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What ‘Triggers’ Mortgage Default?*

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Abstract: This paper assesses the relative importance of two key drivers of mortgage default: negative equity and illiquidity. To do so, we combine loan-level mortgage data with detailed credit bureau information about the borrower's broader balance sheet. This gives us a direct way to measure illiquid borrowers: those with high credit card utilization rates. We find that both negative equity and illiquidity are significantly associated with mortgage default, with comparably sized marginal effects. Moreover, these two factors interact with each other: The effect of illiquidity on default generally increases with high combined loan-to-value ratios (CLTV), though is significant even for low CLTV. County-level unemployment shocks are also associated with higher default risk (though less so than high utilization) and strongly interact with CLTV. In addition, having a second mortgage implies significantly higher default risk, particularly for borrowers who have a first-mortgage LTV approaching 100 percent.

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The “option model” of mortgage default is traditionally interpreted as implying that borrowers should default if and only if they have negative equity in their home. However, numerous studies have found that many borrowers with negative equity do not default;¹ and, conversely, default is often associated with “shocks,” such as unemployment.²

One standard way of reconciling the model and the data is to introduce transaction costs of defaulting, such as moving costs, reputation costs (e.g., lost access to credit), and stigma. But such costs can be difficult to identify. Moreover, properly understood, the option model does not imply that negative equity alone is sufficient for default. By defaulting today, one gives up the option to default in the future; as a result, even with negative equity, one might prefer to wait and see if house prices recover (James Kau et al., 1994).

This paper focuses on another — not mutually exclusive — explanation. The cost of continuing to pay one’s mortgage also depends on one’s idiosyncratic discount factor and thus on one’s liquidity position. For someone who is very illiquid, it can be costly to wait for house prices to recover. Indeed, in the extreme, he might literally not be able to find the cash to make the next mortgage payment. See Peter Elmer and Steven Seelig (1999), Kristopher Gerardi et al. (2007), and Patrick Bajari et al. (2008).³

This paper assesses the relative importance of these two factors for mortgage default: negative equity and illiquidity. To do so, we combine loan-level mortgage data with detailed credit bureau information about the borrower’s broader balance sheet. This gives us a direct way to identify illiquidity, using credit-card utilization rates. Sumit Agarwal et al. (2007) and David

¹ For example, Chester Foster and Robert Van Order (1984), and Neil Bhutta et al. (2010).

² Some papers have noted that it might be the “double-trigger” combination of negative equity and shocks that leads to default. See, for example, the discussion in Kerry Vandell (1995). But few papers have actually allowed for an interaction between these variables in the estimation, as we do below; one exception is Christopher Foote et al. (2009).

³ Ethan Cohen-Cole and Jonathan Morse (2009) examine the choice between mortgage versus credit-card default.

B. Gross and Nicholas S. Souleles (2002a) have shown that households who have “maxed-out” their credit cards display high propensities to spend in response to increases in income, consistent with their being liquidity constrained. Also, while illiquidity is conceptually distinct from shocks, high credit-card utilization may reflect prior shocks (e.g., James X. Sullivan, 2008), which otherwise might be hard to observe directly.

Another benefit of using credit bureau data is that it allows us to measure total housing debt and thus the borrower’s combined loan-to-value ratio (CLTV). By contrast, the mortgage data sets typically used in the literature (e.g., from Loan Performance and Lender Processing Services [LPS]) have spotty information on second liens, at best, and so mis-measure the contribution of negative equity to default. This effect can be economically significant. For example, for the 26 percent of borrowers in our sample with a second mortgage, using only the first-mortgage loan-to-value ratio (LTV) underestimates their total CLTV by 15 percentage points.

Disentangling these two determinants of mortgage default (negative equity and illiquidity) is also important for the policy debate over loan modifications. If negative equity dominates, one might tend to focus more on reducing principal, *ceteris paribus*. By contrast, if illiquidity is also important, temporary reductions in payments may also be useful.

I. Data

Our mortgage data are from the LPS dataset.⁴ We focus on first mortgages originated in 2005 and 2006, since these cohorts are the most likely to have negative equity during our sample period. The LPS data cover about 70 percent of all mortgage originations in these years. For

⁴ Formerly known as McDash, this dataset has been used extensively to study mortgage default. See, for example, Ronel Elul (2009) and the references therein.

brevity, we limit our sample to fixed-rate mortgages (FRMs).⁵ We further restrict attention to owner-occupied houses and exclude multifamily properties. We consider the three most common maturities: 15, 30, and 40 years. This sample represents about three-quarters of all FRMs in the LPS data. We follow our borrowers through April 2009.

Our credit bureau data are from Equifax, one of the three major credit reporting agencies in the United States. The dataset contains a random subsample of credit users. The data include comprehensive summaries of key characteristics of the different types of debt held by individual borrowers (e.g., total credit-card balances and limits). In addition, the dataset includes loan-level information on these borrowers' mortgage trades. We linked this dataset to the LPS dataset through the characteristics of the first mortgages, in particular, open date, initial balance and ZIP code. (To be conservative, we used only unique matches.) We matched about one-third of the potential overlap between the two datasets. Our final sample consists of approximately 364,000 FRMs. We also added MSA-level house price indexes from the Federal Housing Finance Agency and county-level unemployment rates from the Bureau of Labor Statistics. Since the house-price index and bureau data are available quarterly, we follow the mortgages quarterly.⁶

II. Methodology

We estimate dynamic logit models for mortgage default that are equivalent to discrete duration models.⁷ Our dependent variable is a dummy variable indicating when a mortgage first becomes 60+ days delinquent.

⁵ In preliminary analysis of adjustable rate mortgages, we found qualitatively similar baseline results.

⁶ Summary statistics are reported in Table 1. Further details about our data and results can be found in the online version of the paper.

⁷ As in David B. Gross and Nicholas S. Souleles (2002b), we use a fifth-order polynomial in account age to allow the associated hazard function to vary nonparametrically. We also include state and quarter dummy variables. Standard errors are clustered at the loan level. In preliminary analysis, we obtained similar baseline results when using a Cox proportional hazard model.

The independent variables include standard mortgage and borrower characteristics from the LPS dataset (e.g., initial LTV and FICO score), taken from the time of origination.⁸ We also estimate the current CLTV, dividing the sum of first and second mortgage balances (from the LPS and bureau data, respectively) by an estimate of the current house price. The latter is obtained by updating the house value at origination using the change in the local house price index since origination. From the bureau data, we obtain the mortgage borrower's total bankcard utilization rate (i.e., total balances relative to total limits across all cards held), and their total second mortgage balance, which is the sum of all active home equity installment and home equity revolving mortgage loan balances. For comparison, we also use the change in the county-level unemployment rate over the previous year, as a canonical measure of a shock. Finally, we also consider whether the utilization and unemployment rates interact with CLTV.

Recall that the data set is constructed to be quarterly. To clarify the timing, we consider whether an individual i defaults in a given quarter, i.e., in months $t+1$, $t+2$, or $t+3$. The independent variables are all lagged relative to this quarter. The LPS mortgage control variables, most notably the first mortgage balance, come from month t . To be conservative, the variables from the other datasets are lagged one month further. The bureau data are from the last month of the previous quarter, i.e., month $t-1$. The house price index is the average for the previous quarter, i.e., over months $t-3$, $t-2$ and $t-1$. Finally, the change in the county unemployment rate is taken from months $t-13$ to $t-1$.

To motivate our analysis, we begin by plotting nonparametric default hazard functions, for different levels of utilization, CLTV, and unemployment, in Figure 1. The x-axis gives the mortgage age (in months), and the y-axis gives the probability of default in the next quarter,

⁸ One exception is the investor type (Portfolio [omitted category], Private Securitized, GSE, or FHA), which is determined within the first year following origination. See Elul (2009) for details.

conditional on not having defaulted before. In Panel A, starting with the lowest line and moving upwards: Notice that when both CLTV and utilization are low (below 90 and 80 percent, representing about 85 percent and 87 percent of the sample, respectively), default risk is also relatively low. High CLTV raises default risk substantially, even with low utilization. Conversely, high utilization with low CLTV is even riskier, with the hazard rate of default rising to over 1 percentage point per quarter (pp/q) when the mortgage is 40 months old. In Panel B, large increases in unemployment (≥ 1.25 pp, about 13 percent of the sample) on their own with low CLTV have little effect on default. However, when both unemployment and CLTV are high, then the default probability increases substantially. We will now study these effects more formally in a multivariate setting, including the potential for interactions between these variables.

III. Estimation Results

Table 1 reports the point estimates and marginal effects for our baseline specification. The marginal effects for the variables commonly used in mortgage default studies have the expected signs. For example, broker-originated loans have a 0.21 pp/q higher risk of default than the omitted category, retail-originated loans. This is a sizable effect, relative to a sample average default rate of about 0.9 pp/q.

Our primary variables of interest are CLTV, the credit-card utilization rate, and unemployment. These are modeled flexibly using indicator variables. Notice that the marginal effect of CLTV is monotonic and statistically and economically significant. For example, going from CLTV below 50 to above 120 raises default risk by 1.3 pp/q. Nonetheless, even after controlling for CLTV and the other variables, utilization is also significant and monotonic. The marginal effect of high utilization (e.g., considering both indicators for being above 80 percent)

is comparable in magnitude to that of high CLTV (e.g., above 90). This result suggests that both negative equity and illiquidity are significantly associated with mortgage default.⁹ More broadly, the result highlights the importance of having broader balance-sheet information to model mortgage default (Sumit Agarwal et al., 2009). The change in the local unemployment rate is also significant and monotonic, though the marginal effects are much smaller in magnitude.¹⁰

To this baseline specification we now add interactions of utilization and unemployment with CLTV. For brevity, Table 2 uses just a single indicator for high utilization (above 80 percent), or for a large increase in unemployment (≥ 1.25 pp), and focuses on the interaction terms.¹¹ Panel A includes the indicator for high utilization and also interacts it with the CLTV indicators (still including the original unemployment and uninteracted CLTV variables). The average marginal effect of high utilization (relative to low utilization), including the effect through the interaction terms, is 1.1 pp/q (top row). The rest of the panel shows the marginal effect of high utilization for different levels of CLTV. Even for low CLTV (below 50), utilization has a significant effect: 0.65 pp/q. The effect becomes stronger, however, as CLTV rises, peaking at 1.5 pp/q for CLTV near 100.

Panel B instead interacts CLTV with large increases in unemployment (again including the original four utilization indicators). By contrast with utilization, there is little effect of

⁹ In addition to illiquidity, high utilization could also reflect individuals expecting to default on both their credit cards and mortgage. To minimize such possibilities, as an extension we froze the bureau variables (utilization and second-mortgage balances) from the month before the mortgage becomes 30-days delinquent for the first time and also used the scheduled balance (determined as of origination) on the first mortgage in place of the actual balance. The main results were similar. Alternatively, we lagged the bureau variables up to nine additional months, again using the scheduled balance. While, not surprisingly, the marginal effects of high utilization (above 80) decline in magnitude, they remain statistically significant, and e.g. much larger than the effects of the unemployment rate.

¹⁰ Of course, CLTV and utilization are individual-specific, whereas we have only county-level unemployment rates. Also, the state and time dummies limit the utilized variation in unemployment, to avoid spurious correlations.

¹¹ The results for the other variables are similar to those in Table 1. The conclusions were similar when we interacted CLTV with the full set of utilization and unemployment indicators in Table 1. Note that in nonlinear models like the logit, the coefficients on interaction terms can have different signs than the corresponding marginal effects.

unemployment for CLTV below 50. But the effect increases monotonically and dramatically with high CLTV, reaching 1.1 pp/q for CLTV above 120. Hence, there is a strong positive interaction between unemployment shocks and CLTV.¹²

Recall that another benefit of using the bureau data is the availability of information on second mortgages. In Panel C we replace the CLTV indicators with the corresponding indicators for just the first-mortgage LTV and interact the latter with an indicator for having a second mortgage (including the original four utilization and unemployment indicators). On average, the extra risk from having a second mortgage is 0.22 pp/q, which is a significant effect, though smaller than that for CLTV and utilization. For first-mortgage LTV below 50, a second mortgage has little effect on default risk. But the effect increases with LTV, peaking when LTV hits 100, at which point the extra risk from a second mortgage is 0.54 pp/q, a substantial effect.

IV. Conclusions

We found that both negative equity and illiquidity, as measured by high credit-card utilization, are significantly associated with mortgage default, with comparably sized marginal effects. Moreover, the two factors interact with each other: the effect of utilization generally increases with CLTV (peaking at CLTV near 100), though is significant even for low CLTV.

County-level unemployment shocks are also associated with higher default risk (though less so than high utilization) and strongly interact with CLTV. In addition, having a second mortgage implies significantly higher default risk, particularly for borrowers who have a first-mortgage LTV approaching 100 percent.

¹² Observing any defaults with CLTV below 100 percent is, strictly speaking, inconsistent with a narrow interpretation of the “double trigger” view of mortgage default. However, the strong positive interaction between the unemployment shocks and CLTV suggests more broadly that the effects of shocks and negative equity on default do reinforce each other (and similarly for the generally positive interaction between high utilization and CLTV discussed above).

These results suggest a key role for liquidity in default modeling and highlight the value of using broader balance-sheet information.

Figure 1: Mortgage Default Hazard Functions

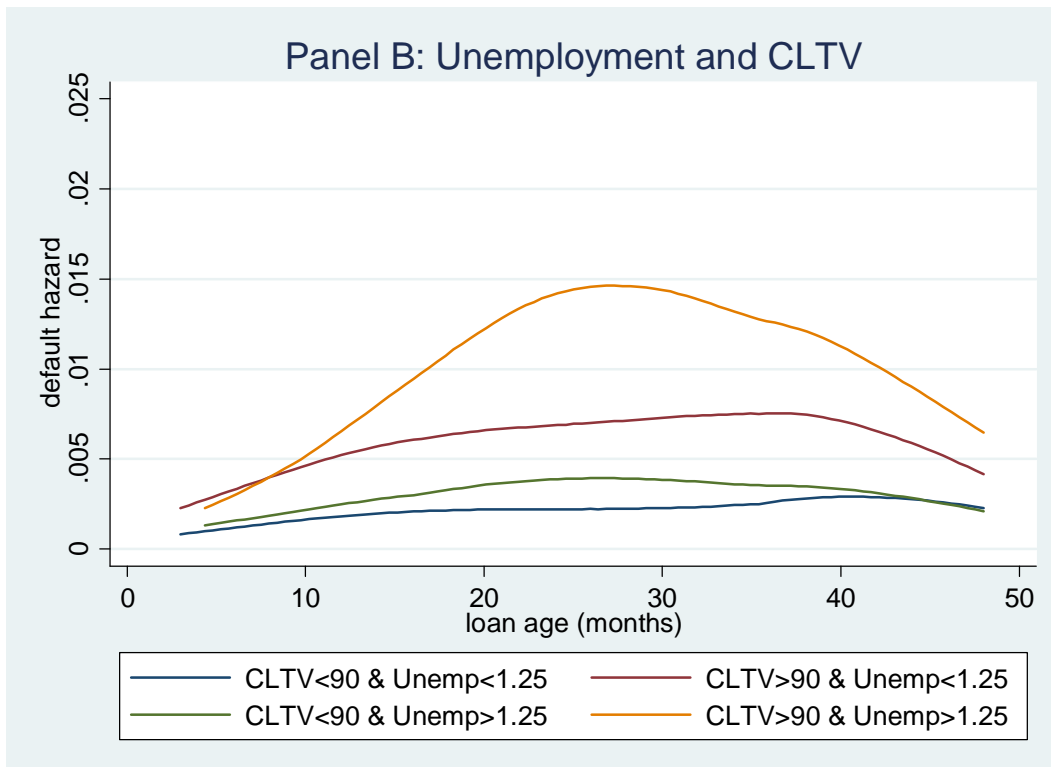
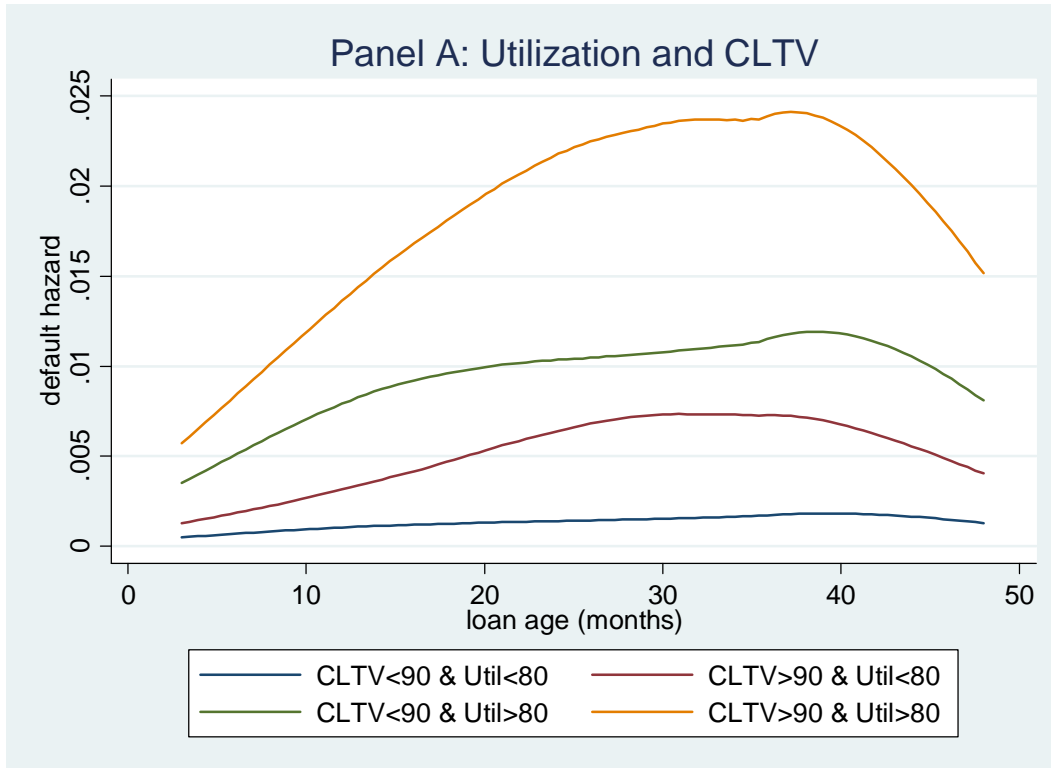


Table 1: Mortgage Default - Baseline Results¹³

| | Coef. | SE | | Marginal (pct.) | SE (pct.) | | Variable Means |
|--------------------------|--------|-------|-----|--------------------|--------------|-----|-------------------|
| Interest Rate | 0.363 | 0.010 | *** | 0.301 | 0.009 | *** | 6.14 |
| Initial FICO | 0.020 | 0.002 | *** | -0.007 | 0.000 | *** | 714 |
| FICO ² | 0.000 | 0.000 | *** | | | | |
| ln(initial loan amt) | 0.188 | 0.015 | *** | 0.156 | 0.012 | *** | 5.120 |
| Initial LTV | -0.017 | 0.088 | | -0.014 | 0.073 | | 0.715 |
| Initial LTV=80% | 0.122 | 0.020 | *** | 0.105 | 0.018 | *** | 0.125 |
| Refinancing | 0.000 | 0.018 | | 0.000 | 0.015 | | 0.519 |
| Cash-out Refi | 0.067 | 0.019 | *** | 0.056 | 0.016 | *** | 0.258 |
| Loan has PMI | 0.187 | 0.023 | *** | 0.164 | 0.021 | *** | 0.126 |
| Private Securitized | 0.062 | 0.034 | * | 0.052 | 0.029 | * | 0.174 |
| GSE | -0.123 | 0.033 | *** | -0.102 | 0.028 | *** | 0.715 |
| FHA | -0.048 | 0.038 | | -0.039 | 0.031 | | 0.075 |
| Broker Originated | 0.238 | 0.019 | *** | 0.212 | 0.018 | *** | 0.161 |
| Correspondent Orig. | 0.139 | 0.017 | *** | 0.119 | 0.015 | *** | 0.270 |
| Transferred to servicer | 0.333 | 0.021 | *** | 0.309 | 0.022 | *** | 0.075 |
| Condo | -0.043 | 0.021 | ** | -0.035 | 0.017 | ** | 0.132 |
| Interest Only | 0.632 | 0.033 | *** | 0.688 | 0.046 | *** | 0.016 |
| Low/no-doc | 0.044 | 0.019 | ** | 0.037 | 0.017 | ** | 0.154 |
| Unknown doc-type | 0.064 | 0.016 | *** | 0.053 | 0.013 | *** | 0.458 |
| Term: 15 years | -0.219 | 0.035 | *** | -0.166 | 0.024 | *** | 0.122 |
| Term: 40 years | 0.400 | 0.041 | *** | 0.394 | 0.047 | *** | 0.007 |
| CLTV ∈ [50,70) | 0.415 | 0.040 | *** | 0.193 | 0.016 | *** | 0.286 |
| CLTV ∈ [70,80) | 0.718 | 0.044 | *** | 0.390 | 0.020 | *** | 0.228 |
| CLTV ∈ [80,90) | 0.985 | 0.046 | *** | 0.616 | 0.023 | *** | 0.160 |
| CLTV ∈ [90,100) | 1.226 | 0.049 | *** | 0.872 | 0.029 | *** | 0.111 |
| CLTV ∈ [100,110) | 1.361 | 0.053 | *** | 1.042 | 0.044 | *** | 0.020 |
| CLTV ∈ [110,120) | 1.550 | 0.060 | *** | 1.318 | 0.066 | *** | 0.008 |
| CLTV ≥ 120 | 1.566 | 0.058 | *** | 1.343 | 0.064 | *** | 0.010 |
| Utilization ∈ [50,70) | 0.470 | 0.022 | *** | 0.291 | 0.015 | *** | 0.095 |
| Util ∈ [70,80) | 0.713 | 0.026 | *** | 0.500 | 0.023 | *** | 0.042 |
| Util ∈ [80,100) | 1.090 | 0.018 | *** | 0.936 | 0.018 | *** | 0.105 |
| Util ≥ 100 | 1.798 | 0.022 | *** | 2.284 | 0.046 | *** | 0.025 |
| Δunemployment ∈ [-0.5,0) | 0.006 | 0.024 | | 0.004 | 0.017 | | 0.299 |
| Δunemp ∈ [0,0.7) | 0.084 | 0.026 | *** | 0.063 | 0.019 | *** | 0.266 |
| Δunemp ∈ [0.7,1.25) | 0.183 | 0.033 | *** | 0.145 | 0.027 | *** | 0.100 |
| Δunemp ≥ 1.25 | 0.400 | 0.036 | *** | 0.352 | 0.032 | *** | 0.134 |

¹³ Coefficients on time and state dummies, and quintic in mortgage age, not reported. Baseline categories are: CLTV < 50; utilization < 50; Δunemployment < -0.5; portfolio investor type; single-family (not condo) property type; full documentation; 30-year term. Refinancing is relative to purchase loans. (Cash-out refi is the extra risk on top of refi.) N = 3.05 million. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Table 2: Mortgage Default - Interactions¹⁴

| | Coef. | SE | | Marginal (pct.) | SE (pct.) | |
|--|--------|-------|-----|--------------------|--------------|-----|
| Panel A: Utilization \geq 80 percent | | | | | | |
| Utilization \geq 80 | 1.314 | 0.064 | *** | 1.102 | 0.018 | *** |
| Interact: Util \geq 80 \times | | | | | | |
| CLTV < 50 | | | | 0.650 | 0.049 | *** |
| CLTV \in [50,70) | 0.005 | 0.071 | | 0.952 | 0.033 | *** |
| CLTV \in [70,80) | -0.153 | 0.069 | ** | 1.085 | 0.035 | *** |
| CLTV \in [80,90) | -0.235 | 0.069 | *** | 1.288 | 0.039 | *** |
| CLTV \in [90,100) | -0.336 | 0.069 | *** | 1.458 | 0.050 | *** |
| CLTV \in [100,110) | -0.506 | 0.082 | *** | 1.331 | 0.100 | *** |
| CLTV \in [110,120) | -0.743 | 0.099 | *** | 1.082 | 0.160 | *** |
| CLTV \geq 120 | -0.762 | 0.095 | *** | 1.059 | 0.153 | *** |
| Panel B: Δunemployment \geq 1.25 percentage points | | | | | | |
| Δ unemployment \geq 1.25 | 0.076 | 0.077 | | 0.219 | 0.022 | *** |
| Interact: Δ unemp \geq 1.25 \times | | | | | | |
| CLTV < 50 | | | | 0.029 | 0.030 | |
| CLTV \in [50,70) | 0.143 | 0.085 | * | 0.130 | 0.028 | *** |
| CLTV \in [70,80) | 0.114 | 0.083 | | 0.149 | 0.033 | *** |
| CLTV \in [80,90) | 0.130 | 0.081 | | 0.208 | 0.038 | *** |
| CLTV \in [90,100) | 0.226 | 0.082 | *** | 0.388 | 0.051 | *** |
| CLTV \in [100,110) | 0.266 | 0.092 | *** | 0.491 | 0.083 | *** |
| CLTV \in [110,120) | 0.414 | 0.110 | *** | 0.808 | 0.133 | *** |
| CLTV \geq 120 | 0.586 | 0.112 | *** | 1.068 | 0.129 | *** |
| Panel C: Have Second Mortgage | | | | | | |
| Have Second Mortgage | 0.157 | 0.061 | *** | 0.224 | 0.015 | *** |
| Interact: Have Second \times | | | | | | |
| LTV < 50 | | | | 0.059 | 0.024 | ** |
| LTV \in [50,70) | 0.112 | 0.067 | * | 0.173 | 0.019 | *** |
| LTV \in [70,80) | 0.086 | 0.066 | | 0.210 | 0.023 | *** |
| LTV \in [80,90) | 0.127 | 0.069 | * | 0.328 | 0.042 | *** |
| LTV \in [90,100) | 0.091 | 0.076 | | 0.363 | 0.072 | *** |
| LTV \in [100,110) | 0.162 | 0.106 | | 0.535 | 0.159 | *** |
| LTV \in [110,120) | 0.102 | 0.146 | | 0.485 | 0.264 | * |
| LTV \geq 120 | -0.070 | 0.155 | | 0.156 | 0.260 | |

¹⁴ Regressions also include the other covariates from Table 1. See text for details. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

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