estimated results for the controls of the non-zero LGD equation presented in Table 8 are intuitive and consistent with previous studies. Non-cure loans are associated with higher credit quality (i.e., higher FICO score) and have a lower non-zero LGD. This result implies that the credit score (FICO score) is not only a driver of default but also explains LGD. However, the FICO – LGD relation may be misinterpreted if we combine both cure and non-cure loans in the estimation due to the borrower's behaviour in making decisions on whether to maintain the credit profile or to foreclose a loan. This behaviour has been discussed earlier in the analysis of the FICO effect on the probability of cure. We find that defaulted loans with an adjustable mortgage rate are associated with higher loss severities in comparisons with other loan types, whereas owner-occupied mortgage loans experience significantly lower loss severities than other loan types. These results are consistent with our expectation and supported by previous studies as ARM loans are associated with higher risk while owner-occupied loans contain less risk than other loan types (see, Qi and Yang, 2009; and Zhang et al., 2010).

We also find that loans with higher interest rate are associated with higher non-zero LGDs, which supports Zhang et al. (2010). The relation between non-zero LGD and loan size

exhibits a convex parabolic shape, which is consistent to findings of Pennington-Cross (2003). Regarding state foreclosure laws on property, we find states with a judicial process (e.g., Clauretie and Herzog, 1990; Pennington-Cross, 2003; and Qi and Yang, 2009), states with a statutory right of redemption (e.g., Clauretie and Herzog, 1990; and Qi and Yang, 2009) and states which prohibit deficiency judgement (e.g., Clauretie and Herzog, 1990) have higher non-zero LGD than other states. The judicial process and statutory right of redemption may prolong the foreclosure and liquidation process when the defaulted loans do not cure, which leads to larger loss severities. In states that prohibit the deficiency judgement, the lenders lack an effective method to cover the difference if the foreclosure sales cannot compensate the outstanding loan balances and associated resolution costs.

Regarding the macroeconomic environment, we find that increases in house prices or real GDP growth have a negative effect on the non-zero LGD while an increase in the unemployment rate elevates the non-zero LGD. These results are consistent with previous studies, for example, Clauretie and Herzog (1990) and Zhang et al. (2010) for house price appreciation, and Clauretie and Herzog (1990) for unemployment rate.

5.4 Robustness check

There are a number of zip-code level house prices available and we confirm consistency of our results for Zillow HPI as well as the 3-digit and 5-digit Zip Code FHFA HPI. Bogin et al. (2018) outline the methodology of the 3-digit and 5-digit Zip Code FHFA HPI. We note that the 5-digit Zip Code dataset is only available at an annualfrequency. As can be seen from the following tables, the results are consistent with the main findings using the MSA level FHFA HPI.

Note that the 3-digit, 5-digit Zip Code HPI available on the FHFA "should be considered as experimental or developmental indices" at the current stage. The FHFA also noted that these indices have been produced to "stimulate discussion and comment".[18]

[Table 10 about here]

[Table 11 about here]

6. Findings

We investigate the effect of borrower liquidity constraints and home equity on LGD using US residential defaulted mortgage loans observed between Q2 2005 and Q1 2015. We find robust evidence that the relation between borrower liquidity constraints and probabilities of cure exhibits an asymmetric v-shape with an increasingly long right-tail. Further, the home equity – probability of cure relation has an asymmetric tilde (~) – shape which is positive monotone on both sides and flat in the middle. These results indicate that borrower liquidity constraints and positive equity are more associated with cure loans while the negative equity is more related to non-cure loans. Higher levels of positive equity lead to lower non-zero LGDs, while higher levels of negative equity trigger higher non-zero LGDs.

The above findings provide an important economic-rationale for modeling structures that differentiate between the dynamics of cure and non-cure loans in residential mortgage loans. It is important to consider cure event and non-zero LGD in two-steps. The first step models probability of cure and the second step models non-zero LGD if the defaulted loan is non-cured. This approach captures the bimodal property of the LGD distribution, in which a large fraction of defaulted loans does not generate losses. Economically, this approach is an

[18] See www.fhfa.gov/PolicyProgramsResearch/Research/PaperDocuments/wp1601_FAQs_ZIP5_HPIs.pdf.

important refinement of bank risk models and underlying prudential regulation that considers the probability of cure as a risk mitigating factor.

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Appendix A: Derivation of likelihood for model estimation

Following the selection mechanism shown in Figure 2, we derive the two main components for the likelihood function as follows:

1. If the defaulted loan *i* is cured ($C_{it} = 1$):

$$\Pr(C_{it} = 1) = \Pr\left(C_{it}^* > 0 \middle| X_{i,t-1}\right) = \Pr\left(X'_{i,t-1}\beta + u_{it} > 0\right) = \Pr\left(u_{it} > -X'_{i,t-1}\beta\right)$$

$$= 1 - \Phi\left(-X'_{i,t-1}\beta\right)$$

$$= \Phi\left(X'_{i,t-1}\beta\right) \tag{9}$$

where $\Phi(.)$ denotes the cumulative distribution function of the standardized normal distribution.

2. If the defaulted loan *i* is non-cured ($C_{it} = 0$):

In this case, we can observe the non-zero LGD. As the non-zero LGD is bounded by 1, we have two possibilities which build up the density of the L_{it}:

First, $L_{it} = 1$

$$\Pr(L_{it} = 1, C_{it} = 0) = \Pr\left(L_{it}^* \geq 1, C_{it}^* \leq 0 \middle| X_{i,t-1}, Z_{i,t-1}\right)$$

$$= \Pr\left(\frac{\varepsilon_{it}}{\sigma_\varepsilon} \geq \frac{1 - Z'_{i,t-1}\alpha}{\sigma_\varepsilon}, u_{it} \leq -X'_{i,t-1}\beta\right)$$

$$= \Phi_2\left(-\frac{1 - Z'_{i,t-1}\alpha}{\sigma_\varepsilon}, -X'_{i,t-1}\beta, -\rho_{u\varepsilon}\right) \tag{10}$$

where $\Phi_2(.)$ denotes the cumulative distribution function of standardized bivariate normal distribution.

Second, $0 < L_{it} < 1$,

$$\Pr(L_{it}, C_{it} = 0) = \Pr(L_{it}, C_{it}^* \leq 0 | X_{i,t-1}, Z_{i,t-1})$$

According to the Bayes rule, we have:

$$\Pr(L_{it}, C_{it}^* \leq 0 | X_{i,t-1}, Z_{i,t-1})$$

$$= f\left(L_{it} \middle| Z_{i,t-1}\right) \Pr\left(C_{it}^* \leq 0 \middle| L_{it}, X_{i,t-1}, Z_{i,t-1}\right) \tag{11}$$

In Eq. (7), following density function of normal distribution it is easy to see that:

$$f\left(L_{it}\middle|Z_{i,t-1}\right) = f(\varepsilon_{it}) = \frac{1}{\sigma_\varepsilon}\phi\left(\frac{L_{it} - Z'_{i,t-1}\alpha}{\sigma_\varepsilon}\right) \tag{12}$$

where $\phi(.)$ denotes probability density function of standardized normal distribution.

The remaining part of Eq. (7) can be derived as follows:

$$\Pr\left(C_{it}^* \leq 0\middle|L_{it}, X_{i,t-1}, Z_{i,t-1}\right) = \Pr\left(C_{it}^* \leq 0\middle|\varepsilon_{it}, X_{i,t-1}\right) = \Pr(u_{it} \leq -X'_{i,t-1}\beta\,|\varepsilon_{it}) \tag{13}$$

The conditional distribution of u_{it} given ε_{it} can be written as:

$$u_{it}|\varepsilon_{it} \sim N\left[\frac{\rho_{u\varepsilon}}{\sigma_\varepsilon}\left(L_{it} - Z_{i,t-1}\alpha\right), 1 - \rho_{u\varepsilon}^2\right] \tag{14}$$

Hence, Eq. (8) is equivalent with:

$$\Pr\left(\frac{u_{it} - \frac{\rho_{u\varepsilon}}{\sigma_\varepsilon}(L_{it} - Z'_{i,t-1}\alpha)}{\sqrt{1-\rho_{u\varepsilon}^2}} \leq \frac{-X'_{i,t-1}\beta - \frac{\rho_{u\varepsilon}}{\sigma_\varepsilon}(L_{it} - Z'_{i,t-1}\alpha)}{\sqrt{1-\rho_{u\varepsilon}^2}}\right)$$

$$= \Phi\left(-\frac{X'_{i,t-1}\beta + \frac{\rho_{u\varepsilon}}{\sigma_\varepsilon}(L_{it} - Z'_{i,t-1}\alpha)}{\sqrt{1-\rho_{u\varepsilon}^2}}\right) \tag{15}$$

Combining the components of likelihood function from the two main events we have the full likelihood function of the model as:

$$L$$

$$= \prod_{t=1}^{T}\prod_{i=1}^{N}\left[\Phi\left(X'_{i,t-1}\beta\right)\right]^{C_{it}} \cdot \left[\Phi_2\left(-\frac{1 - Z'_{i,t-1}\alpha}{\sigma_\varepsilon}, -X'_{i,t-1}\beta, -\rho_{u\varepsilon}\right)\right]^{(1-C_{it})\cdot I(L_{it}=1)}$$

$$\cdot\left[\frac{1}{\sigma_\varepsilon}\phi\left(\frac{L_{it} - Z'_{i,t-1}\alpha}{\sigma_\varepsilon}\right)\right.$$

$$\left.\cdot\,\Phi\left(-\frac{X'_{i,t-1}\beta + \frac{\rho_{u\varepsilon}}{\sigma_\varepsilon}\left(L_{it} - Z'_{i,t-1}\alpha\right)}{\sqrt{1-\rho_{u\varepsilon}^2}}\right)\right]^{(1-C_{it})\cdot I(0<L_{it}<1)} \tag{16}$$

where $I(.)$ denotes the indicator function.

Appendix B: Model performance

To ensure that our methodology is appropriate, we compare our approach (including both full-information and limited information framework[21]) with the standard OLS model:

$$E(L^A{}_{it}|Z_{i,t-1}) = Z'_{i,t-1}\delta \qquad (17)$$

where L^A_{it} includes all observations of zero and non-zero LGDs of defaulted loans. Under this OLS framework, the out-of-time predicted LGDs can be calculated as, $E(\widehat{L^A}_{i,t+1}) = Z'_{it}\hat{\delta}$.

Meanwhile, the out-of-time predicted LGDs in our framework can be calculated as,

$$E\left(\widehat{L^A}_{i,t+1}\right) = \left[1 - \widehat{Pr}(C_{i,t+1} = 1)\right] E\left(\hat{L}_{i,t+1}\right) \qquad (18),$$

in which, $E\left(\hat{L}_{i,t+1}\right) = Z'_{it}\hat{\alpha}$ and $\widehat{Pr}(C_{i,t+1} = 1) = \Phi\left(X'_{it}\hat{\beta}\right)$ as derived from Eq. (4.2) and (4.1) (see Appendix A), respectively.

[Table 12 about here]

We compare the out-of-time predictive performance between the models using Root Mean Square Errors (RMSE). The forecasting window spans through five consecutive years from 2008 to 2012.[22] Table 10 shows the RMSE statistics and the difference in the out-of-time forecasting performance of our models with the OLS model. To assess the statistical significance of the difference between the performances of considered models, we conduct the two-sample t-test for difference in mean of the square errors of predictions. We find that separating LGDs into cure and non-cure loans in modeling produces a 4.8% better forecasting quality in term of RMSE than the current benchmark OLS model during the GFC. Analyses for other periods do not show a significant difference between models' performance. Consistent with Do et al. (2018), the difference we observe between model's performance in the GFC is

[21] In the full-information framework, we impose no restriction on the correlation between cure and non-zero LGDs. Meanwhile, in the limited information framework we restrict the correlation to be zero. Besides, we find that the OLS model specification with no spline terms provides the best out-of-time predictive performance in terms of Root Mean Square Errors. Therefore, we employ this specification for a forecasting comparison.

[22] We do not assess the years from 2013 to 2015 to avoid a loss information bias as most of the non-zero losses are observed within three years of the default events.

mostly due to an ability to forecast high-value ranges of LGDs. The OLS model does not consider the variation of the cure events and omits part of the LGD uncertainty. This problem is more pronounced during financial turbulence periods when variables tend to be highly correlated.

Appendix C - Tables and figures

Table 1: Cure rates and average LGD by origination and observation year

This table reports the number of defaults (D), number of cured loans (C), average cure rates (i.e., cure per number of defaults, C/D), average LGD ($\overline{LGD}$, i.e., average of both zero and non-zero LGD) and average non-zero LGD ($\overline{LGD^*}$) by origination year and observation year.

Origination Years						Observation Years					
Year	**D**	**C**	**C/D**	$\overline{LGD}$	$\overline{LGD^*}$	**Year**	**D**	**C**	**C/D**	$\overline{LGD}$	$\overline{LGD^*}$
1990	514	389	0.757	0.105	0.431						
1991	32	23	0.719	0.064	0.226						
1992	45	35	0.778	0.057	0.258						
1993	120	92	0.767	0.068	0.292						
1994	136	96	0.706	0.129	0.439						
1995	234	147	0.628	0.210	0.566						
1996	333	205	0.616	0.229	0.595						
1997	723	407	0.563	0.274	0.628						
1998	1,388	783	0.564	0.272	0.624						
1999	2,330	1,237	0.531	0.307	0.654						
2000	1,965	862	0.439	0.385	0.685						
2001	2,566	1,182	0.461	0.280	0.518						
2002	8,084	3,489	0.432	0.294	0.518						
2003	18,020	8,088	0.449	0.273	0.496						
2004	51,984	19,887	0.383	0.310	0.502						
2005	126,188	35,386	0.280	0.398	0.553	2005	15,656	6,707	0.428	0.259	0.454
2006	227,029	58,808	0.259	0.462	0.624	2006	44,839	14,817	0.330	0.327	0.488
2007	63,945	18,190	0.284	0.458	0.640	2007	102,548	19,345	0.189	0.479	0.590
2008	3,653	727	0.199	0.411	0.513	2008	136,482	25,499	0.187	0.517	0.636
2009	60	24	0.400	0.456	0.761	2009	96,033	28,746	0.299	0.424	0.606
2010	10	4	0.400	0.305	0.508	2010	43,551	15,711	0.361	0.383	0.600
2011	3	2	0.667	0.320	0.959	2011	30,183	12,292	0.407	0.339	0.571
2012	46	32	0.696	0.112	0.370	2012	18,834	9,690	0.515	0.248	0.511
						2013	13,436	9,733	0.724	0.123	0.446
						2014	7,494	7,204	0.961	0.012	0.319
						2015	352	351	0.997	0.001	0.322
Total	509,408	150,095	0.295	0.417	0.591		509,408	150,095	0.295	0.417	0.591

Table 2: Definition of the explanatory variables

Variable groups	Description
Loan characteristics	
Home equity	Home equity is calculated as, 1 – *CLTV*, where *CLTV* is the current loan-to-value ratio that is approximated using the HPI at the MSA level. We construct the splines of home equity at knots (thresholds) -0.2, 0, 0.1 and 0.2 which are respectively denoted as *Home equity*$_{s-0.2}$, *Home equity*$_{s0}$, *Home equity*$_{s0.1}$, and *Home equity*$_{s0.2}$.
Loan size	Loan size represents log transformation of loan amount at origination.
Adjustable rate mortgage (*ARM*)	Indicator variable *ARM* is one if loan has an adjustable rate and zero otherwise.
Current Interest Rate (*Current IR*)	*Current IR* denotes the interest rate of the loan at observation time.
Borrower characteristics	
FICO	*FICO* is the credit score of a borrower at loan origination, representing the credit quality of a borrower at loan approval. A higher score indicates a higher credit quality. This score is a popular indicator of the credit quality used by lenders, rating agencies and investors.
(Borrower) Liquidity constraint	The borrower liquidity constraint represents the incapacity of a borrower to fulfil the loan repayment obligations as scheduled. We construct the splines of borrower liquidity constraints at knots (thresholds) 0, 0.04, 0.08 and 0.52 denoted as *Liquidity constraints*$_{s0}$, *Liquidity constraints*$_{s0.04}$, *Liquidity constraints*$_{s0.08}$, and *Liquidity constraints*$_{s0.52}$.
Property characteristics	
State foreclosure laws on property	Variables *JP*, *SRR* and *PDJ* indicate states where judicial process is allowed (*JP*=1, 0 otherwise), statutory right of redemption is permitted (*SRR*=1, 0 otherwise) and deficiency judgment is prohibited (*PDJ*=1, 0 otherwise).
Owner-occupied	An indicator variable receiving value of one if the property is owner occupied and zero otherwise.
Economic and market conditions	
House price appreciation (*HPA*)	House price appreciation is calculated as the difference of the natural logarithm of current HPI and that of HPI in the previous quarter. The HPI is collected at the MSA level.
Unemployment rate (*Unemployment rate*)	Unemployment rate is collected quarterly at state level from the Bureau of Labour Statistics (BLS).
Real GDP growth rate (*Real growth rate*)	Real GDP growth rate is calculated from quarterly real GDP collected at state level from Bureau of Economic Analysis (BEA).
Default to end of observation (*DefaultToEOO*)	Time gap between default events and the time of last available loss information. This variable controls for resolution bias.

Table 3: Relative frequency of control dummy variables in %

This table reports the relative frequency (%) of dummies used as control variables in both cured and non-cured loans. We refer to Table 2 for a description of variables.

	ARM	Owner Occ.	PDJ	SRR
Panel A: Defaulted loans				
0	26.8	13.1	66.4	89.0
1	73.2	86.9	33.7	11.0
Panel B: Cured loans				
0	38.8	11.1	74.3	92.1
1	61.2	88.9	25.7	7.9
Panel C: Non-cured loans				
0	21.8	13.9	63.0	87.7
1	78.2	86.1	37.0	12.3

Table 4: Descriptive statistics of continuous control variables

This table provides mean, standard deviation (Std.Dev), 5th percentile (P5) and 95th percentile (P95) of continuous variables for defaulted loans, cure loans and non-cure loans. We refer to Table 2 for a description of variables.

Variable	Defaulted loans				Cure loans				Non-cure loans			
	Mean	Std.Dev	P5	P95	Mean	Std.Dev	P5	P95	Mean	Std.Dev	P5	P95
Liquidity constraint (%)	0.20	0.31	-0.36	1.03	0.28	0.36	0.00	1.03	0.17	0.28	-0.36	0.81
Equity	0.09	0.22	-0.40	0.44	0.15	0.23	-0.34	0.45	0.07	0.22	-0.40	0.37
FICO	646	67	528	756	643	71	520	757	648	66	532	756
Loan size	12.20	0.73	10.98	13.31	12.19	0.76	10.92	13.36	12.21	0.71	11.00	13.29
Current IR (%)	7.60	1.88	4.09	10.75	7.23	1.98	3.32	10.63	7.76	1.81	4.67	10.79
Unemployment rate (%)	7.12	2.52	3.80	11.70	7.30	2.50	3.90	11.60	7.05	2.53	3.80	11.70
HPA (%)	-1.97	3.53	-8.29	2.06	-0.93	3.03	-7.01	3.10	-2.40	3.63	-9.20	1.64
Real growth rate (%)	-0.12	1.37	-2.72	1.64	0.06	1.31	-2.22	1.80	-0.19	1.39	-2.93	1.62
DefaultToEOO	6.19	1.85	2.50	8.75	5.56	2.36	1.00	9.00	6.46	1.52	3.50	8.75
Observations	509,408				150,095				359,313			

Table 5: Correlation matrix of continuous variables

This table provides pairwise correlations between cure rate, non-zero LGD and continuous variables. We refer to Table 2 for a description of the variables.

Variables	Cure	Non-zero LGD	Liquidity constraints	Home Equity	FICO	Loan size	Current IR	Unemployment rate	HPA	Real growth rate	DefaultToEOO
Cure	1	-									
Non-zero LGD	-	1									
Liquidity constraints	0.16	-0.04	1								
Home equity	0.16	-0.22	0.18	1							
FICO	-0.03	-0.09	-0.14	-0.29	1						
Loan size	-0.02	-0.25	-0.21	-0.36	0.36	1					
Current IR	-0.13	0.2	-0.19	0.25	-0.4	-0.34	1				
Unemployment rate	0.05	0.09	0.13	-0.53	0.29	0.18	-0.38	1			
HPA	0.19	-0.19	0.25	0.39	-0.2	-0.28	-0.02	-0.09	1		
Real growth rate	0.08	-0.15	0.13	0.2	-0.1	-0.04	-0.05	-0.11	0.18	1	
DefaultToEOO	-0.22	-0.03	-0.34	0.29	-0.2	-0.08	0.43	-0.58	-0.07	-0.03	1

Table 6: Relative frequencies for cure and non-cure by liquidity constraint and home equity categories

This table reports the relative frequency (%) of cure and non-cure loans for different ranges of borrower liquidity constraint and home equity. P5 denotes the 5th percentile and P95 denotes the 95th percentile.

Panel A: Borrower liquidity constraints					
	[P5, 0]	(0, 0.04]	(0.04, 0.08]	(0.08, 0.52]	[0.52, P95]
Non-cure	72.9	84.0	82.8	72.0	52.5
Cure	27.1	16.0	17.2	28.0	47.5
Panel B: Home equity					
	[P5, -0.2]	(-0.2, 0]	(0, 0.1]	(0.1, 0.2]	(0.2, P95]
Non-cure	77.8	74.6	76.0	75.0	60.9
Cure	22.2	25.4	24.0	25.0	39.1

Table 7: Parameter estimates for probability of cure equation

This table reports the parameter estimates for the probability of cure equation with no control and with control variables for *two* samples, the Full sample (Q2/2005-Q1/2015) and the Crisis subsample (Q3/2007-Q2/2009). We refer to Table 2 for a description of the variables. FICO is divided by 1,000; Loan size, Current IR and DefaultToEOO are divided by 10; Unemployment rate is a percentage; Real growth rate and HPA are in their levels. Standard errors are reported in parentheses. ***, ** and * denote that the estimates are statistically significant at 1%, 5% and 10% level. AUROC denotes the Area Under the Receiver Operating Characteristics curve, which is a popular measure for discrimination in credit risk. We do not report the estimated intercepts of these equations.

Parameter	Full sample		Crisis sub-sample	
	No control	With controls	No control	With controls
Borrower liquidity constraint				
Liquidity constraint	0.265***	-0.277***	-0.08***	-0.328***
	(0.025)	(0.026)	(0.031)	(0.032)
Liquidity constraint$_{s0}$	-12.556***	-7.441***	-8.93***	-5.555***
	(0.381)	(0.398)	(0.469)	(0.492)
Liquidity constraint$_{s0.04}$	17.128***	12.443***	12.268***	9.224***
	(0.763)	(0.789)	(0.939)	(0.968)
Liquidity constraint$_{s0.08}$	-3.523***	-4.592***	-2.332***	-3.245***
	(0.407)	(0.418)	(0.511)	(0.523)
Liquidity constraint$_{s0.52}$	-0.931***	-0.283***	-0.856***	-0.031
	(0.036)	(0.038)	(0.072)	(0.074)
Home equity				
Home equity	0.879***	1.325***	0.618***	0.864***
	(0.058)	(0.06)	(0.093)	(0.094)
Home equity$_{s-0.2}$	-0.98***	-1.351***	-0.875***	-0.761***
	(0.104)	(0.108)	(0.157)	(0.161)
Home equity$_{s0}$	0.194	0.565***	1.171***	1.098***
	(0.138)	(0.144)	(0.194)	(0.199)
Home equity$_{s0.1}$	-0.406**	-0.546***	-0.436*	-0.86***
	(0.16)	(0.166)	(0.227)	(0.232)
Home equity$_{s0.2}$	4.079***	4.025***	2.887***	3.179***
	(0.102)	(0.106)	(0.154)	(0.159)
Controls				
FICO		-1.147***		-0.659***
		(0.037)		(0.057)
Current IR		-0.482***		-0.446***
		(0.014)		(0.024)
Loan size		3.822***		-0.226
		(0.687)		(1.16)
Loan size square		-0.793***		0.846*
		(0.281)		(0.472)
PDJ		-0.231***		-0.236***
		(0.005)		(0.008)
SRR		-0.214***		-0.184***
		(0.007)		(0.011)
ARM		-0.297***		-0.356***
		(0.005)		(0.007)

Owner occupied		0.119***		0.099***
		(0.006)		(0.009)
DefaultToEOO		-1.56***		-3.282***
		(0.015)		(0.094)
HPA		4.322***		1.28***
		(0.07)		(0.098)
Real growth rate		1.357***		1.172***
		(0.152)		(0.219)
Unemployment rate		-0.005***		-0.004
		(0.001)		(0.003)
Log Likelihood	-361,263	-288,257	-152,317	-115,612
Pseudo R^2	10.4%	21.7%	6.1%	12.7%
AUROC	0.66	0.741	0.63	0.70
Number of Observations	509,408		259,815	

Table 8: Parameter estimates for non-zero loss equation

This table reports the parameter estimates for the non-zero loss equation with no control and with control variables for *two* samples, the Full sample (Q2/2005-Q1/2015) and the Crisis subsample (Q3/2007-Q2/2009). We refer to Table 2 for a description of the variables. FICO is divided by 1,000; Loan size, Current IR and DefaultToEOO are divided by 10; Unemployment rate is in percentage terms; Real growth rate and HPA are in their level (i.e., in absolute terms). Standard errors are reported in parentheses. ***, ** and * denote that the estimates are statistically significant at 1%, 5% and 10% level. We do not report the estimated intercepts of these equations.

Parameter	Full sample		Crisis sub-sample	
	No control	With controls	No control	With controls
Borrower liquidity constraint				
Liquidity constraint	-0.042***	-0.01**	0.018***	0.01**
	(0.006)	(0.005)	(0.006)	(0.005)
Liquidity constraint$_{s0}$	2.969***	1.112***	2.572***	0.782***
	(0.076)	(0.067)	(0.081)	(0.072)
Liquidity constraint$_{s0.04}$	-2.835***	-1.658***	-2.232***	-1.238***
	(0.15)	(0.131)	(0.16)	(0.14)
Liquidity constraint$_{s0.08}$	-0.326***	0.443***	-0.535***	0.375***
	(0.081)	(0.071)	(0.088)	(0.077)
Liquidity constraint$_{s0.52}$	0.193***	0.162***	0.277***	0.118***
	(0.01)	(0.008)	(0.016)	(0.014)
Home equity				
Home equity	-0.201***	-0.332***	-0.169***	-0.217***
	(0.013)	(0.011)	(0.017)	(0.015)
Home equity$_{s-0.2}$	0.12***	0.24***	0.001	0.052**
	(0.023)	(0.021)	(0.029)	(0.025)
Home equity$_{s0}$	-0.121***	-0.227***	-0.042	-0.149***
	(0.031)	(0.027)	(0.036)	(0.031)
Home equity$_{s0.1}$	-0.5***	-0.222***	-0.399***	-0.329***
	(0.037)	(0.032)	(0.043)	(0.037)
Home equity$_{s0.2}$	0.268***	-0.302***	0.124***	-0.27***
	(0.026)	(0.023)	(0.033)	(0.029)
Controls				
FICO		-0.228***		-0.223***
		(0.008)		(0.01)
Current IR		0.187***		0.146***
		(0.003)		(0.004)
Loan size		-15.296***		-14.653***
		(0.162)		(0.218)
Loan size square		5.677***		5.36***
		(0.066)		(0.089)
JP		0.119***		0.128***
		(0.001)		(0.001)
PDJ		0.042***		0.027***
		(0.001)		(0.002)
SRR		0.037***		0.023***
		(0.001)		(0.002)
ARM		0.018***		0.011***
		(0.001)		(0.001)
Owner occupied		-0.076***		-0.07***

		(0.001)		(0.002)
DefaultToEOO		-0.016***		1.017***
		(0.005)		(0.017)
HPA		-1.374***		-1.044***
		(0.014)		(0.016)
Real growth rate		-1.127***		-1.25***
		(0.03)		(0.038)
Unemployment rate		0.006***		0.024***
		(0.000)		(0.000)
σ_ε	0.271***	0.235***	0.251***	0.217***
	(0.000)	(0.000)	(0.000)	(0.000)
$\rho_{u,\varepsilon}$	-0.02	0.035***	-0.008	-0.056***
	(0.012)	(0.013)	(0.016)	(0.015)
Log Likelihood	-361,263	-288,257	-152,317	-115,612
Adjusted R^2	8.1%	29.6%	8.3%	30.3%
Number of Observations	509,408		259,815	

Table 9: Parameter estimates for samples partitioned for liquidity constraint and negative equity

This table reports the parameter estimates for the probability of cure equation (PC) and non-zero loss equation ($\overline{LGD^*}$) with control variables for samples partitioned by liquidity constraint (i.e., *Liquidity constraint* > 0) and negative equity (i.e., *CLTV* >1). *Pure NE sample* includes the defaulted loans that only experienced negative equity but no liquidity constraints in previous quarter. *LC and NE sample* includes the defaulted loans that experienced both liquidity constraints and negative equity in the previous quarter. *No LC and NE sample* includes the defaulted loans that did not experience any of liquidity constraints and negative equity in the previous quarter. *Pure LC sample* includes the defaulted loans that only experienced liquidity constraints but not negative equity in the previous quarter. We refer to more details in Table 2 for a description of the variables. FICO is divided by 1,000; Loan size, Current IR and DefaultToEOO are divided by 10; Unemployment rate is in percentage; Real growth rate and HPA are in their level (i.e., in absolute terms). Standard errors are reported in parentheses. ***, ** and * denote the estimates are statistically significant at 1%, 5% and 10% level. For brevity, we do not report the estimations of intercepts and control variables. The set of control variables is identical and estimates consistent with those presented in Table 7 and 8.

Parameter	Pure NE sample		LC and NE sample		No LC and NE sample		Pure LC sample	
	PC	$\overline{LGD^*}$	PC	$\overline{LGD^*}$	PC	$\overline{LGD^*}$	PC	$\overline{LGD^*}$
Borrower liquidity constraint								
Liquidity constraint$_{(\leq 0)}$	-0.067*	-0.04***			-0.502***	-0.057***		
	(0.038)	(0.005)			(0.041)	(0.008)		
Liquidity constraint$_{s0}$			-6.15***	-0.399*			-2.141*	-0.303
			(1.473)	(0.215)			(1.159)	(0.236)
Liquidity constraint$_{s0.04}$			7.911***	0.437			6.565***	-0.079
			(2.074)	(0.292)			(1.49)	(0.302)
Liquidity constraint$_{s0.08}$			-1.531*	-0.074			-4.36***	0.267***
			(0.823)	(0.111)			(0.5)	(0.1)
Liquidity constraint$_{s0.52}$			-0.608***	0.105***			-0.176***	0.151***
			(0.076)	(0.013)			(0.044)	(0.012)
Home equity								
Home equity$_{(\leq 0)}$	1.342***	-0.344***	1.139***	-0.237***				
	(0.085)	(0.013)	(0.088)	(0.014)				
Home equity$_{s-0.2}$	-1.083***	0.116***	-0.778***	-0.02				
	(0.169)	(0.023)	(0.167)	(0.027)				
Home equity$_{s0}$					0.939***	-0.144***	0.445**	-0.299***
					(0.22)	(0.042)	(0.178)	(0.038)
Home equity$_{s0.1}$					-1.543***	-0.185***	-0.047	-0.202***

					(0.331)	(0.063)	(0.257)	(0.056)
Home equity$_{s0.2}$					4.152***	-0.415***	3.56***	-0.383***
					(0.196)	(0.043)	(0.133)	(0.034)
Intercept	Yes		Yes		Yes		Yes	
Controls	Yes		Yes		Yes		Yes	
σ_ε	0.162***		0.204***		0.233***		0.27***	
	(0.001)		(0.001)		(0.001)		(0.001)	
$\rho_{u,\varepsilon}$	0.03		0.828***		-0.011		-0.008	
	(0.067)		(0.006)		(0.028)		(0.02)	
Log Likelihood	-16,167		-21,174		-63,951		-165,566	
Pseudo/Adjusted R^2	12.1%	29.9%	23%	34.2%	17.7%	24%	25.6%	29.2%
Number of Observations	73,802		72,786		115,601		247,219	

Table 10: Parameter estimates for probability of cure equation using zip code level HPIs

This table reports the parameter estimates for the probability of cure equation without control and with control variables for the Full sample (Q2/2005-Q1/2015). Three analyses are considered, Home Equity is updated using (i) the developmental 3-digit Zip Code FHFA HPI (quarterly); (ii) the developmental 5-digit Zip Code FHFA HPI (annually); and (iii) Zip Code Zillow HPI (quarterly). Bogin et al. (2018) outline the methodology of the developmental Zip Code FHFA HPI.. FICO is divided by 1,000; Loan size, Current IR and DefaultToEOO are divided by 10; Unemployment rate is a percentage; real growth rate and HPA are in their levels. Standard errors are reported in parentheses. ***, ** and * denote that the estimates are statistically significant at 1%, 5% and 10% level. We do not report the estimated intercepts of these equations.

Parameter	(i) 3-digit Zip Code FHFA HPI		(ii) 5-digit Zip Code FHFA HPI		(iii) Zip code Zillow HPI	
	No control	With controls	No control	With controls	No control	With controls
Borrower liquidity constraint						
Liquidity constraints	0.266***	-0.283***	0.287***	-0.293***	0.307***	-0.295***
	(0.025)	(0.026)	(0.025)	(0.026)	(0.026)	(0.027)
Liquidity constraint$_{s0}$	-12.562***	-7.448***	-12.916***	-7.799***	-12.776***	-7.95***
	(0.381)	(0.399)	(0.384)	(0.402)	(0.405)	(0.424)
Liquidity constraint$_{s0.04}$	17.121***	12.474***	17.711***	12.763***	17.968***	13.271***
	(0.763)	(0.789)	(0.77)	(0.797)	(0.814)	(0.842)
Liquidity constraint$_{s0.08}$	-3.506***	-4.615***	-3.717***	-4.498***	-4.147***	-4.851***
	(0.407)	(0.419)	(0.411)	(0.423)	(0.435)	(0.447)
Liquidity constraint$_{s0.52}$	-0.933***	-0.287***	-0.97***	-0.327***	-0.946***	-0.341***
	(0.036)	(0.038)	(0.036)	(0.038)	(0.038)	(0.04)
Home equity						
Home equity	0.82***	1.236***	0.563***	0.768***	0.379***	0.765***
	(0.052)	(0.054)	(0.03)	(0.032)	(0.03)	(0.031)
Home equity$_{s-0.2}$	-1.004***	-1.298***	-0.732***	-0.925***	-0.654***	-0.809***
	(0.098)	(0.102)	(0.076)	(0.079)	(0.075)	(0.079)
Home equity$_{s0}$	0.384***	0.725***	0.117	0.713***	0.227	0.34**
	(0.138)	(0.144)	(0.138)	(0.144)	(0.14)	(0.146)

Home equity$_{s0.1}$	-0.513***	-0.668***	-0.203	-0.417**	0.014	0.014
	(0.161)	(0.167)	(0.164)	(0.171)	(0.173)	(0.179)
Home equity$_{s0.2}$	4.074***	4.037***	4.085***	3.889***	3.786***	3.693***
	(0.103)	(0.107)	(0.105)	(0.109)	(0.114)	(0.119)
Controls						
FICO		-1.146***		-1.146***		-1.203***
		(0.037)		(0.037)		(0.039)
Current IR		-0.484***		-0.457***		-0.474***
		(0.014)		(0.014)		(0.015)
Loan size		4.205***		5.051***		3.548***
		(0.69)		(0.714)		(0.778)
Loan size square		-0.954***		-1.405***		-0.768**
		(0.282)		(0.292)		(0.317)
PDJ		-0.226***		-0.219***		-0.23***
		(0.005)		(0.005)		(0.005)
SRR		-0.214***		-0.214***		-0.227***
		(0.007)		(0.007)		(0.008)
ARM		-0.297***		-0.306***		-0.304***
		(0.005)		(0.005)		(0.005)
Owner occupied		0.121***		0.122***		0.109***
		(0.006)		(0.006)		(0.007)
DefaultToEOO		-1.585***		-1.599***		-1.619***
		(0.015)		(0.015)		(0.016)
HPA		4.349***		4.747***		4.609***
		(0.07)		(0.07)		(0.073)

Real growth rate		1.286***		1.31***		1.419***
		(0.152)		(0.153)		(0.162)
Unemployment rate		-0.005***		-0.004***		-0.001
		(0.001)		(0.001)		(0.001)
Log Likelihood	-360,681	-287,066	-350,131	-279,011	-284,299	-228,968
Number of Observations		508,555		499,884		448,392

Table 11: Parameter estimates for non-zero loss equation using zip code level HPIs

This table reports the parameter estimates for the non-zero loss equation without control and with control variables for the Full sample (Q2/2005-Q1/2015). Three analyses are considered, Home Equity is updated using (i) the developmental 3-digit Zip Code FHFA HPI (quarterly); (ii) the developmental 5-digit Zip Code FHFA HPI (annually); and (iii) Zip Code Zillow HPI (quarterly). Bogin et al. (2018) outline the methodology of the developmental Zip Code FHFA HPI. FICO is divided by 1,000; Loan size, Current IR and DefaultToEOO are divided by 10; Unemployment rate is in percentage terms; real growth rate and HPA are in their level (i.e., in absolute terms). Standard errors are reported in parentheses. ***, ** and * denote that the estimates are statistically significant at 1%, 5% and 10% level. We do not report the estimated intercepts of these equations.

Parameter	(i) 3-digit Zip Code FHFA HPI		(ii) 5-digit Zip Code FHFA HPI		(ii) Zip Code Zillow HPI	
	No control	With controls	No control	With controls	No control	With controls
Borrower liquidity constraint						
Liquidity constraints	-0.042***	-0.007	-0.042***	-0.003	-0.05***	-0.003
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Liquidity constraint$_{s0}$	2.995***	1.117***	3.097***	1.227***	2.933***	0.996***
	(0.076)	(0.067)	(0.076)	(0.067)	(0.075)	(0.067)
Liquidity constraint$_{s0.04}$	-2.872***	-1.668***	-3.064***	-1.807***	-3.18***	-1.528***
	(0.15)	(0.131)	(0.149)	(0.131)	(0.147)	(0.132)
Liquidity constraint$_{s0.08}$	-0.318***	0.446***	-0.243***	0.451***	0.065	0.434***
	(0.081)	(0.071)	(0.08)	(0.071)	(0.079)	(0.071)
Liquidity constraint$_{s0.52}$	0.196***	0.165***	0.206***	0.177***	0.18***	0.15***
	(0.01)	(0.008)	(0.01)	(0.008)	(0.009)	(0.008)
Home equity						
Home equity	-0.23***	-0.362***	-0.209***	-0.317***	-0.205***	-0.335***
	(0.012)	(0.01)	(0.007)	(0.006)	(0.006)	(0.006)
Home equity$_{s-0.2}$	0.16***	0.257***	0.101***	0.151***	0.035**	0.17***
	(0.022)	(0.019)	(0.017)	(0.015)	(0.016)	(0.014)
Home equity$_{s0}$	-0.142***	-0.202***	-0.105***	-0.117***	-0.16***	-0.144***

	(0.031)	(0.027)	(0.031)	(0.027)	(0.029)	(0.026)
Home equity$_{s0.1}$	-0.462***	-0.233***	-0.403***	-0.101***	-0.269***	-0.195***
	(0.037)	(0.032)	(0.037)	(0.033)	(0.036)	(0.033)
Home equity$_{s0.2}$	0.257***	-0.282***	0.225***	-0.31***	0.209***	-0.168***
	(0.027)	(0.024)	(0.027)	(0.024)	(0.027)	(0.024)
Controls						
FICO		-0.226***		-0.231***		-0.231***
		(0.008)		(0.008)		(0.008)
Current IR		0.188***		0.181***		0.189***
		(0.003)		(0.003)		(0.003)
Loan size		-15.473***		-15.534***		-11.751***
		(0.163)		(0.166)		(0.175)
Loan size square		5.752***		5.829***		4.353***
		(0.066)		(0.068)		(0.071)
JP		0.12***		0.127***		0.13***
		(0.001)		(0.001)		(0.001)
PDJ		0.041***		0.034***		0.044***
		(0.001)		(0.001)		(0.001)
SRR		0.038***		0.043***		0.021***
		(0.001)		(0.001)		(0.001)
ARM		0.018***		0.019***		0.015***
		(0.001)		(0.001)		(0.001)
Owner occupied		-0.077***		-0.077***		-0.057***
		(0.001)		(0.001)		(0.001)
DefaultToEOO		-0.012**		-0.016***		-0.016***

		(0.005)		(0.005)		(0.005)
HPA		-1.401***		-1.541***		-1.411***
		(0.014)		(0.014)		(0.014)
Real growth rate		-1.102***		-1.127***		-0.946***
		(0.03)		(0.03)		(0.03)
Unemployment rate		0.006***		0.005***		0.001***
		(0.000)		(0.000)		(0.000)
σ_ε	0.27***	0.235***	0.268***	0.234***		0.222***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
$\rho_{u,\varepsilon}$	-0.019	0.035***	-0.005	0.081***		0.068***
	(0.012)	(0.013)	(0.012)	(0.013)		(0.013)
Log Likelihood	-360,681	-287,066	-350,131	-279,011	-284,299	-228,968
Number of Observations		508,555		499,884		448,392

Table 12: Out-of-time forecasting comparison

This table reports the Root Mean Square Errors (RMSE) of the Out-of-time forecasts for the full information model, limited information model and the popular OLS model used in practice. The table also shows the two-sample *t*-test for difference in mean of the square errors (MSE) of the forecasts between Full information model and Limited information/ OLS model. The null hypothesis, H_0: $MSA_{Model\ A} = MSA_{Model\ B}$. T-statistics are reported in parentheses. ***, ** and * indicate rejections of the null hypothesis H_0 at 1%, 5% and 10% level of significance, respectively.

	RMSEs of Out-of-Time prediction			**Difference in RMSE (%)**	
	Full information (1)	**Limited information (2)**	**OLS (3)**	$\frac{(1)-(2)}{(2)}$	$\frac{(1)-(3)}{(3)}$
Forecasting year: 2008					
In-sample 2005-2007	0.31645	0.31657	0.33252	-0.04%	**-4.83%**
				(-0.13)	**(-17.24)*** **
Forecasting year: 2009					
In-sample 2005-2008	0.33682	0.3359	0.3346	0.28%	0.66%
				(0.85)	(2.09)
Forecasting year: 2010					
In-sample 2005-2009	0.32639	0.32625	0.32567	0.04%	0.22%
				(0.11)	(0.52)
Forecasting year: 2011					
In-sample 2005-2010	0.31703	0.31688	0.31577	0.05%	0.40%
				(0.10)	(0.81)
Forecasting year: 2012					
In-sample 2005-2011	0.30318	0.30312	0.30368	0.02%	-0.16%
				(0.03)	-(0.26)

Figure 1: Distribution of Loss Given Default

This figure shows the bimodal LGD distribution with a large fraction of defaulted loans that do not generate losses (zero LGDs or cures). Almost 30% of defaulted loans are cured.

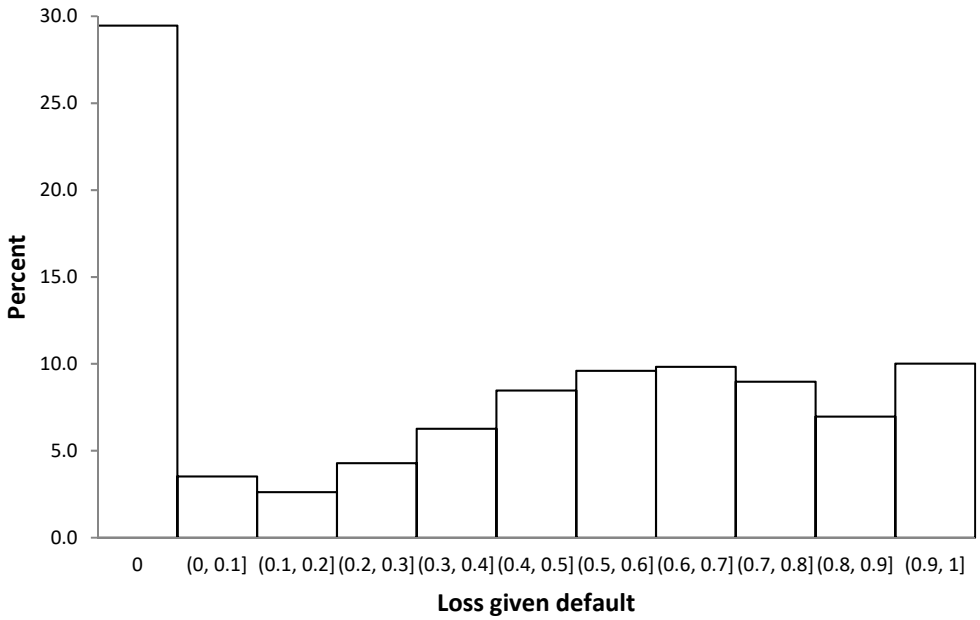


Figure 2: Selection mechanism for cure and non-zero LGD

This figure shows the selection mechanism for cure and non-zero LGD that our model is based on. The mechanism indicates that the cure events are observed if loan *i* defaults, while the non-zero LGD can only be observed if the defaulted loan *i* is non-cured. This mechanism is implemented by a joint probability framework between cure and non-zero losses for modeling purposes in this paper.

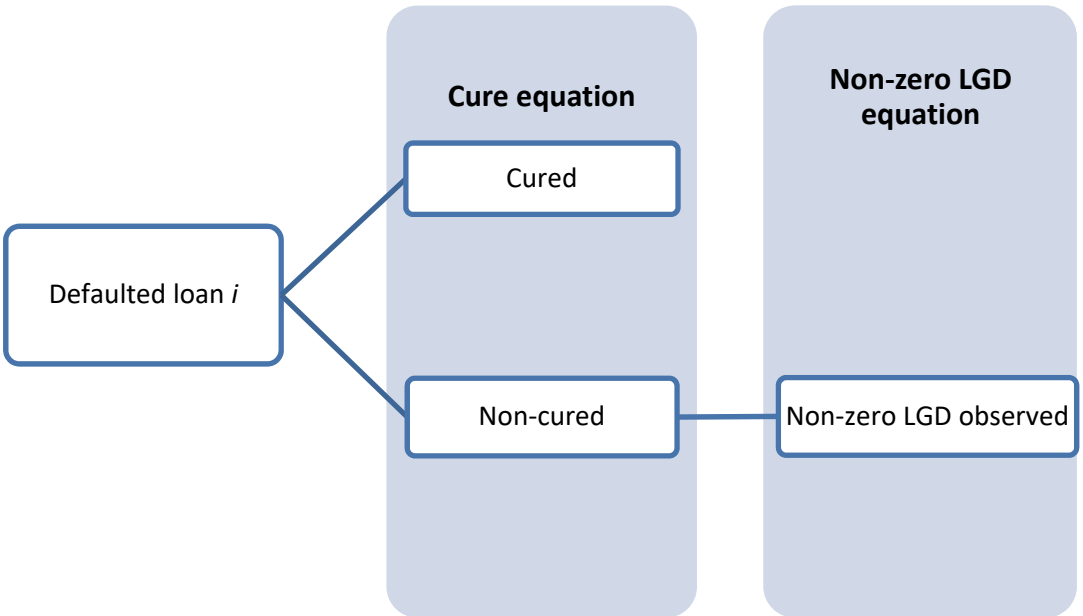


Figure 3: Average cure rate by ranges of liquidity constraint

This figure shows average cure rates by ranges of borrower liquidity constraints, which is marked by their mid-points on the left vertical axis and the number of observations in each range on the right vertical axis. The dashed bounds on each bar represent the 95% confidence interval for the cure rate.

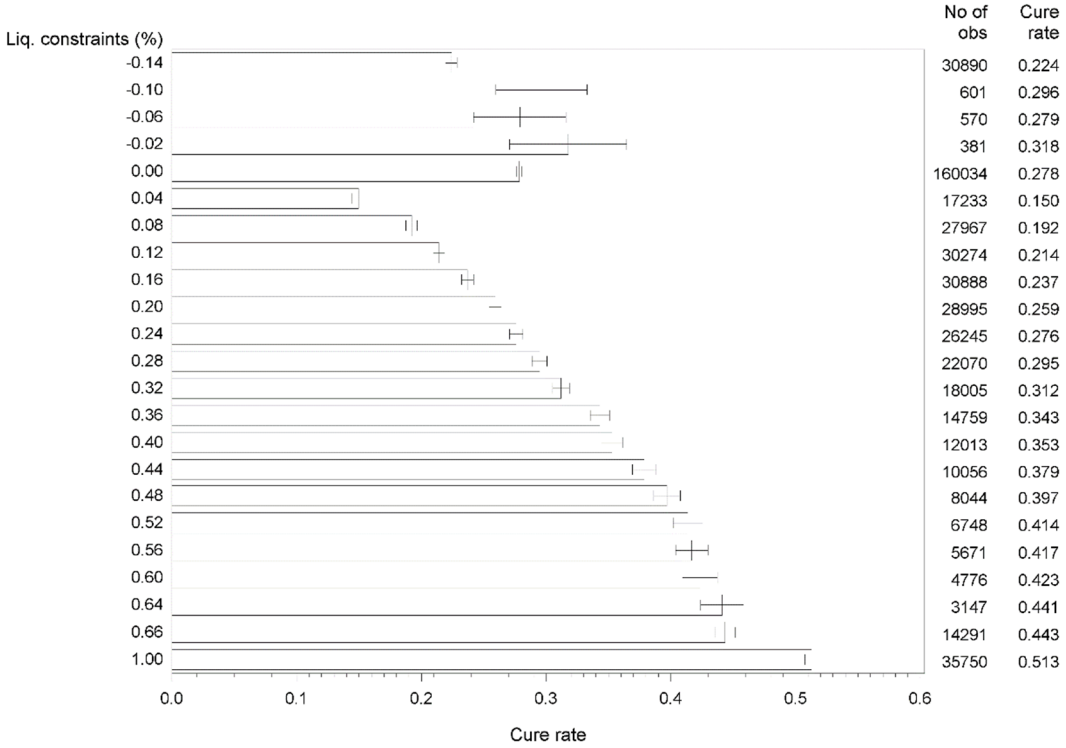


Figure 4: Average cure rate by ranges of home equity

This figure shows the average cure rate by ranges of home equity, which is marked by their mid-points on the left vertical axis and the number of observations in each range on the right vertical axis. The dashed bounds on each bar represent the 95% confidence interval for the cure rate.

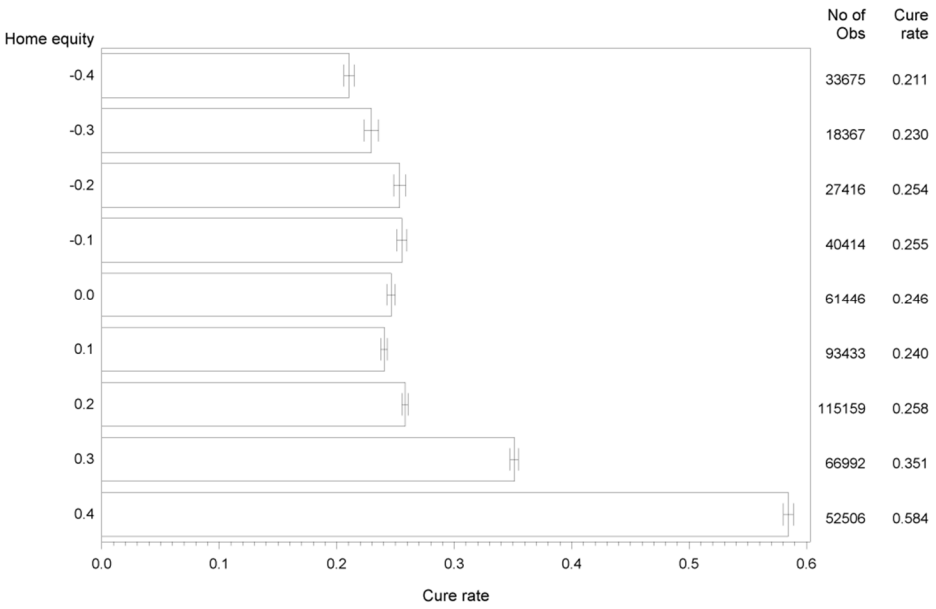


Figure 5: Average unemployment rate, borrower liquidity constraint and home equity by time

This figure shows the average unemployment rate, borrower liquidity constraint and home equity by time. The time varying behaviour of unemployment rate is negatively related with home equity, while the borrower liquidity constraint co-moves with home equity in some periods. There is a time-delayed reflection of the impact of the unemployment rate on the borrower liquidity constraint by one year.

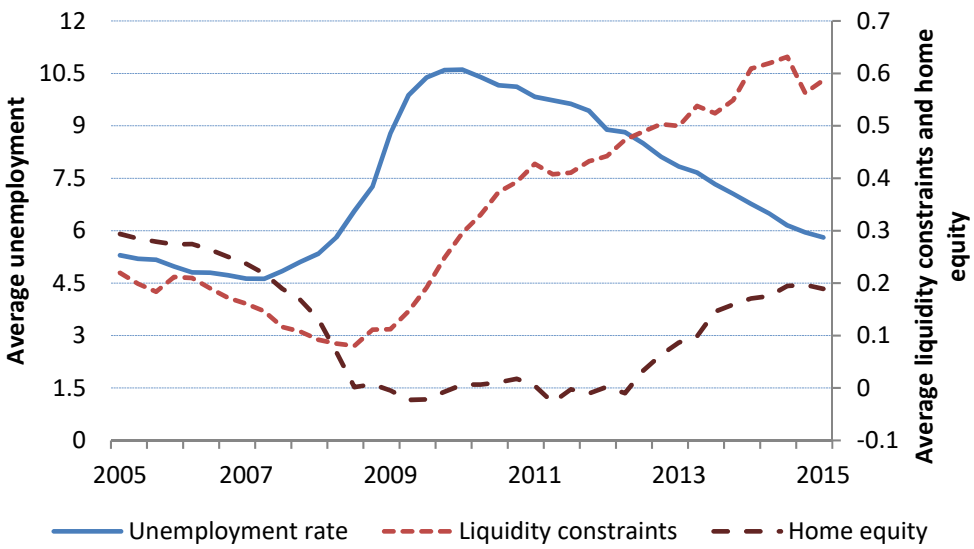


Figure 6: Scatter plots of average liquidity constraint, cure rate and average non-zero LGD by time

This figure shows scatter plots of average liquidity constraint, cure rates by time and average non-zero LGD by time. The first two plots relate to the cure rate and the second two plots to the non-zero LGD. The cure rate and non-zero LGD is contemporary for the first and third plot and lagged by four periods for the second and fourth plot. The ellipses show 95% confidence interval and the solid lines are the regression lines.

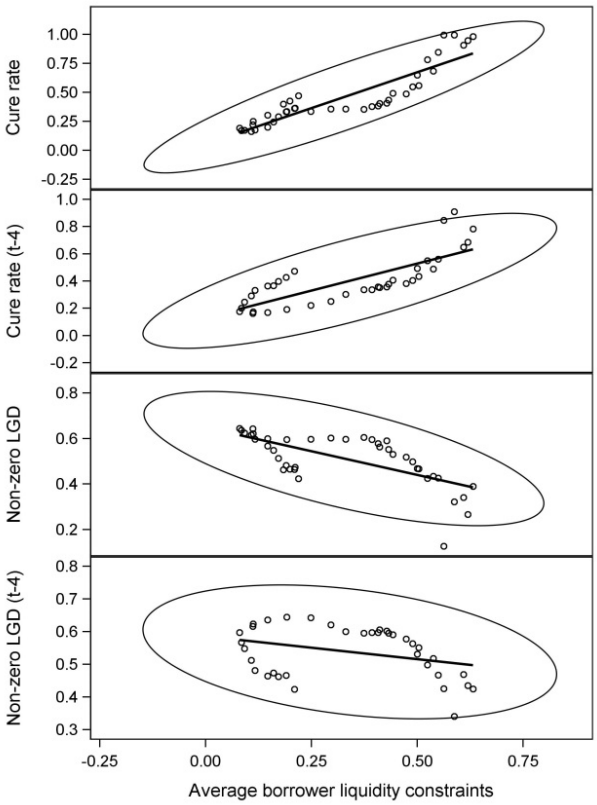
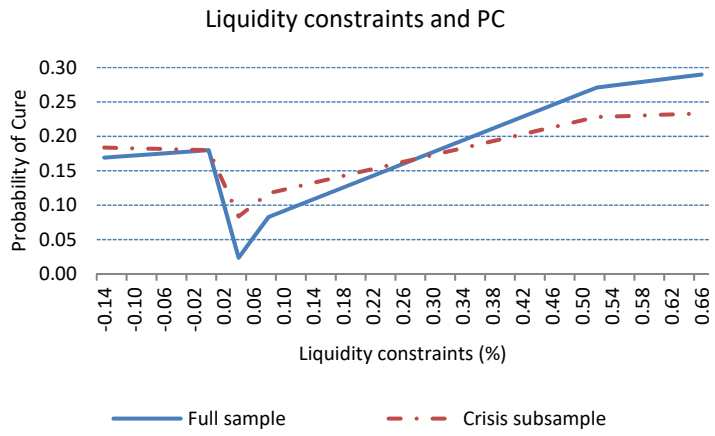
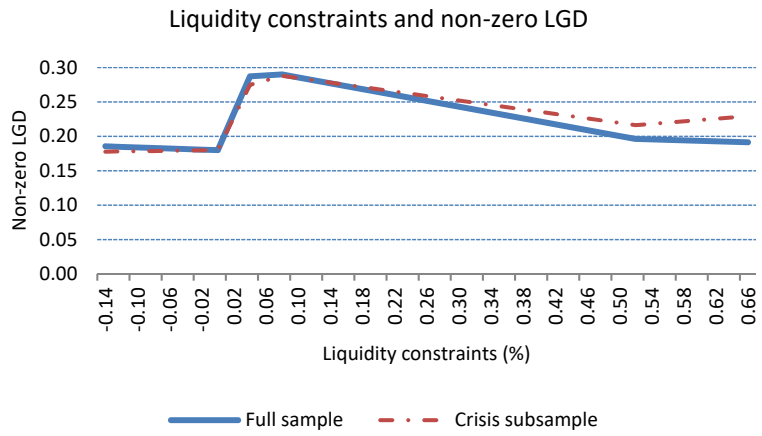


Figure 7: Relation between liquidity constraint, probability of cure and non-zero LGD

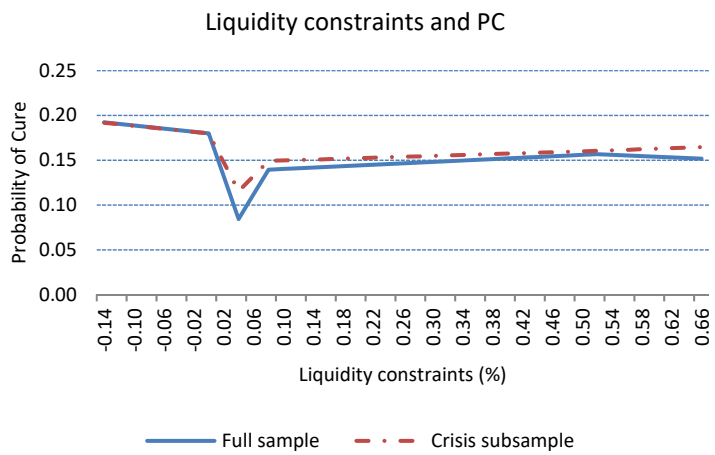
This figure depicts the relations between borrower liquidity constraint, probability of cure and non-zero LGD for the estimated parameters from Table 7 and 8.

Panel A: Relations estimated from model without controls





Panel B: Relations estimated from model with controls



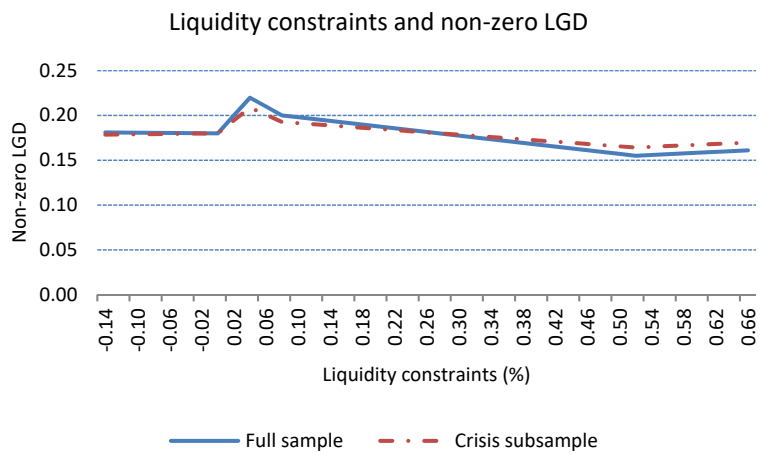


Figure 8: Relation between liquidity constraint, probability of cure and non-zero LGD for partitioned samples

This figure shows the relations between borrower liquidity constraints, probability of cure and non-zero LGD for four partitioned samples that distinguish positive and negative liquidity constraints on the horizontal direction, positive and negative equity on the vertical direction. The relations are visualized for the estimated parameters from Table 9.

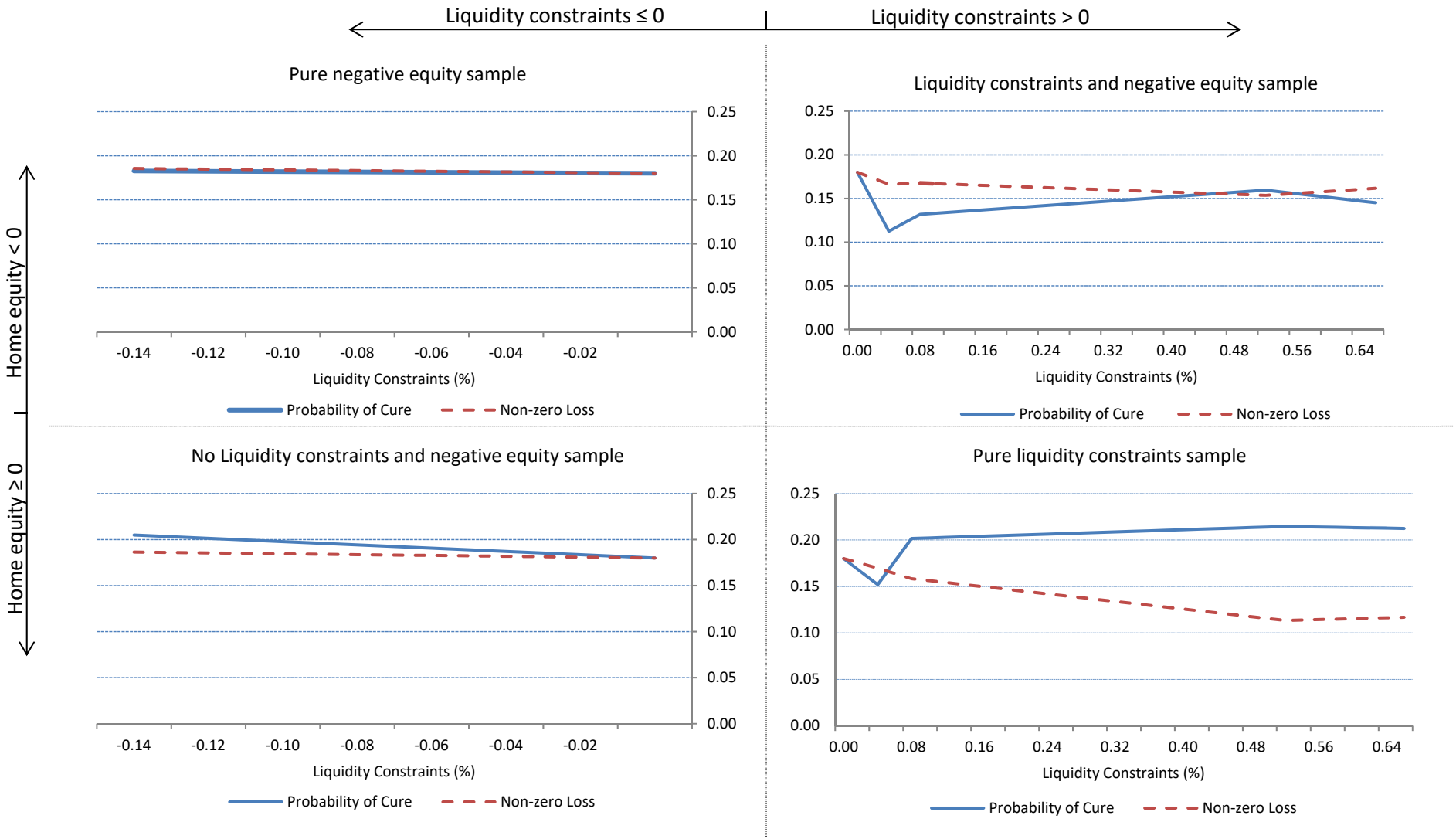
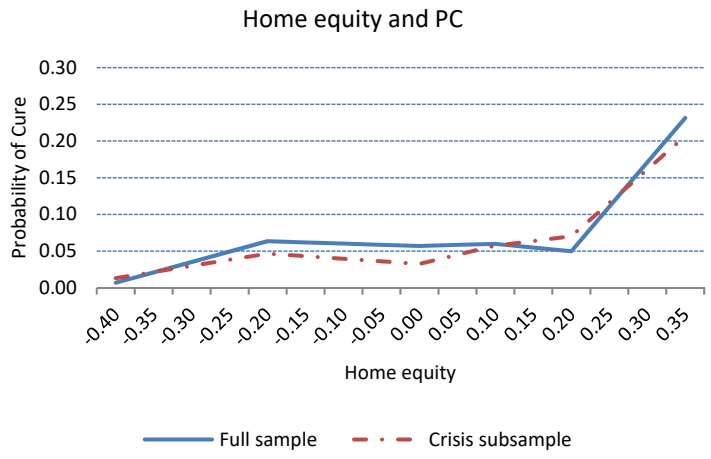
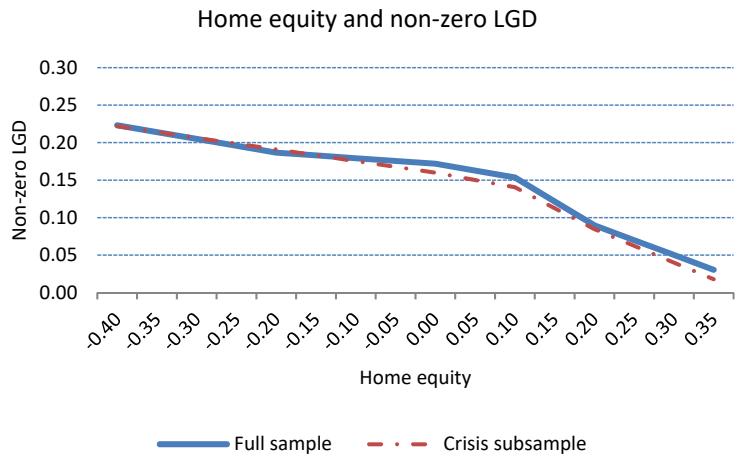


Figure 9: Relation between home equity, probability of cure and non-zero LGD

This figure depicts the relations between home equity, probability of cure and non-zero LGD for the estimated parameters from Table 7 and 8.

Panel A: Relations estimated from model without controls





Panel B: Relations estimated from model with controls