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Delinquency Priority in Consumer Credit: Evidence from Thai Microdata

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Delinquency Priority in Consumer Credit: Evidence from Thai Microdata

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Abstract

This study examines the question of how consumer prioritize default across products. We find that about a third of Thai individuals who face default decisions on mortgage and non-mortgage loans choose to default on mortgage loans first. As predicted by theory, their decisions are influenced by relative debt burden and amount of housing equity, consistent with both the ability to pay and the willingness to pay channels. We also find a puzzling result that borrowers who hold older mortgage loans are more likely to default on their mortgages; we hypothesize that this is perhaps related to refinancing.

JEL Classifications: G21, G33
Keywords: mortgage loan, unsecured debt, delinquency priority, pecking order

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1. Introduction

Understanding how individuals behave and respond to economic shocks is crucial for informed policymaking. With greater availability of microeconomic data, economists have gained the ability to take a closer look at how agents and economic forces interact. For example, with credit bureau data, we are able to see for the first time that indebtedness in Thailand is actually concentrated among few borrowers. Chantarat et al. (2017) document that 10% of Thai borrowers are responsible for more than 60% of debt in the financial system, and that borrowers are rare: only 4% of Thai population have mortgage loans, and only 9% have credit cards.

Compared to other types of credit, research on consumer credit and consumer financial decision making (e.g. do consumers choose the best contract) is still in its early stage but growing thanks to the recent attention brought about by the Great Recession in the United States (for a concise review, see Mian and Sufi, 2010). We understand, for example, what triggers mortgage default (Elul et al., 2010) and how high-cost lending affects the real economy (Melzer, 2011). However, surprisingly few studies examine the question of how consumers prioritize default *across products*, even in developed countries. For example, do they keep their home while they default on other types of credit? The conventional wisdom is that borrowers tend to prioritize their mortgages, but Andersson et al. (2013) and Cohen-Cole and Morse (2010) show that a significant proportion of U.S. borrowers, in fact, default on their mortgage loans and keep servicing their credit cards. In particular, Andersson et al. (2013) find that the proportion is about 10% in early 2000s, rising to about 35% toward 2008.

In this paper, we provide a first look into default priority issue in a developing economy. Using nine years of monthly account-level microdata of 1 million individuals from Thailand's National Credit Bureau (NCB), we can identify individuals with multiple loan products and analyze their default decisions. As mortgage loans account for a third of outstanding credit and almost 20% of non-performing loans, we focus on the decision to default on mortgage loans versus other non-mortgage personal loans. We document 3 stylized facts. First, only a small subset of Thais are multi-class debtors: only 12.9% of individuals in the sample have mortgage loans, and only 9.4% have both mortgage and non-mortgage loans. Second, the proportion of multi-class debtors who default on both types of loans simultaneously is rising over time (see Figure 2). Third, excluding simultaneous defaulters, about a third of borrowers who face default decision on mortgage and non-mortgage loans choose to default on mortgage loans first.

Using binary logistic regression to compare default priority, we find that the affordability channel (measured by relative monthly payments between mortgage and non-mortgage loans) is very influential, while liquidity channel (available credit line) does not seem to have any meaningful impact. Housing equity (traditionally used in the literature to investigate strategic default but not applicable in Thailand due to the unlimited liability nature of mortgage loans) is also associated with lower likelihood of mortgage default, highlight the importance of borrowers' sense of ownership in mortgage default risk. Finally, borrowers with older mortgages tend to default on mortgage loans more, a puzzling result. We hypothesize that this finding is perhaps related to refinancing. We investigate these findings further to the best extent that our data allows, so it is inevitable that – in addition to the answers we provide – our paper raises further questions for future research.

To our best knowledge, our paper is the first in developing Asia that attempts to answer this increasingly important question. Much of the academic literature we rely on are based on the Western legal setting and market convention, where mortgage interest rates tend to be fixed (in Thailand, rates are adjustable), mortgage loans are non-recourse (in Thailand, borrowers are liable for any deficiencies after underlying properties are foreclosed and sold), and cultural values are different (Petersen et al., 2015, find that national culture affects consumer financial decision making). Understanding the dynamics and interconnectivity between different classes of debt is more important than ever as the use of debt becomes more widespread (and even necessary) in today's world. We hope that our early results can form a basis for further policy discussions.

The rest of the paper is organized as follow: section 2 reviews literature on determinants of default and the pecking order among different classes; section 3 describes the data and methodology used; section 4 presents and discusses the results; and section 5 concludes.

2. Literature Review

Much of the existing literature on consumer default tends to focus on mortgage loans, and the reasons for default (as with any other classes of debt) can broadly be classified into two: *ability to repay*, which is circumstantial and often referred to as liquidity channel in academic literature, and *willingness to repay*, which is often strategic and driven by negative housing equity (and we will refer to this as the equity channel).[1] Vandrell (1994) refers to the latter as "ruthless" default, as the borrower in principle can still afford to service the mortgage loan but decides to stop.

Empirical research in consumer finance typically relies on credit bureau data and/or loan origination and servicing data, which limits the scope of investigation that could be carried out as the econometrician does not observe the circumstance (or even the financial statements) of individual borrowers. Nevertheless, researchers have been able to use proxies and structural features of the market to identify the impact of each driver. For example, Elul et al. (2010) use credit card utilization as proxy for liquidity constraint, and Bajari et al. (2008) and Pennington-Cross and Ho (2010) use interest rate reset on adjustable rate mortgages as payment shock to identify the effect of ability to repay on default. Because the ability to strategically default depends on the institutional environment, variations in laws and regulations or government policies can also be used as identification strategy. For example, Li et al. (2011) use the 2005 bankruptcy reform in the U.S. and differences in recourse laws across states that affects the difficulty and value of strategic default to show how it affects default decisions of borrowers with negative equity, and Mayer et al. (2014) exploit a mortgage modification scheme lawsuit that arose out of a lawsuit between U.S. state government and a subprime lender to show that some borrowers strategically default in order to qualify for the modification.

[1] Negative housing equity refers to a situation where the value of the underlying property [asset] is less than outstanding debt. In jurisdictions where mortgage loans are non-recourse (that is, lenders can only seize the underlying collateral and cannot pursue the borrower for any additional shortfall), borrowers have a strategic incentive to default on the mortgage in order to discharge the debt. Deng et al. (2000) show that strategic default can be thought of as a put option on the mortgage.

There is ample evidence that both channels are important drivers of defaults.[2] However, most studies tend to analyze mortgage defaults in isolation from other types of debt, but recently a few studies in the U.S. address the "pecking order" of consumer defaults explicitly.

The convention wisdom for the consumer finance industry in the U.S. is that consumers would prioritize keeping their mortgage and instead choose to default on other financial obligations first. Cohen-Cole and Morse (2010) show that many individuals in 2007, in fact, continue paying credit card bills but default on their mortgage loans, which they interpret as evidence of the need to preserve precautionary liquidity through maintaining credit line. Andersson et al. (2013) track mortgage loans over 2001 to 2009 and find that consumers were indeed prioritizing mortgage payments prior to the crisis, but their behavior change when strategic default becomes more valuable as house prices fall. The study by Chan et al. (2016) is similar to Cohen-Cole and Morse (2010) but utilize data that spans a longer period of time (2002 to 2006) and exploit legal variations across states that affect the value of strategic default to show that mortgage borrowers do indeed prioritize mortgage defaults in states where mortgage loans are non-recourse.

3. Data and Methodology

3.1. Data

In order to investigate the priority of default between mortgage and non-mortgage loans, it is important to have a comprehensive picture of a borrower's debt profile. In this paper, we use anonymized account-level credit bureau files of 1 million randomly sampled individuals between 2010 and 2018. According to Chantarat et al. (2018), there are 60.51 million accounts from 19.25 million borrowers in July 2016. NCB is the only credit bureau in Thailand and its members include most of the financial institutions in the formal financial sector (commercial banks, specialized financial institutions run by the government, non-bank consumer finance companies, and insurance companies).[3] The credit bureau files contain information on many classes of loans, for example, housing, automobile, motorcycle, credit card, personal consumption, business, agricultural, and others.

In this paper, we restrict our attention to just housing, credit card and personal consumption loans (which we will refer to the latter two as non-housing loans) as we want to compare the decisions of individuals who face a choice of defaulting on either one of the two types of debt. In NCB's classification, personal consumption loans (also referred to as p-loans in Thailand) include both credit line for cash withdrawal (which is marketed in a similar fashion as credit card but often carries higher interest rate) and term loan, which can be secured (e.g. by real estate or vehicles) or unsecured. In our analysis, we group credit card and credit line p-loans together. Of the 1 million individuals, 481,072 have non-housing loans (term loan and credit line) and 129,496 have housing

[2] See, for example, Bajari et al., 2008; Burke and Mihaly, 2010; Elul et al., 2010; Fuster and Willen, 2017; Gerardi et al., 2017; Guiso et al., 2013); Li et al., 2011; Mayer et al., 2014; Seiler et al., 2012). For a comprehensive survey of research in consumer finance, see Guiso and Sodini (2013).

[3] For details of the credit bureau data, its members and Thailand's household debt profile, see Chantarat et al. (2017, 2018).

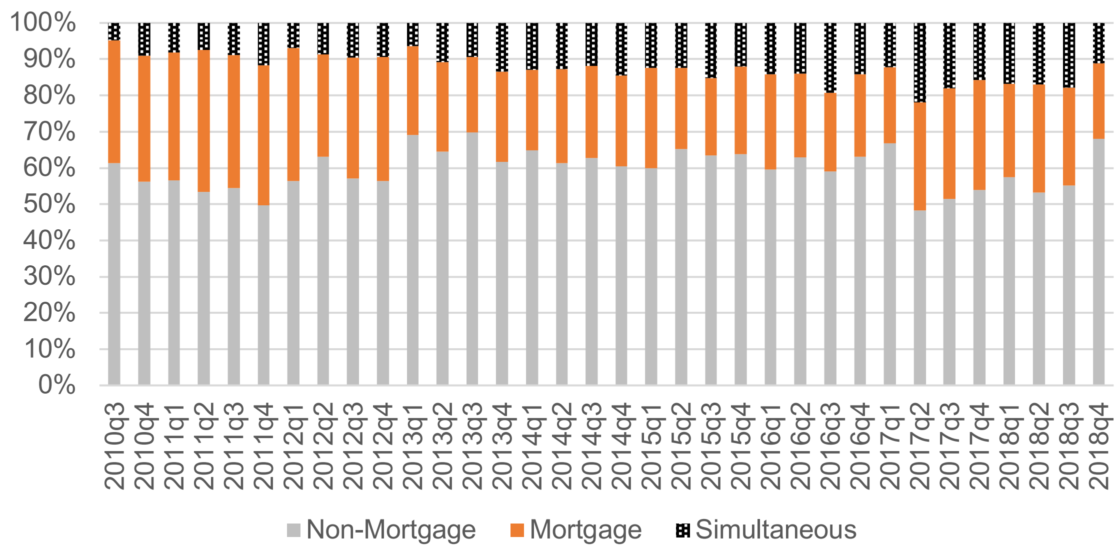
loan. The intersection of the two groups leaves us with 94,208, or approximately 9.4% of borrowers in our sample, but represents 73% of borrowers with housing debt.

The definition of default in our sample is at least 60 days past due and we require borrowers to be current for at least 6 months on all outstanding loans. Of the 94,208 borrowers in our sample, 9,521 default, representing approximately 10%. It is important to note that borrowers who face severe adverse shocks may not have a choice and thus default on both types of loans simultaneously, which is not the subject of our investigation. Consequently, we require that borrowers who default on one type of loan not default on another for at least 3 months; otherwise, we classify those who do as simultaneous defaulters and exclude them from our sample. There are 1,202 simultaneous defaulters, leaving the final sample with 8,319 individuals, 2,678 (32.2%) of whom default on housing loans first. The temporal distribution of defaults in our sample is visualized in Figure 1.

Incidences of simultaneous defaults could reveal useful insight about how vulnerable borrowers are. Figure 2 plots the proportion of simultaneous defaulters over time and the figure reveals a slight upward trend. Taken together with the rising level and depth of household debt as documented by Chantarat et al. (2017, 2018), this finding could be a potential sign for macroeconomic concern.

Figure 1: Temporal distribution of multiclass debtors' default

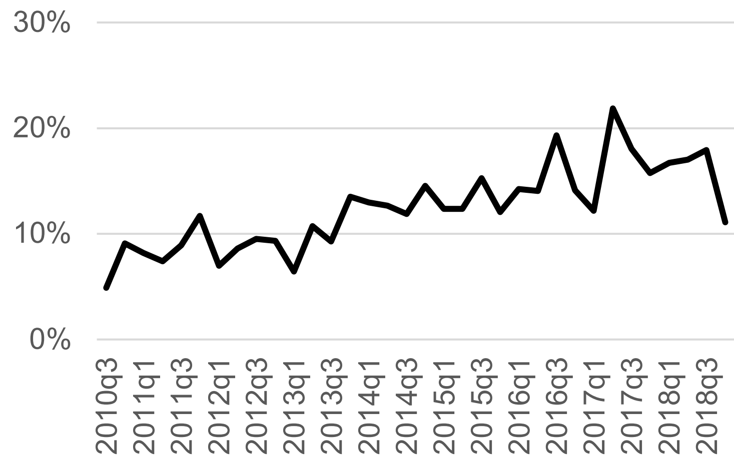
This figure plots the proportion of the 9,521 borrowers who (1) default on mortgage loans first, (2) default on non-mortgage loans first, and (3) default on both at the same time. In our definition of simultaneous defaulters, we also include borrowers who defaults of both classes within 3 months of each other to allow for potential time lag in response. The frequency of aggregation is quarterly.



Next we plot the proportion of the remaining borrowers who default on housing loans first on as Figure 3. The average in the first 2 years of the sample (2010-2011) is higher at around 40%, and drops to 30% for the rest of the sample. Compared to the U.S. result of Anderson et al. (2013), Thais choose to default more on housing loans over non-housing loans.

Figure 2: Proportion of simultaneous defaults over time

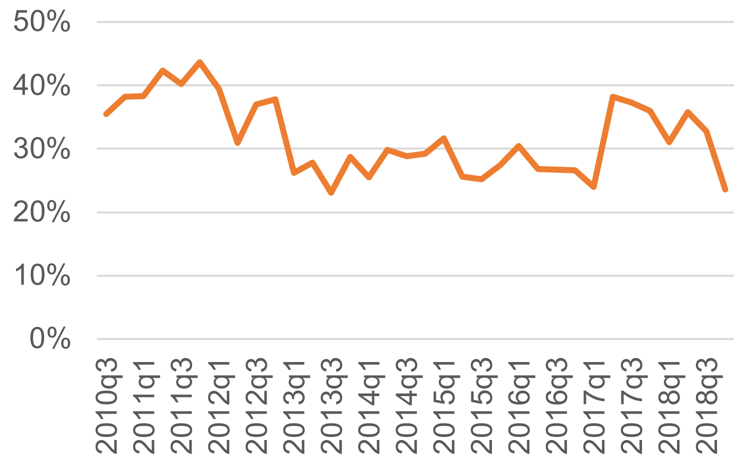
This figure plots the proportion of borrowers who default on both mortgage and non-mortgage loans simultaneously over time. In our definition of simultaneous defaulters, we also include borrowers who defaults of both classes within 3 months of each other to allow for potential time lag in response. The frequency of calculation is quarterly.



The NCB data contains limited information on borrower’s demographic and loan characteristics. From this, we are able to obtain borrower’s age (in years), monthly mortgage payments (in thousands Baht), minimum credit card / credit line p-loan minimum payments (in thousands Baht, estimated as 10% and 5% of outstanding balances respectively, per industry standard), monthly term p-loan payments (in thousands Baht), available credit line (in 10 thousands Baht), mortgage amortization (calculated as origination balance less outstanding balance, in 10 thousands Baht) and mortgage age (in months). Due to data limitation, we are unable to observe the loan-to-value ratio of mortgages and their tenor. In addition, bureau-generated credit score does not exist yet in Thailand. All data is winsorized at 1% and 99% level. Summary statistics are reported in Table 1.

Figure 3: Proportion of non-simultaneous defaulters who default on mortgage loans first

This figure plots the proportion of borrowers who default on mortgage loans first, excluding borrowers who default on both types of loans simultaneously. The frequency of calculation is quarterly. The average over the sample period is 32.2%.



3.2. Empirical Strategy

A borrower with multiple types of debt facing the choice of defaulting on mortgage or non-mortgage loans must perform a cost-benefit analysis, so the problem can be thought of as discrete choice modeling. Similar to Andersson et al. (2013) and Cohen-Cole and Morse (2010), we employ the binary logistic regression of the form:

$$Pr\left(y_j = 1 \middle| \boldsymbol{X_j}\right) = \frac{exp\left(\boldsymbol{X_j}\beta\right)}{1 + exp\ (\boldsymbol{X_j}\beta)} \qquad (1)$$

where y_j is an indicator variable which takes value of 1 if the borrower decides to default on mortgage loan first, and X_j represents all the components that enter the consumer's cost-benefit analysis, which can be broadly classified into 4 components: affordability, liquidity, housing equity and other characteristics.

Affordability variables are monthly mortgage payments, minimum credit line payments, monthly non-mortgage term payments, and indicator variables based on their ratios to represent the comparative magnitudes of payments to allow for non-linearity in their relationships. More debt burden should be associated with more likelihood of default on respective classes of debt.

In the past, research on the liquidity channel has focused on the interplay between debt service and adverse shocks due to data limitation, since much of the research relies on mortgage origination and servicing data. The argument is that liquidity constrained borrowers with high debt service burden is more vulnerable, and credit score is used as proxy for access to credit (e.g. Bajari et al., 2008). Over time, the availability of credit bureau data and information on credit line available allows the inference on liquidity constraint to be made more accurately.

The inclusion of credit line in default analysis is relatively new (and the literature on default priority is even more limited), and there are two opposing theories about how it matters. From a precautionary saving perspective, borrowers may choose to default on mortgage to protect credit line, as mortgage default will make it more difficult for borrowers to obtain credit in the future. In this interpretation, the higher the remaining credit line, the more likely the borrower will default on mortgage loan. The alternative theory is the fungibility of credit, where borrowers can use remaining credit line to finance mortgage payments in the event of adverse shock. In this interpretation, more remaining credit line should be associated with lower likelihood of mortgage default.

Liquidity variables are the combined available credit line for credit cards and personal loan credit line. We also include an indicator variable for borrowers with negative credit line, which represents borrowers who have maxed out their limits. Following Andersson et al. (2013), we also include a linear spline for the ratio between available credit line and mortgage payment, which would be particularly important if borrowers decide to use credit line to make mortgage payment.

Because we do not have access to loan-to-value data and localized housing price changes, identification of housing equity is particularly difficult in our context. Instead, we compute amortized amount based on the difference between outstanding mortgage and origination balance. In our setting, amortized amount represents housing equity that borrowers have built in addition to the down payment they made at origination. We include the value as linear spline to accommodate the non-linearity because of the option-like payoff in decision-making. We also include an indicator variable for borrowers with negative mortgage amortization.

Legally, mortgages in Thailand are non-recourse, as specified in the Civil and Commercial Code, Section 733. However, lenders often require borrowers to sign a separate agreement that make them liable for any deficiencies after foreclosure, a practice which is endorsed by Supreme Court ruling 541/2545 of 2012, making Thailand effectively a recourse mortgage jurisdiction. Thus, the there is no motivation for strategic default in the traditional sense. In addition, property prices in Thailand have been generally rising during the sample period, so borrowers are more unlikely to have negative equity.

For other characteristics, we include borrower age as indicator variables of various age range to allow for both non-linearity and non-monotonicity. We are more interested in remaining number of payments to capture how close borrowers are to their finish line, but this information is not available in our data, and loan tenor can vary in Thailand; there is no standardization due to the lack of secondary mortgage market and securitization. For this reason, we include mortgage age, which is inferred from the difference between current date and date of origination, as indicator variables. In further analyses, we also include indicator variables for additional information about the borrower, for example, whether the borrower has more than 1 mortgage, or whether the borrower also has an auto loan.

Each borrower enters the sample only once, and the variables included are information as of the default date. In other words, the logit regression is static and there are only as many observations as there are borrowers, so there is no concern for potential serial correlation. Consequently, we use Huber-White (1985) heteroskedastic standard errors in our analysis. Under our specification of discrete choice, variables with positive coefficients on the logistic regressions are factors that influence borrowers to default on mortgage loans over non-mortgage loans.

4. Results

4.1 Univariate Analysis

First, we begin with a simple univariate comparison of the mean and median in Table 2. Borrowers who default on non-mortgage loans first tend to have more non-mortgage payments due. Borrowers who default on mortgage loans first, on the other hand, tend to have less available credit line and slightly less mortgage amortization. There is no noticeable difference in borrower and mortgage age. Borrowers who default on both types of loans simultaneously (who are not in our sample but are presented for comparison) tend to have higher debt payment of all types and less available credit line, which is consistent with the view that these borrowers are more heavily indebted and thus more vulnerable to adverse shocks. The result here suggests that relative debt burden should play in important role in default priority.

4.2 Baseline Logistic Regression

Next, we turn to the baseline logistic regression where we include the 4 dimensions of explanatory variables and the result is reported in column 1 of Table 3. Consistent with the univariate result in Table 2, relative affordability has a very strong influence on priority of default; greater relative non-mortgage payments are associated with lower likelihood of non-mortgage defaults, similar to the finding of Andersson et al. (2013). For the same level of relative payment, the odds ratio is lower for term non-mortgage loan payments than credit line minimum payments, which is likely due to the obligatory nature of term loans.

For available credit line (which could capture the precautionary saving hypothesis or fungibility hypothesis, both of which have been found in prior research in the U.S.) is more surprising. Contrary to earlier univariate comparison which seems to support the fungibility hypothesis where borrowers could be using credit line to finance mortgage payments, in this multivariate setting, available credit line does not seem to matter.

Empirically, we believe this discrepancy between the univariate and multivariate result is attributable to borrowers with negative credit line available, who have much higher likelihood of defaulting on non-mortgage loans. So, what does this variable capture? A borrower with negative credit line has already maxed out her credit line and only been making minimum payments in the past (in our sample, all borrowers are current on all outstanding debt in the past 6 months, so in principle, she should not have missed any payments).[4] While we could interpret them as extremely fragile borrowers who are vulnerable to adverse shocks, there is no clear reason why they should

[4] Borrowers who have maxed out their credit line are liquidity constrained, as documented by Agarwal et al. (2007) in their study of individual consumption response to tax rebate using detailed credit card data.

prioritize keeping mortgage over non-mortgage loans. Potential clue could lie in what happens after default. If non-mortgage lenders are more inclined to negotiate and settle than force bankruptcy in their collection process, borrowers with maxed out credit line could be making a deliberate decision to continue their mortgage payments in order to keep their homes.

Still, conditional on attributing the effect of borrowers with negative credit line, the amount of available credit does not matter in the data. We do not have a good way of disentangling the two hypotheses in our research design, so it could be that both hypotheses are in action in the data but their opposing effect on borrower behavior results in zero average effect, or it could be that neither are present. In Thailand (and perhaps other developing economies also), access to credit from family, friends and the informal financial sector is relatively easy, so using formal credit line as proxy for borrower's access to credit may not be capturing the complete picture.

Next, we turn to housing equity, which, due to data limitation, only measures borrowers' incremental ownership in addition to down payments made at origination. The coefficients on the linear spline measure the contribution per unit change in covariate, so at lower levels of housing equity, borrowers are much more likely to default on their mortgage loan as housing equity declines. If we interpret housing equity as skin-in-the-game (in other words, sense of ownership) that increases commitment (or even attachment) to the underlying asset, then this result suggests LTV limit policies could be important in reducing mortgage default risk. While this knowledge may already be common in academic literature and among practitioners, we would like to emphasize the aspect of our research design that makes our result noteworthy. Borrowers in our sample have multiple classes of debt and prioritize keeping their mortgage (secured) loans by choosing to default on non-mortgage loans instead. It is the effect of ownership on debt prioritization that is the important insight.

Borrowers with negative amortization have elevated odds ratio in favor of defaulting on mortgage loans first. It is tempting to interpret this as strategic default, but our research design does not allow for that interpretation. First, because we do not observe LTV and cannot measure local hosing price changes, we cannot infer negative equity. Second, mortgage loans in Thailand are effectively full recourse, so there is no incentive to strategically default on mortgage. So, what does this variable capture? Since Thailand does not have negative amortization mortgage, this variable could capture borrowers who have made too little payments to even cover monthly interest charges and thus have unpaid interest expenses accrued to their balance (recall that all borrowers in our sample are current on all loans in the past 6 months). The natural interpretation for this result is that they are borrowers who simply cannot afford to keep their mortgage loans.

For other variables, we first begin with borrower age. There is positive but weak relationship between age and mortgage default for borrowers aged 55 and above, which is approximately 10% of our sample. Note that this does not mean older borrowers default on mortgage loans more, since all individuals in our sample are in default; rather, older borrowers are more likely to default on mortgage loans before non-secure loans.[5] Next, we turn to mortgage age, which is measured in months. Borrowers who have older mortgages are more likely to choose mortgage default, which seems to contradict intuition. After all, borrowers who have held

[5] There is evidence from Chantarat et al. (2018) that older borrowers are increasingly more indebted and default more.

mortgages for longer should have built up more equity (which we already control for with housing equity) and be more likely to feel attached to the property, so why would they choose to default on their mortgage more?

The baseline result confirms some findings in existing literature on default priority (that relative affordability and housing equity matter) and, at the same time, raises further questions. We try to address these questions to the best extent that our research design allows.

4.3 Extended Logistic Regressions

The richness of the NCB data allows us to generate additional borrower attributes that could be used for further investigation, for example, information on borrower's loan portfolio and lending financial institution. We do not observe the name of individual financial institution since the data is anonymized to ensure privacy, and each financial institution is assigned a unique identification number. We use this information to create an indicator variable to classify individuals that have mortgage and non-mortgage loans from the same financial institution. In the first extension of the model (Table 3, column 2), we add 2 loan portfolio indicator variables and in the second extension (Table 3, column 3), we add the financial institution indicator variable.

The main determinants from the baseline regression remain intact, and the additional variables reveal further insights. Borrowers with multiple mortgages are more likely to choose mortgage default, while borrowers with both types of loans from the same financial institution are less likely to choose mortgage default. Our research design does not permit further investigation on the influence of same financial institutions, but one possible explanation could be based on lender intervention to avoid costly collection process.

Consider a situation where borrower has exactly two loans: say, one mortgage loan and one credit card, and the borrower is at risk of default. If the two loans are originated by different lenders, the borrower could end up defaulting on both when facing adverse shock. Suppose, however, that both loans are originated by the same lender. Given that collection process for mortgage loans tend to be lengthier and more costly since it involves repossession and foreclosure, the lender may have an incentive to steer the borrower to default on non-mortgage loan and stay current on the mortgage loan (or even help restructure) to avoid the costly collection process.

Who are these borrowers with multiple mortgages? Why do they choose to default on mortgage loans first? The answers to these questions are very important, especially from policymaking perspective. Fortunately, the data allows us to take a deeper dive to gain better understanding about this group.

4.4 Why do borrowers with multiple mortgages choose to default on mortgage loans first?

For readers to gain better understanding of our research context, we begin this section by comparing our data to what is available and used in academic literature (which tends to be U.S.-centric). The mortgage literature often uses combined LTV ratio (CLTV) in their analyses, allowing the inference of borrowers' effective down payment at origination or even whether the loan was a "cash-out" loan (where borrowers receive cash for general purpose use rather than for purchase of the property). This is possible because private companies collect and commercialize data on mortgage origination and servicing data. Researchers are able to see whether two mortgage loans are made on the same property or not. In addition, the data also distinguishes between mortgage loans that are made for a property purchase versus refinance, and for purchase mortgages, whether the property is for primary residence or investment purpose (required by the Home Mortgage Disclosure Act of 1975). Credit bureau data, a recent addition to the literature, is used as supplement rather than the main dataset.

The NCB data used in our paper contains only a subset of origination and servicing data and contains no information on the dimensions aforementioned. Consequently, we rely on classification schemes based on financial market practices and what we have t to generate an approximate classification scheme that allows us to glean further insights on who these borrowers with multiple mortgages are.

Multiple mortgages can be made on the same property as there can be multiple liens on the same property. The liens can be pari passu or subordinated and can, in principle, be placed by different mortgagors. Subordinated lien mortgage loans (referred to colloquially as piggyback loans) are often made in order to circumvent LTV limits, which could be in place because of financial regulation (e.g. the case of Thailand) or market restriction (e.g. government-sponsored securitization in the U.S.). The first lien mortgage loan would then comply with the limit (so it can be bought by government-sponsored entities such as Fannie Mae and Freddie Mac), while any further risks are taken on by the subordinated lien lender (which could still be securitized by private entities. In Thailand, lenders do not take second lien position, so piggyback loans are generally made by the same lender. We use this practice to create an indicator variable to identify mortgage loans made by the same lender on the same date. For these loans, we assume that they are made on the same property and hence proxies for borrowers whose CLTV ratios exceed the regulatory limit.

With this variable, we proceed with our further investigations in the following steps. First, we partition our sample into 2 subsamples: first, those who have exactly 1 mortgage loan (model A), and second, those who have more than 1 mortgage loans (model B). Next, we select borrowers that have exactly 2 mortgage loans and include an indicator variable for simultaneously opened mortgage loans (model C). The idea is to distinguish between (1) borrowers who have 2 mortgage loans on the same property (which we classify as high LTV borrowers), or (2) a borrower with 2 mortgage loans on two different properties (which we classify as investors). With this classification, borrowers who fall into the first category have only 1 property, so we can pool them with those with exactly 1 mortgage and perform another logistic regression (model D). In this model, the comparison is made between single property borrowers who use only 1 mortgage loans (standard) versus 2 (high LTV). The results are reported in Table 4.

The determinants of default priority for borrowers with single and multiple mortgages are similar, as illustrated by the first and second column of Table 4. The baseline default priority (as indicated by the constant in the regression) for borrowers with multiple mortgages is inclined toward mortgage default, consistent with evidence from Table 3. Relative payment sizes, negative credit lines and older mortgages are still influential, but for borrowers with single mortgage loans, amount of available credit line is statistically significant at 5% level. The sign of the coefficient is negative, which supports the fungibility hypothesis where borrowers with available credit line can use liquidity to keep current on mortgage payments. If we were to treat multiple mortgages as multiple properties, then this finding could be interpreted as the lack of desire for borrowers with multiple properties to hold on since they still have outside options.

The next difference in finding is negative amortization, which is only influential for borrowers with multiple mortgages. We confirm that this is not driven by differences in covariate distribution, as the proportion for borrowers with negative amortization is approximately 1.7% across the two groups. One possible explanation, though unobservable in the data, could be differences in wealth or access to outside financing. If borrowers with multiple mortgages (thus multiple properties) have other means of servicing the debt, they may decide to keep mortgage loans as it means retaining control over an economically valuable asset, while defaulting on non-mortgage loans does not necessitate a loss of control, or at least with lower probability.

Finally, the next major difference is indicator for borrowers who have both types of loans from the same financial institution. It would be more insightful if we were able to obtain information on whether the mortgage loan was made for residential or investment purpose. Nevertheless, if we were to make the same assumption as before that borrowers with multiple mortgages are investors, then the lack of influence of the same financial institution on the likelihood of mortgage default could be interpreted as lenders' hesitation to compromise and prolong mortgage loans made for investment purpose. This may sound incongruous at first; after all, why would a lender not want to help mortgage borrowers, since properties can both generate income and benefit from capital appreciation. But it is important to remember that these borrowers are at risk of default (otherwise, they will not be in the sample in the first place), which most likely indicates that said investment properties are not generating income. Unlike residential borrowers, investors are not as committed to keeping their properties in the long run, so lenders may prefer to not compromise and let borrowers default instead.

Model C takes a deeper dive and investigates borrowers with exactly 2 mortgages, who are the majority of borrowers with multiple mortgages (2,031 out of 2,921). The determinants are broadly the same model B, but the addition of the indicator variable for simultaneously opened mortgage loans (739 individuals or 36.4%) allows us to distinguish high LTV borrowers from investors. The result suggests that there is no meaningful difference between the two group.

Lastly, model C looks at single-property borrowers: those with 1 mortgage loans (standard borrowers) and 2 mortgage loans simultaneously originated by the same lender (high LTV borrowers; 739 individuals or 12%). The determinants are similar to model A, and high LTV borrowers have significantly higher odds (statistically and economically) of defaulting on their mortgage loans. This result further corroborates the importance of housing equity on default priority.

4.5 Why are borrower with older mortgages more likely to default on them first?

Interest rates on mortgage loans in Thailand are adjustable, so mortgage payments can vary over time; higher interest rate can translate in to increased debt burden for borrowers. Drawing on the finding of Pennington-Cross and Ho (2010) that payment shocks from adjustable-rate mortgage loans significantly contributed to subprime defaults in early 2000s, we investigate whether changes in monthly payments are associated with default priority. In model E, we add two indicator variables based on monthly mortgage payments at the time of default compared to at origination to the earlier single-property borrower specification (model D). Approximately 27.7% of borrowers have higher payments, while 7.4% have lower payments.

The regression result suggests that borrowers who face increased monthly payments are more likely to default on their mortgage loans. However, unlike the U.S. setting documented by Pennington-Cross and Ho (2010), mortgage payment changes in Thailand tend to be small in magnitude and adjustments tend to occur in effective loan tenor instead (that is, if interest rate increases, it will take borrowers longer to pay off the loan if they keep making similar payments). This is because most mortgage loans are held on lenders' balance sheet, so there is no external pressure from securitization to standardize maturity. When lenders expect interest rate to increase in the long run, they build in small increases in the repayment schedule as buffer to ensure that monthly payments will at least keep up with interest charges, so our result may not be attributable to interest rate-induced payment shocks.

For further interpretation, we direct our attention to the coefficient on the indicator variable for mortgage loan between 36 and 60 months, which decrease the most from model D to model E. Similar to the U.S., Thai lenders also offer hybrid adjustable-rate mortgages, where rates can be fixed for short period before reverting to adjustable rate schedule. Lenders often offer "teaser rates" during the early months to attract borrowers, who would then face lockup periods (no prepayment) and prepayment penalties (prepayment is possible for a fee), and the market convention in Thailand is 3 years. This means repayment schedules during the promotional period do not reflect the reality (for example, what the effective debt service burden is, or the speed at which housing equity is built). In other words, moving from the first 36 months to the next 24 months, it is possible that borrowers who face the true schedule reevaluate their financial positions and decide to not continue paying the mortgage loans.

Another possible explanation is based on refinancing. When interest rates are slow to adjust to market changes (or not adjust at all), refinancing offers a way for borrowers to benefit from falling interest rates. Even then, many borrowers do not. Keys et al. (2016) find that 20% of American borrowers do not refinance when it is possible and beneficial for them to do so, and Agarwal et al. (2015) find that even if they do, they do so at the wrong time. The benefit of refinancing in the U.S. is clear as the majority of mortgage loans are made with fixed interest rates, but even for adjustable-rate mortgages, refinancing can be beneficial. First, if value of the underlying collateral has increased from the origination date, borrowers can benefit from loan repricing. Combined with cumulative amortization that has been made prior to refinancing, the repriced loan will have lower LTV and, hopefully, lower interest rate. Second, borrowers can benefit from the promotional offers that is only available to new loans. Even if the borrower does not switch lenders, the fact that she can do so increases her bargaining power to obtain better loan terms from the incumbent lender. In other words, refinancing is an option that is implicit in each mortgage loan, and borrowers could be better off if such options are exercised.

One way to interpret old mortgage loans is that these loans are not refinanced (and thus the options are unexercised), leaving borrows more vulnerable to adverse shocks. We do not test this explanation explicitly due to data limitation, but based on this explanation, policies that encourage refinancing could be beneficial for both borrowers and lenders.

4.6 Robustness

There are two potential challenges with including non-mortgage term loans in the analysis in addition to credit line: first, the prioritization decision is multi-faceted, and second, non-mortgage term loans contain a wide array of products, ranging from secured (real estate, automobile, motorbike) to unsecured). To narrow down the considerations, we limit the scope of comparison to only between mortgage loans and credit line products. This makes our research setting more comparable to Andersson et al. (2013). The comparison is made between borrows with who default on their mortgage loans and credit line product only, and we also require that borrowers have 1 mortgage only, so the sample size is reduced to 3,513.

The result under this tighter definition is reported in Table 5. In the first column, we start with the baseline specification and in the second column we add the indicator variable for borrowers who have both types of loans from the same financial institution. The influential factors in this more stringent specification are similar to earlier results with substantially increased pseudo R2, providing reassurance to our findings.

5. Conclusion

The academic literature and practitioners have a good understanding of why borrowers default, but the question of which type of loans will they default on first remains relatively unanswered. To our best knowledge, our paper is the first study in developing Asia that investigates how borrowers with multiple classes of debt prioritize their default decision. Many findings are useful for policymakers (for example, how relative debt burden and housing equity can tip the scale of default decision) but our paper also leaves many questions to be answered (for example, how often do we and should we refinance in markets where interest rates are adjustable). Understanding the dynamics and interconnectivity between different classes of debt is more important than ever as the use of debt becomes more widespread (and even necessary) in today's world. With greater availability of data, these questions are now becoming more addressable and we hope that our early results can form a basis for further policy discussions.

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Table 1: Summary Statistics

This table reports the summary statistics of borrower's information. Monthly mortgage payments, term personal loan payments (in thousands Baht), and available credit line (in 10 thousands Baht) are obtained directly from NCB data. Cash card refers to personal loan made in the form of credit line. Minimum credit card payment is calculated as 10% of outstanding balance, while minimum cash card payment is calculated at 5%, per industry standard. Mortgage amortization (in 10 thousands Baht) is calculated as the difference between the outstanding balance and the origination balance. Mortgage age (in months) is calculated as the difference between the report data and origination date. Borrower age (in years) is calculated as the difference between the report date and reported date of birth. The sum of term payments across all term loans, minimum payments and available credit line across all credit and cash cards and mortgage amortization are calculated for each borrower. All variable are winsorized at 1% and 99% levels.

Non-Mortgage First	Mean	SD	N	p5	p10	p25	p50	p75	p90	p95
Mortgage payment (in 1,000)	10.2	12.1	5,641	1.5	2.3	3.6	6.3	11.7	22.1	32.5
Min credit/cash card payment (in 1,000)	13.8	21.9	5,641	0.0	0.0	0.5	5.8	16.6	36.9	54.3
Term personal loan payment (in 1,000)	11.5	21.6	5,641	0.0	0.0	0.9	4.0	11.2	30.0	50.0
Available credit line (in 10,000)	8.3	19.1	5,641	-0.8	-0.3	0.0	0.7	7.1	25.5	45.4
Mortgage amortization (in 10,000)	31.1	44.9	5,641	2.1	3.6	7.8	16.8	34.7	68.4	107.2
Mortgage age (months)	71.9	39.9	5,641	16.0	24.0	41.0	66.7	97.0	128.0	149.0
Borrower age (years)	42.4	9.2	5,641	28.0	31.0	36.0	42.0	48.0	54.0	58.0

Mortgage First	Mean	SD	N	p5	p10	p25	p50	p75	p90	p95
Mortgage payment (in 1,000)	10.8	13.1	2,678	1.8	2.3	3.6	6.3	12.5	24.1	35.9
Min credit/cash card payment (in 1,000)	6.7	14.6	2,678	0.0	0.0	0.0	1.7	6.7	18.3	29.9
Term personal loan payment (in 1,000)	9.0	18.7	2,678	0.0	0.0	0.0	2.0	7.5	26.9	50.0
Available credit line (in 10,000)	6.5	16.1	2,678	0.0	0.0	0.0	0.4	4.8	17.7	34.0
Mortgage amortization (in 10,000)	29.2	47.3	2,678	0.6	2.0	5.4	13.7	32.1	69.8	116.6
Mortgage age (months)	73.3	39.6	2,678	19.0	26.0	42.0	67.0	99.0	129.5	148.0
Borrower age (years)	42.8	9.8	2,678	28.0	31.0	35.0	42.0	49.0	56.0	61.0

Simultaneous	Mean	SD	N	p5	p10	p25	p50	p75	p90	p95
Mortgage payment (in 1,000)	13.0	15.5	1,202	1.5	2.3	4.1	7.8	15.3	28.4	42.5
Min credit/cash card payment (in 1,000)	13.3	25.8	1,202	0.0	0.0	0.0	2.8	13.4	40.6	64.1
Term personal loan payment (in 1,000)	11.4	20.4	1,202	0.0	0.0	1.3	3.8	10.1	34.7	50.0
Available credit line (in 10,000)	4.4	15.7	1,202	-1.0	-0.3	0.0	0.0	1.7	8.9	23.7
Mortgage amortization (in 10,000)	30.8	53.4	1,202	-0.1	1.6	5.1	12.7	31.5	70.8	126.0
Mortgage age (months)	60.7	38.9	1,202	11.0	15.0	29.0	53.3	86.0	116.0	132.0
Borrower age (years)	41.9	10.2	1,202	26.0	29.0	35.0	41.0	48.0	55.0	60.0

Table 2: Univariate analysis

This table reports the mean and median for the 3 groups: those that default on non-mortgage loans first (NM), mortgage loans first (M) and simultaneous (SIM). The t-test for differences in mean and k-sample equality-of-medians test are conducted. *, ** and *** correspond to 10%, 5% and 1% statistical level of significance respectively.

	Mean				P50			
	NM	M	p	SIM	NM	M	p	SIM
Mortgage payment (in 1,000)	10.2	10.8	**	13.0	6.3	6.3		7.8
Min credit/cash card payment (in 1,000)	13.8	6.7	***	13.3	5.8	1.7	***	2.8
Term personal loan payment (in 1,000)	11.5	9.0	***	11.4	4.0	2.0	***	3.8
Available credit line (in 10,000)	8.3	6.5	***	4.4	0.7	0.4	***	0.0
Mortgage amortization (in 10,000)	31.1	29.2	*	30.8	16.8	13.7	***	12.7
Mortgage age (months)	71.9	73.3		60.7	66.7	67.0		53.3
Borrower age (years)	42.4	42.8	*	41.9	42.0	42.0		41.0

Table 3: Baseline logistic regression result

This table reports coefficients of the binary logistic regression of the decision to default on mortgage loan first (indicator variable = 1) versus non-mortgage loan first. Variables in the regressions include indicator variables and continuous variables, with some following the linear spline specification to allow for non-monotonicity in the relationship. All 3 regressions models are conducted on the full sample of borrowers. Standard errors used in the estimation process are Huber-White (1985). *, ** and *** correspond to 10%, 5% and 1% statistical level of significance respectively.

	Model 1	Model 2	Model 3
Affordability			
Mortgage payment (in 1,000)	0.009*	0.006	0.011**
	-0.003	-0.003	-0.004
Min credit/cash card payment (in 1,000)	-0.008***	-0.008***	-0.008***
	-0.002	-0.002	0.00
Term personal loan payment (in 1,000)	0.0000	0.0000	0.00
	-0.002	-0.002	0.00
Indicator for min card / mortgage (0, 0.5]	-0.608***	-0.656***	-0.644***
	-0.084	-0.085	-0.09
Indicator for min card / mortgage (0.5, 1.0]	-0.647***	-0.696***	-0.686***
	-0.092	-0.094	-0.09
Indicator for min card / mortgage (0.5, max)	-1.022***	-1.040***	-1.029***
	-0.091	-0.092	-0.09
Indicator for term loan / mortgage (0, 0.5]	-0.815***	-0.865***	-0.793***
	-0.073	-0.074	-0.08
Indicator for term loan / mortgage (0.5, 1.0]	-1.040***	-1.097***	-1.055***
	-0.086	-0.087	-0.09
Indicator for term loan / mortgage (0.5, max)	-1.171***	-1.218***	-1.160***
	-0.08	-0.081	-0.08
Liquidity			
Available credit line (in 10,000)	-0.003	-0.004	-0.01
	-0.002	-0.002	0.00
Indicator for negative credit line	-0.770***	-0.767***	-0.775***
	-0.102	-0.104	-0.10
Spline for credit line / mortgage (0, 1]	0.012	0.025	0.02
	-0.105	-0.106	-0.11
Spline for credit line / mortgage (1, 4]	-0.065	-0.051	-0.02
	-0.046	-0.047	-0.05
Spline for credit line / mortgage (4, max)	-0.08	-0.066	-0.08
	-0.043	-0.043	-0.04
Housing Equity			
Indicator for negative amortization	1.378***	1.217***	1.269***
	-0.231	-0.24	-0.244
Spline for amortized amount (0, 100k]	-0.076***	-0.094***	-0.096***
	-0.013	-0.013	-0.013
Spline for amortized amount (100k, 200k]	-0.026**	-0.039***	-0.036***
	-0.009	-0.009	-0.009
Spline for amortized amount (200k, max)	0.000	0.000	0.000

	-0.001	-0.001	-0.001
Other Characteristics			
Indicator for mortgage age (36, 60]	0.521***	0.523***	0.498***
	-0.08	-0.081	-0.082
Indicator for mortgage age (60, 120]	0.659***	0.721***	0.673***
	-0.084	-0.085	-0.086
Indicator for mortgage age (120, max)	0.814***	0.973***	0.903***
	-0.113	-0.117	-0.118
Indicator for borrower age (35, 45]	0.08	0.055	0.071
	-0.066	-0.067	-0.067
Indicator for borrower age (45, 55]	0.03	0.01	0.023
	-0.077	-0.078	-0.078
Indicator for borrower age (55, max)	0.204*	0.217*	0.276**
	-0.104	-0.106	-0.106
Indicator for borrower with more than 1 mortgage		0.611***	0.547***
		-0.058	-0.06
Indicator for borrower with auto loan		0.071	0.067
		-0.055	-0.055
Indicator for borrower with both types of loans from same FI			-0.369***
			-0.067
Constant	0.872***	0.886***	0.917***
	-0.115	-0.115	-0.116
Pseudo R2	0.107	0.118	0.121
Observations	8,319	8,319	8,319

Table 4: Further partition based on mortgage information

This table reports coefficients of the binary logistic regression of the decision to default on mortgage loan first (indicator variable = 1) versus non-mortgage loan first. Variables in the regressions include indicator variables and continuous variables, with some following the linear spline specification to allow for non-monotonicity in the relationship. The 5 regression models are estimated on different subsamples of borrowers. The samples for model A and B are mutually exclusive partitions of the full sample based on number of mortgage loans borrowers hold. The sample for model C is a subsample of model B but includes borrows with exactly 2 mortgage loans. The sample for model D and E is a combination of model A (single mortgage) and subset of model C (2 mortgages originated by the same financial institution on the same date). The rational for the sample partition of model D and E is to identify borrowers likely to have a single property and thus a residential borrower rather than an investor. Standard errors used in the estimation process are Huber-White (1985). *, ** and *** correspond to 10%, 5% and 1% statistical level of significance respectively.

Partitioned by number of mortgages	Single	Multiple	2 Mort	Single*	Single*
Affordability	(A)	(B)	(C)	(D)	(E)
Mortgage payment (in 1,000)	0.002	0.011*	0.013	0.006	0.007
	-0.005	-0.005	-0.007	-0.005	-0.005
Min credit/cash card payment (in 1,000)	-0.015***	-0.003	-0.004	-0.012**	-0.012**
	-0.005	-0.003	-0.004	-0.004	-0.004
Term personal loan payment (in 1,000)	0.003	-0.001	0.002	0.003	0.003
	-0.002	-0.003	-0.003	-0.002	-0.002
Indicator for min card / mortgage (0, 0.5]	-0.543***	-0.841***	-0.897***	-0.670***	-0.667***
	-0.118	-0.134	-0.168	-0.108	-0.108
Indicator for min card / mortgage (0.5, 1.0]	-0.464***	-1.036***	-1.008***	-0.603***	-0.597***
	-0.128	-0.149	-0.184	-0.117	-0.117
Indicator for min card / mortgage (0.5, max)	-0.792***	-1.448***	-1.579***	-0.931***	-0.930***
	-0.123	-0.158	-0.194	-0.115	-0.115
Indicator for term loan / mortgage (0, 0.5]	-1.048***	-0.608***	-0.731***	-0.999***	-1.011***
	-0.108	-0.113	-0.141	-0.098	-0.099
Indicator for term loan / mortgage (0.5, 1.0]	-1.261***	-0.869***	-0.738***	-1.180***	-1.186***
	-0.118	-0.14	-0.165	-0.106	-0.107
Indicator for term loan / mortgage (0.5, max)	-1.275***	-1.049***	-1.211***	-1.226***	-1.222***
	-0.103	-0.143	-0.175	-0.095	-0.095
Liquidity					
Available credit line (in 10,000)	-0.016**	-0.003	-0.005	-0.013**	-0.014**
	-0.005	-0.003	-0.005	-0.004	-0.005
Indicator for negative credit line	-0.898***	-0.661***	-0.832***	-0.807***	-0.817***
	-0.137	-0.164	-0.204	-0.125	-0.125
Spline for credit line / mortgage (0, 1]	-0.186	0.266	0.3	-0.106	-0.114
	-0.148	-0.165	-0.199	-0.136	-0.136
Spline for credit line / mortgage (1, 4]	0.071	-0.108	-0.076	0.079	0.094
	-0.062	-0.085	-0.106	-0.058	-0.059
Spline for credit line / mortgage (4, max)	-0.068	0.031	0.004	-0.086	-0.09
	-0.058	-0.087	-0.104	-0.052	-0.052

Housing Equity					
Indicator for negative amortization	2.066***	0.056	-0.108	1.555***	1.612***
	-0.314	-0.444	-0.556	-0.275	-0.276
Spline for amortized amount (0, 100k]	-0.084***	-0.115***	-0.148***	-0.090***	-0.089***
	-0.016	-0.034	-0.04	-0.015	-0.015
Spline for amortized amount (100k, 200k]	-0.037**	-0.003	0.01	-0.030**	-0.026*
	-0.012	-0.016	-0.019	-0.011	-0.011
Spline for amortized amount (200k, max)	0.001	-0.001	-0.003	0.001	0.001
	-0.002	-0.001	-0.002	-0.001	-0.001
Other Characteristics					
Indicator for mortgage age (36, 60]	0.498***	0.434**	0.522**	0.520***	0.453***
	-0.105	-0.141	-0.178	-0.096	-0.098
Indicator for mortgage age (60, 120]	0.712***	0.595***	0.725***	0.705***	0.676***
	-0.111	-0.153	-0.196	-0.102	-0.102
Indicator for mortgage age (120, max)	0.876***	0.959***	1.340***	0.910***	0.918***
	-0.152	-0.213	-0.265	-0.141	-0.141
Indicator for borrower age (35, 45]	0.025	0.08	0.048	0.007	0.019
	-0.086	-0.116	-0.137	-0.079	-0.079
Indicator for borrower age (45, 55]	0.041	0.008	-0.142	-0.07	-0.067
	-0.101	-0.133	-0.161	-0.094	-0.094
Indicator for borrower age (55, max)	0.335*	0.301	0.049	0.276*	0.292*
	-0.137	-0.188	-0.236	-0.127	-0.127
Indicator for borrower with both types of loans from same FI	-0.644***	0.127	-0.027	-0.627***	-0.544***
	-0.088	-0.116	-0.148	-0.084	-0.087
Indicator for simultaneously opened mortgage			-0.166	0.344***	0.287**
			-0.119	-0.098	-0.099
Indicator for increase in monthly payment since origination					0.289***
					-0.077
Indicator for decrease in monthly payment since origination					-0.054
					-0.134
Constant	0.968***	1.856***	2.242***	1.120***	1.092***
	-0.227	-0.369	-0.449	-0.206	-0.206
Pseudo R2	0.154	0.119	0.142	0.145	0.147
Observations	5,398	2,921	2,031	6,137	6,137

Table 5: Restrictive sample to compare mortgage loan and credit line defaults

This table reports coefficients of the binary logistic regression of the decision to default on mortgage loan first (indicator variable = 1) versus credit line first. Variables in the regressions include indicator variables and continuous variables, with some following the linear spline specification to allow for non-monotonicity in the relationship. The sample in this regression is different from our baseline model because we require borrowers to have exactly 1 mortgage and compare default decision between mortgage loan and credit line only, resulting in smaller sample size, for comparability with Andersson et al. (2013). Standard errors used in the estimation process are Huber-White (1985). *, ** and *** correspond to 10%, 5% and 1% statistical level of significance respectively.

	Baseline	Augmented
Affordability		
Mortgage payment (in 1,000)	-0.004	0.004
	-0.004	-0.009
Min credit/cash card payment (in 1,000)	-0.020***	-0.019***
	-0.005	-0.005
Indicator for min card / mortgage (0, 0.5]	-3.879***	-3.985***
	-0.336	-0.342
Indicator for min card / mortgage (0.5, 1.0]	-3.993***	-4.088***
	-0.338	-0.343
Indicator for min card / mortgage (0.5, max)	-4.261***	-4.382***
	-0.343	-0.349
Liquidity		
Available credit line (in 10,000)	-0.007	-0.013*
	-0.005	-0.006
Indicator for negative credit line	-1.177***	-1.213***
	-0.142	-0.151
Spline for credit line / mortgage (0, 1]	-0.773***	-0.856***
	-0.172	-0.184
Spline for credit line / mortgage (1, 4]	0.002	0.163*
	-0.067	-0.071
Spline for credit line / mortgage (4, max)	-0.087	-0.153*
	-0.064	-0.066
Housing Equity		
Indicator for negative amortization	1.422**	1.579**
	-0.489	-0.531
Spline for amortized amount (0, 100k]	-0.095***	-0.106***
	-0.022	-0.023
Spline for amortized amount (100k, 200k]	-0.060***	-0.045**
	-0.015	-0.016
Spline for amortized amount (200k, max)	0.001	0.002
	-0.002	-0.002
Other Characteristics		
Indicator for mortgage age (36, 60]	0.540***	0.489***

	-0.143	-0.147
Indicator for mortgage age (60, 120]	0.896***	0.780***
	-0.146	-0.153
Indicator for mortgage age (120, max)	1.064***	0.870***
	-0.192	-0.205
Indicator for borrower age (35, 45]	-0.064	-0.025
	-0.109	-0.113
Indicator for borrower age (45, 55]	-0.18	-0.101
	-0.131	-0.136
Indicator for borrower age (55, max)	0.373*	0.658***
	-0.187	-0.198
Indicator for borrower with both types of loans from same FI		-0.980***
		-0.116
Constant	4.649***	4.996***
	-0.336	-0.423
Pseudo R2	0.326	0.358
Observations	3,513	3,513