The implications of loan maturity on the probability of default: evidence from Peruvian long-term loans*

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Abstract

This paper analyzes the impact of a limited set of credit risk drivers (collateral and number of bank-debtor relationships) on long-term loans, and evaluates the effect of loan maturity on the probability of default (PD). In our estimates, we treat households and firms separately and include variables that reflect repayment ability, debtor characteristics, loan conditions, and macroeconomic factors as controls. Our dataset includes more than twenty-six million loans granted by Peruvian financial institutions for the period 2012-2016. Using a set of logit models, we find evidence of a positive correlation between loan maturity and the PD for firms and households. Overall, credit risk drivers appear as heterogeneous when different loan maturities are considered. Furthermore, our results suggest that the impact of collateral on the PD is negative for firm loans, but positive for household loans, while the number of bank-debtor relationships has a positive impact among all models estimated. These findings can ultimately result in policy actions to mitigate the scarcity of long-term loans in the country.

Keywords: long-term loans, probability of default, logit model, long-term credit risk, collateral, bank-debtor relationship.

JEL Codes: C35, C55, E51, G21.

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1 Introduction

This paper analyzes the determinants of the probability of default (PD) of loans granted by the financial system, differentiating them by type of debtor (firms and households). Specifically, we focus on the effects of the loan maturity (short, medium, and long-term) on the PD, while controlling for other factors related to the debtors financial behavior, her demographic characteristics, repayment ability, loan conditions, and macroeconomic factors. This approach is based on the idea that loans of different maturities do not serve the same purpose, and thus their credit risk drivers might differ.

There are two main questions we attempt to answer: the first one focuses on how the determinants of the PD vary over different loan maturities. Our hypothesis suggests that some key credit risk drivers show a different behavior when comparing short, medium and long-term loans, based on evidence from the literature and credit lending policies from Peruvian banks. The second question refers to the impact of the loan maturity on the PD. Although there is no consensus regarding the correlation between these two variables, we expect that loans with longer maturities show a higher PD. This might be a possible explanation for the scarcity of long-term lending in emerging economies, which discourages expenditure and investment decisions that affect financial development and economic growth. Furthermore, we focus on the role of collateral and the number of financial institutions with which the debtor is indebted (number of bank-debtor relationships) as determinants of credit risk by different maturities.

Most of the contribution of this paper to the literature about long-term credit risk is based on the large dataset on loan operations for which data on ex-post risk is available. We gather information on the more than 25 million loans granted by the Peruvian financial institutions from 2012 to 2016. This information is collected on a monthly basis by the Financial Supervisory Authority through the Credit Report of Debtors[1], and two additional databases used for in-situ and extra-situ supervisory procedures that reflect the loan conditions and repayment ability. This is a key fact since much of the existing literature relies on data from surveys or time series that do not allow a debtor-level analysis. For the Peruvian case, there are only a few studies on the financial system that rely on such a large dataset. Moreover, our dataset includes different types of loans, therefore allowing finding differences in the determinants between households and companies.

[1]Reporte Crediticio de Deudores (RCD).

This paper is structured as follows: section II presents the literature review related to the importance of long-term lending, the main credit risk drivers, and techniques to estimate the probability of default; section III shows some stylized facts about the Peruvian financial system and the characteristics of long-term loans; section IV describes the data used in this study, section V presents the methodological approach, section VI shows the results, and section VII concludes.

2 Literature review

2.1 Importance of long-term lending in emerging economies

The scarcity of long-term lending in emerging markets is recognized as an obstacle to economic growth. Caprio and Demirg-Kunt (1997) find that firms in developing countries use significantly less long-term debt than their industrial country counterparts, even after controlling for firm characteristics, macro-factors, government subsidies, financial development level, and legal and institutional factors. They show that firms that grew faster than predicted exhibited higher levels of long-term debt (as a share of total assets). Therefore, long-term financing tends to be associated with higher productivity.

However, there is little empirical evidence that focuses on the determinants of loans by maturity. Most of the research shows that banks grant short-term loans because it is easier to monitor short-term credit risk through more frequent renegotiations of loans conditions. This behavior also mitigates informational asymmetries between lenders and borrowers. Diamond (2004) says that in emerging markets where financial benefits from pursuing legal enforcement are small, lenders might engage in what is called lender passivity. Instead of relying on the weak legal protection of lender rights or on higher interest rates, a passive lender will employ non-price mechanisms such as the maturity of loans to effectively control credit risk.

Recent research explores the credit availability and cross-country differences in the maturities of loans in emerging economies. However, this literature is related to the effect of laws and institutions on loan contracts. Fan, Titman, and Twite (2006) show that banks in countries with strong legal systems and customer protection rights tend to exhibit lower leverage but higher long-term debt (as a share of total debt). Qian and Strahan (2007) find that contracting costs, represented by legal formalism, affect the maturity of loans. As a consequence, in countries where legal formalism is higher, domestic banks are more likely to lend to firms without financial history, offering them loans with longer maturities but collateralized. Tasic and Valev (2008) show that long-term loans are granted in countries with strong institutions, low inflation rates, large financial markets, and minor informational asymmetries. They also show that the maturity of loans is important for economic growth. Park et al. (2015) empirically examine the determinants of credit at different maturities across European Union countries during the last decade. By classifying loans according to their maturity, they explain how commercial long-term loans in EU emerging countries grew substantially faster than the rest of the region. They also find that in these economies, domestic saving and foreign liabilities were more important sources of funding in a context of trade openness.

To sum up, the prior literature reveals the importance of long-term lending to enhance economic growth in emerging economies. It also asserts that the maturity of loans should be shorter in countries with weak legal protection systems and more risky borrowers. Very little is known about the determinants of credit risk, for which we attempt to extend the literature on credit availability in emerging economies by focusing on the determinants of credit risk among different maturities.

2.2 Drivers of credit risk

The Basel Committee on Banking Supervision (BCBS) defines credit risk as the likelihood that a bank borrower or counterparty would default on its obligations in accordance with agreed terms. Based on this definition, BCBS (2005) asserts that credit risk can be settled as the quantification of four key parameters: (i) probability of default, (ii) loss-given-default, (iii) exposure at default, and (iv) effective maturity.

One important aspect of credit risk is its meaning for the determination of the capital requirement for banks. This context lead to the need of the development of reliable credit risk models, which support various decision-makers in the estimation and management of credit risk as well as in the pricing of financial instruments dealing with credit risk. In this document, we focus our analysis on the determinants of ex-post credit risk in Peru. Particularly, we defined the probability of default as the likelihood that a borrower will be unable to meet her debt obligations (either because of inability or unwillingness to pay).

Several studies have assessed the existence of a relationship between credit risk and different groups of variables, such as loan conditions, demographic and socioeconomic characteristics, financial behavior, and macroeconomic factors. Some of these ideas are listed in Table 1, and the most relevant are discussed in this section.

a. Debtor's repayment ability and financial behavior

In the case of personal lending, willingness and ability of the borrower to repay the loan are the primary factors to be considered in any evaluation of credit risk. The second criterion, ability to repay, can be tested by several standards: by personal characteristics such as age, sex and family status; and by the borrower's occupational or economic position, income and net worth. For instance, Alfaro et al. (2010) and Gutiérrez et al. (2011) found evidence that the level of income is a key factor in estimating the probability of default for debtors in Chile and Colombia, respectively.

While modeling credit risk, the behavior of the debtor plays an important role. In this area, the relationship between a bank and the borrower can have a significant impact on the PD, as found in Jiménez & Saurina (2004). According to these authors, a debtor that holds loans granted by more than one lender tends to exhibit a lower PD, supporting the existence of informational rents for the bank in the case of a close relationship with the customer, thus considerably diminishing the incentives to finance higher-risk borrowers. However, in the case of Italy, Foglia et al. (1998) find that relationships with multiple banks are associated with greater borrower risk. In addition, Fiordelisi et al. (2013) also find that longer banking relationships lower financial distress on firms, especially on small ones. Our hypothesis is in line with these results since it is common in Peru to find firms working with many banks at the same moment, constantly searching for funding sources to cover their expenses [2] . Hence, we consider the number of institutions with which the debtor holds a loan (hereinafter number of bank-debtor relationships for each debtor) as a measure of over-indebtedness and thus, expect a positive correlation with the PD.

[2]Furthermore, according to the World Bank (2013), one of the drivers of over-indebtedness is rooted in lenders motivation. They assure that selling products more expensive to borrowers with limited knowledge of financial products is a general practice in financial institutions in order to increase profits.

b. Loan conditions

The problems of asymmetric information are present in every loan operation between lenders and borrowers. According to the so-called observed-risk hypothesis, banks can observe the firms risk ex-ante, and therefore they can modify the terms of the credit contract to adjust pricing to the riskiness of the loan (Blazy & Weill, 2006). In fact, the problems of asymmetric information arise for all loans, although these problems worsen as the relative debt level increases.

Although we include the most relevant loan conditions in our estimations, our main variable of interest is the loan maturity. The literature about the relationship between credit risk and maturity is varied. Structural models of credit risk, mainly based on Mertons framework, highlights that changes in credit spread in response of time to maturity $T - t$ depend on the leverage ratio of the firm. On the other hand, reduced-form models, which model the default of a company as a rather unpredictable event, show a split behavior in terms of the relationship between credit spreads and maturity. In this line, Truck et al. (2004) investigate the term structure of credit spreads and credit default swaps (CDS) for different rating categories based on a large sample of Eurobonds and domestic bonds from EWU countries. They find a positive relationship between maturity and spreads for CDS and corporate bonds for investment grade debt.

Furthermore, empirical evidence for banking loans is rather ambiguous. According to Jiménez & Saurina (2004 and 2006) the PD decreases as the time horizon of the loan increases. The authors suggest that the low PD for long term loans (i.e. those over 5 years) points towards the importance of screening. Given that the borrowers financial health and repayment ability could change significantly over such a long period, the bank examines the application rigorously. However, these results go in the opposite direction of the findings from Johnston et al. (2015) and Flannery (1986). The latter discusses the signaling hypothesis, supporting the idea that borrowers with a sounder economic position thus less risky- would prefer to raise short-term funds. On the other hand, riskier borrowers prefer long-term funding in order to pay lower loan fees. Despite both positions are supported by empirical evidence, the hypothesis proposed by Flannery (1986) might be more appropriated for the Peruvian context, serving as an explanation of the scarcity of long-term funding in the country.

Regarding other loan conditions, one of the main factors discussed in the literature is the role of the collateral as a determinant of borrower risk. Jiménez & Saurina (2004) find that collateral increases the ex-post PD of a loan. By analyzing Spanish bank loans, they find strong evidence in favor of the symmetry and screening theories, which assert that in the presence of asymmetries between banks and borrowers, collateral will be demanded from riskier borrowers. These results are in line with Rajan & Winton (1995), Fiordelisi et al. (2013), and Manove & Padilla (1999 and 2001), who argue that collateral might decrease the screening efforts that banks incur in the repayment capability assessment.

Nevertheless, Calcagnini et al. (2004) show that interest rates levels are significantly affected by collateral. They find that in the case of firms, collateral decreases the probability of default, solving adverse selection problems. On the other hand, collateralized household loans show a higher probability of default, which might be evidence of moral hazard problems. Furthermore, collateralized loans tend to have lower interest rates, which supports the idea that collateral helps solving adverse selection problems once customer riskiness is controlled. Since our specification consists of two different models (differentiating by firms and families) that follow different dynamics, it is possible to expect different outcomes regarding the effect of collateral.

The size of the loan and the interest rate can also serve as indicators of credit risk, besides providing a solution to information problems and allowing banks to impose greater discipline on the borrower. As for the size of the loan, its effect on the PD is not clear. Jiménez & Saurina (2004) show that there is an inverse relationship between the size of the loan and the probability of default since larger loans passed a more rigorous screening process. Nevertheless, larger loans require a greater repayment effort on the part of the debtor (considering all other factors constant) thus increasing the PD. We address the possibility of a non-linear relationship between the PD and the size of the loan by including the square of the variable in our regressions. This consideration is important for emerging economies, where it is not unusual to deal with inaccurate screening processes.

c. Other factors

The stage of the economy's credit cycle defines the credit risk performance in the banks' loan portfolio. Recessions and financial crises lead to peaks in the probability of default, whereas boom phases are characterized by declines. Quagliarello (2006) finds that loan-loss provisions and "new" bad debts in Italy are affected by the business cycle evolution. Aver (2008) analyzes the credit risk factors of the Slovenian banking system through a linear regression model. The study concludes that certain macroeconomic factors unemployment rate, short and long-term interest rates, and the value of the Slovenian stock exchange index have a major influence on the loan portfolio credit risk. We attempt to collect these macroeconomic effects by including year dummies in our estimations.

Finally, factors related to the characteristic of the financial institution that acts as a lender can also play an important role in explaining credit risk. A common way to address this issue is to differentiate between banking and non-banking institutions, as proposed by Jiménez & Saurina (2004)[3] and Glennon & Nigro (2005).

2.3 Measures of the probability of default

The methodologies for estimating the probability of default are various and can be separated into three main groups: historical, parametric, and semiparametric. In the first approach, information from a set of variables in a predetermined time window is used to estimate the corresponding risk parameter. In the second (parametric) approach, simulations are conducted to infer, under certain confidence intervals, the values of the PD. The third approach (semiparametric) seeks to combine the advantages of the two approaches mentioned previously.

As for the historical approaches, credit migration matrices are used to describe and predict the movement that a debtor (or portfolio) takes through different credit rating classes. Gunnvald (2014) provides an interesting and complete theoretical framework around credit migration, based on the Markov chain theory. In the same line, Schuermann & Hanson (2004) propose different methods of estimating credit migration matrices in discrete and continuous time, namely the cohort and the parametric duration methods.

To estimate annual credit migration matrices under the cohort approach, observed proportions of individuals for each rating category from the beginning to the end of the year (and possibly experimented changes in their risk categories) are taken as estimates of migration probabilities. Let $t_0, t_1, ..., t_n$ be discrete time points such as an arbitrary time interval $t_{k+1} - t_k = \Delta t_k$, where Δt_k is constant. As described by Christensen et al. (2004), the probability of default PD_k over one time period is then $PD_k = \frac{n_{ij}(\Delta t_k)}{n_i(t_k)}$, where $n_{ij}(\Delta t_k)$ is the number of debtors that have moved from state i (non-default) to state j (default) between time t_k and t_{k+1}, and $n_i(t_k)$ are the number of debtors in state i at time t_k.

[3] They use the concept of savings bank, commercial banks, and credit cooperatives.

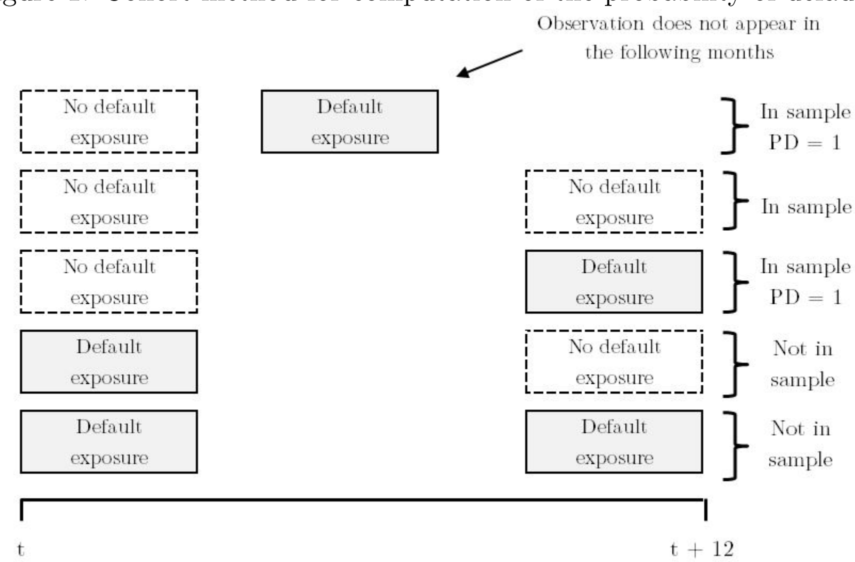
Table 1: Literature Review

Author(s)	Methodology	Dependent variable	Main signs
Aver (2008)	OLS	Probability of default	Real interest rate for short-term consumer loans (+), Slovenian stock exchange index (+), employment rate (-), reference interest rate (+), interbank interest rate (-), real interest rate on home loans (+)
Bonfim (2009)	Discrete choice model, duration model	Corporate credit default	Credit growth (+), interest rate (+), bond yields (+), stock market index (-), solvency ratio (-), ROA (-), sales growth(-)
Fiordelisi et al. (2013)	Probit model	Probability of default	Concentration of lenders (-), length of credit relationship (-), size of the firm (-), collateral (+), HHI (+)
Glennon & Nigro (2005)	Discrete-time Hazard model	Probability of Default	Corporate structure (-), new firms (+), guarantee (+), loan amount (-), economic growth (-)
Jappelli & Pagano (1999)	OLS	Loan-loss provision, index of credit risk	Level of information (-), GDP growth rate (-), lender rights (-)
Jimenez & Saurina (2006)	Random effect logit	Probability of default	Credit growth rate of bank (+), maturity (-), collateral (+), size (-)
Jimenez & Saurina (2004)	Binomial logit model	Probability of default	Collateral (+), maturity (-),bank-debtor relationship (-), saving banks versus commercial banks (+), size (-)
Johnston et al. (2015)	Logit	Loss-given-default	Loan size (-), "age" of loan at default (-), maturity (+), interest rate premium (-) judicial foreclose (+), bank size (-)
Li (2014)	OLS, Logistic model survival analysis	Probability of default of individual mortgages	Unemployment rate (+), house price volatility (+), personal loan interest rate (+) house price (-), GDP growth (-), loan-to-value ratio (+), loan size (-),income (-) volatility of income (+), leverage and indebtedness (+), non-housing wealth (-)
Quagliariello (2007)	Panel	Loan-loss provision, "new" bad debts	Growth of performing loans (-), bank cost-to-income ratio (+), non-performing loans to total loans ratio (+), GDP growth rate (-), interest rate of long-term debt (+), stock exchange index (-), interest rate spread (-)

Source: SBS

This procedure does not take into account any changes in the risk category of the debtor within the period of analysis (Schuermann & Hanson, 2004). In this study, we use the cohort approach of credit migration with a 12-month window to identify the determinants of the probability that a debtor defaults (i.e. migrating from an initial state to a default situation). This methodology is illustrated in Figure 1 and Annex 1.

Figure 1: Cohort method for computation of the probability of default



3 Stylized Facts on the Peruvian Financial System

3.1 Basic Stats

As of December 2016, the Peruvian financial system englobed 55 credit institutions divided into five categories: banking institutions, finance companies, municipal non-banking institutions, rural non-banking institutions and micro & small enterprise development entities[4]. The differences between these categories are mainly two: special entities for SME development institutions cannot hold savings, and only commercial banks and financial companies are authorized to grant credit cards. On the other hand, even though the high number of credit institutions, the financial system has a high degree of concentration in banks (see Table 2).

[4]In Spanish: banca múltiple, empresas financieras, cajas municipales de ahorro y crédito, cajas rurales de ahorro y crédito y entidades de desarrollo para la pequeña y microempresa.

Table 2: Structure of the Peruvian financial system

	Number of institutions	Assets US$ Million	Assets %	Loans US$ Million	Loans %	Savings US$ Million	Savings %
Banking institutions	16	105,979	90.7	70,134	88.7	62,634	90.2
Finance companies	11	3,570	3.1	2,993	3.8	1,655	2.4
Municipal non-banking institutions	12	6,389	5.5	5,118	6.5	4,990	7.2
Rural non-banking institutions	6	408	0.3	317	0.4	186	0.3
Micro & small enterprise development entities	10	537	0.5	484	0.6	-	-
Total	**55**	**116,883**	**100**	**79,047**	**100**	**69,466**	**100**

Source: SBS

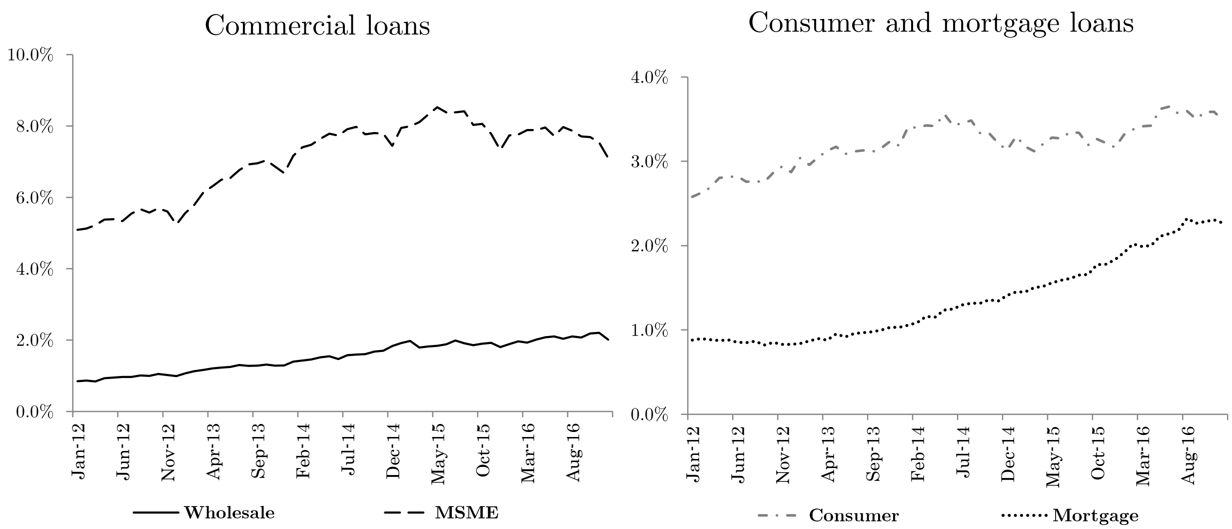
Loans granted by credit institutions are classified into eight different categories:

- Corporates: annual sales over S/ 200 million (around US$ 60 million)
- Big-sized firms: annual sales between S/ 20 and S/ 200 million (around US$ 6 and US$60 million)
- Medium-size firms: loans over S/ 300 thousand (around US$ 90 thousand) and with annual sales lower than S/ 20 million (around US$ 6 million)
- Small-size firms: loans between S/ 20 and S/ 300 thousand (around US$ 6 and US$ 90 thousand)
- Small-size firms: loans lower than S/ 20 thousand (around US$ 6 thousand)
- Revolving consumer loans: mainly credit cards
- Non-revolving consumer loans
- Mortgages

By type of loans, corporate and mortgages loans are the most important in the credit portfolio. However, considering the number of debtors for each loan, consumer loans are the most relevant. For the purpose of this study, the types of loan are aggregated into two categories: “Firms” which includes wholesale loans (corporate and big-size firms) and MSMEs loans (micro, small and medium-sized loans); and “Households”, which includes consumer loans (revolving and non-revolving), and mortgage loans. Consumer and micro-sized loans have the higher interest rates, while mortgage loans stand out as the type of credit with longer maturities (see Annex 2).

One way to evaluate the vulnerability risks of the financial sector is through the analysis of non-performing loans. In the case of Peru, this credit risk measure varies over the type of credit. Particularly, non-performing loans are overdue loans after 15 days since the due date for commercial loans, and after 30 days for small businesses loans. In the case of mortgage, consumer and leasing loans, they are considered overdue after 30 days since the due date only for the non-amortized portion and after 90 days for the whole exposition[5]. According to historical results, non-performing loans appear to have maintained a stable trend in recent years. This standardization is the one used in Peruvian financial regulation (Resolution SBS N 11356-2008). As of December 2016, non-performing loans in the financial system stood at 3.2 percent with MSMEs exhibiting higher levels and thus reflecting the inherent risk associated with this type of borrowers (see Figure 2).

Figure 2: Non-performing Loans by type of loan



Source: SBS

The credit rating of debtors varies over five categories: 0 (normal), 1 (with potential problems), 2 (deficient), 3 (doubtful), and 4 (loss). The definition of each category is different for each type of loan, as shown in Table 3.

Finally, the definition of default is based on the credit rating. For corporate, big, medium-sized firms, and mortgage loans, it is considered that the debtor is in a default situation if its credit rating is 2 or higher. For small, micro-sized, and consumer loans, it is considered that the debtor is in a default situation if its credit rating is 3 or higher. This standardization is

[5]Overdue loans include credits under judicial resolution.

the one used in Peruvian financial regulation (Resolution SBS N 11356-2008).

Table 3: Risk categories by type of loan

Risk categories	**Wholesale loans**	**MSME, Consumer**	**Mortgage**
Normal (0)	0	8	30
W/ Potential Problems (1)	60	30	60
Deficient (2)	**120**	60	**120**
Doubtful (3)	**365**	**120**	**365**
Loss (4)	**+365**	**+120**	**+365**

Considers day past due (up to).

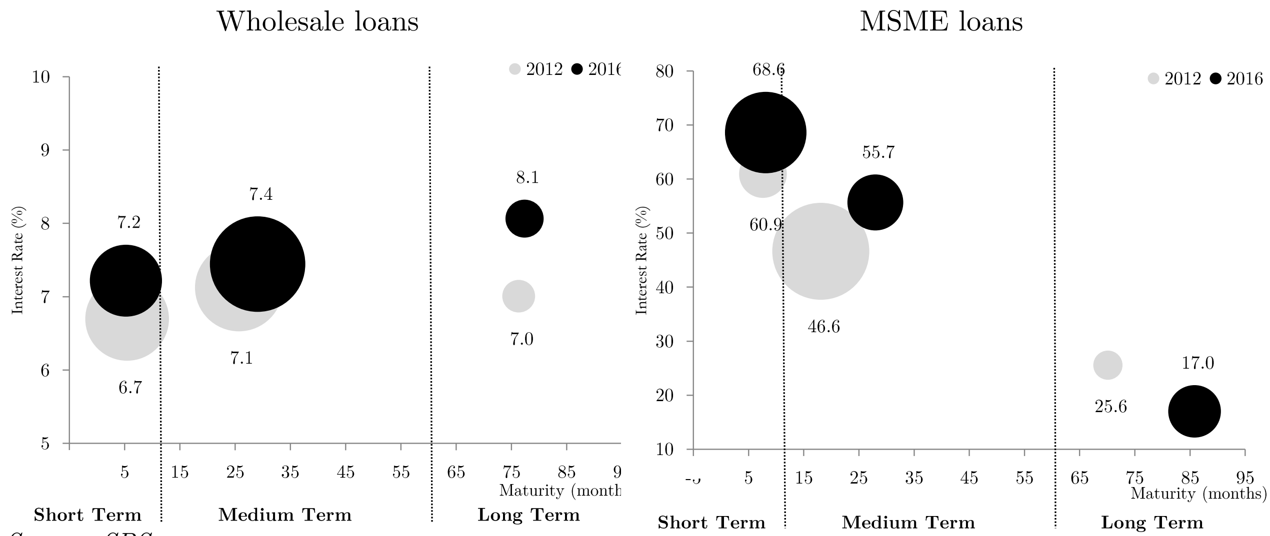
In bold red: threshold for a debtor to be considered as having defaulted on the loan.

3.2 Comparison by loan maturity

Loans granted by the financial system are classified by their maturity into three categories: short, medium, and long-term. Short-term loans have a maturity of less than a year, medium-term loans have a maturity between a year and five years, and long-term loans have a maturity greater than five years. We exclude revolving consumer loans of this segmentation.

In recent years, long-term lending for firms represented less than 12% of total firm lending, which is a reflection of the scarcity of such loans (see Annex 3). Figure 3 and Figure 4 present the evolution of interest rates and average maturity for firms and households, respectively, between 2012 and 2016. It can be noticed that the average interest rates for wholesale loans have slightly increased for all terms, while the evolution of interest rates for MSMEs varies across maturities. For instance, long-term loans for MSME have lower interest rates, which have decreased in the last four years. By contrast, the medium-term interest rates increased for the same period.

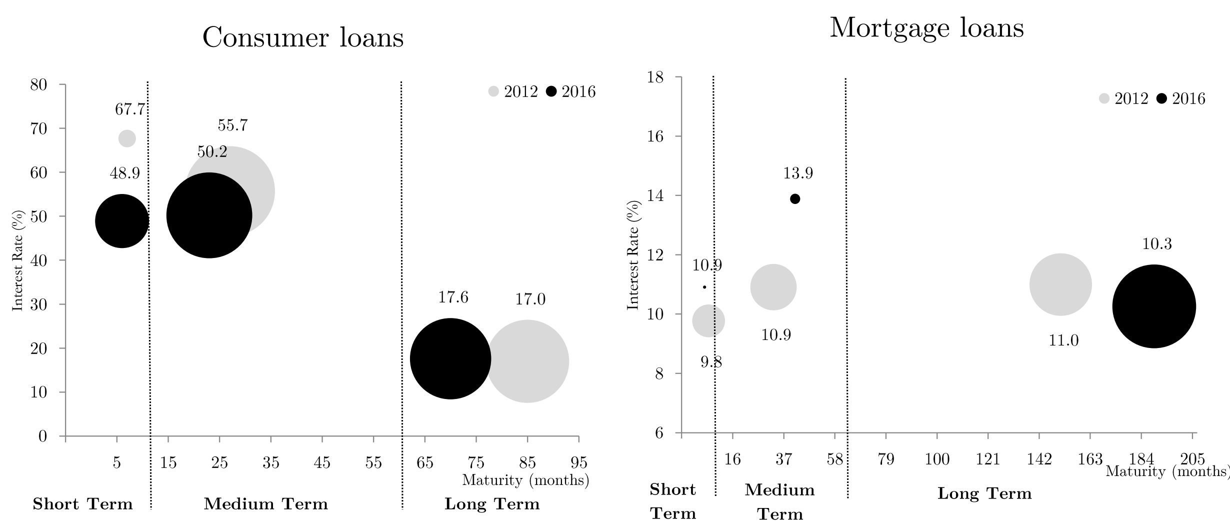
Figure 3: Interest rate and Average Maturity for firms



Source: SBS

The share of long-term loans over total loans for households has increased in the last four years and it is greater than 40% by the end of 2016 (see Annex 3). In the case of consumer loans, the average interest rate decreases with maturity and has increased for short-term and medium-term loans between 2012 and 2016. This upward trend of interest rates for shorter maturities can be related to the more rigorous screening process taken by financial institutions in response to the evolution of economic conditions. Nevertheless, evidence from mortgage loans shows that there is not a defined relationship between the maturity of loans and the interest rate since the average interest rate has an inverted-U-shape form across the maturity for this type of loan.

Figure 4: Interest rate and Average Maturity for households



4 Data

This study relies on three databases compiled by the Financial Regulatory Authority. The main database of this study is the Credit Report of Debtors (Reporte Crediticio de Deudores). This database encloses monthly information on all loans granted by supervised credit institutions in Peru since 2001. The information is at a debtor level and includes variables such as: amount of the debt and the collateral, credit institution on which the debtor holds a loan, loan type, currency; credit rating of the debtor; gender and age of the debtor; and "age" of the debtor in the financial system.

The other two databases are compiled in the financial supervisory process. The second database is the Data Structure (Estructura de Datos), which encloses yearly information on all loans granted by supervised credit institutions in Peru since 2012, is available at a debtor level and includes the interest rate, original loan amount, and maturity of each loan. The third database is also provided by the supervised credit institutions for extra-situ supervisory issues, is available at a debtor level and includes variables for repayment capability: available income (for households) and sales and operating profit (for firms). In the case of wholesale firms (corporate and big-sized firms), the information of the repayment capability comes from financial statements. Table 4 provides a list of variables used in this study.

Table 4: Features of the debtor

Variable	Type	Definition
Variables of interest		
Collateral	Dummy	1 if the loan is collateralized, 0 o/w.
N of bank-debtor relationships	Numerical	Number of financial entities with which the debtor holds a loan.
Short-term loan	Dummy	1 if the term of the loan is less than a year, 0 o/w.
Medium-term loan	Dummy	1 if the term of the loan is between one and five years, 0 o/w.
Controls*		
Repayment ability		
Income	Numerical	Gross sales for firms, disposable income for households (amount is in local currency).
Loan conditions		
Interest rate	Percentage	Average effective annual interest rate charged to debtors in percentage.
Collateral	Dummy	1 if the loan is collateralized, 0 o/w.
Amount of the loan	Numerical	Initial amount of the loan.
Currency	Dummy	1 if the loan is in US dollars, 0 if is in local currency.
Non-banking loan	Dummy	1 if the lending institution is not a bank, 0 o/w.
Debtor characteristics		
Woman	Dummy	1 if the debtor is a female, 0 o/w.
Age	Numerical	Age of the debtor in years.
Province	Dummy	1 if the loan is granted outside Metropolitan Lima (Perus capital city), 0 o/w
MSME loan	Dummy	1 if the debtor holds a MSME loan, 0 o/w.
Credit card loan	Dummy	1 if the debtor holds a credit loan, 0 o/w.
Consumer loan	Dummy	1 if the debtor holds a consumer loan, 0 o/w.
Mortgage loan	Dummy	1 if the debtor holds a mortgage loan, 0 o/w.

5 Methodological Approach

The methodological approach to estimate the probability of default relies on a binomial pooled logit model for each type of agent (firms and households), considering the period 2012-2016. The logit approximation is one of the most employed techniques according to the literature, due to its high predictive power as an empirical model and precision in predicting default.

We follow the strategy used by Jiménez & Saurina (2004) in interaction with the proposal of Glennon & Nigro (2005). Particularly, we estimate a pool model in addition to three different models for short, medium and long-term loans. As mentioned before, the pooled estimation allows identifying the impact of the loan maturity on the PD, while the separate models are useful to explicitly test whether the determinants of default differ among loan maturities.

The endogenous variable y_i is dichotomous, where $y_i = 1$ if the debtor defaults and 0 otherwise. By assumption, the probability of observing $y_i = 1$ is $G(x_i'\beta)$, while the probability of observing $y_i = 0$ is $1 - G(x_i'\beta)$. The non-linear cumulative density function $G(x_i'\beta) = \frac{\exp(x_i'\beta)}{1+\exp(x_i'\beta)}$ is monotonically increasing in $x_i'\beta$, and bounded between 0 and 1 for all values of $(x_i'\beta)$; x_i is a vector of k regressors. In our pool model, the probability that a debtor falls into default can be estimated as a function of observed features as follows:

$$Pr(y = 1|\Pi) = c + \alpha X_{it} + \phi W_i + \delta Y_{it} + \gamma Z_i + \theta T_t$$

where:

- X: variables of interest (includes maturity dummy variables)
- W : repayment ability variable
- Y: loan conditions variables
- Z: debtor characteristics
- T: year dummies

In our specifications by maturity, the model is very similar, but maturity dummies are not included as variables of interest. The binomial logit model is estimated by means of Maximum Likelihood (ML). Thus, the probability of observing the entire sample is:

$$L(y|x_i\beta) = \prod_{i=1}^{N} G(x_i'\beta)^{y_i} \left[1 - G(x_i'\beta)\right]^{1-y_i}$$

where vector x_i includes each of the k variables mentioned before for debtor i, β are the parameters of the model, and y_i is the dependent variable. The predicted value $y_i = x_i'\beta$ is bounded between 0 and 1.

6 Results

In this section, we show the main determinants of the probability of default of long-term loans, differentiating them between firms and households. We focus the analysis on the role of collateral and bank-debtor relationships as credit risk drivers. Furthermore, we address the question whether long-term loans are associated with higher PD in contrast with loans with shorter maturities.

The distinction between firms and households is important since loans granted to these two groups of economic agents meet different long-term financing decisions and are subject to different environments. For example, the scarcity of long-term loans in firms will have a lesser negative impact than the scarcity of long-term loans in households (usually allocated in mortgages), since the latter do not have an alternative financing market in comparison to firms (such as the bond market, foreign banks, etc.).

As mentioned in the previous section, we estimated one pooled model for each type of economic agent. Since the main purpose of this paper is focused on long-term lending, the base-case scenario in this pool model is a long-term loan and dummies for the term of the loans are added. In addition, three models differentiated by the maturity of the loan (short, medium, and long-term) are estimated as well.

6.1 Firms

Table 5 shows the results for the logit estimations applied to data of firms from over the five-year period studied (2012 to 2016). The first three columns show the estimations for this data as divided into three exclusive categories (short, medium, and long-term loans) with each category being estimated by a logit model. These results are shown in the first three models of Table 5. The last column shows the results for the pooled model. In this last model, two dummy variables for short and medium-term loans are added. Numerical variables such as income and amount of the loan are included in natural logarithms. Each model includes a constant which is not reported but should reflect the characteristics of the excluded loans. As can be observed, these estimations are very accurate: the rate of predicted probabilities is around 70%, considering a success threshold of 0.5. This is mostly due to the high number of observations (6,543,845).

Table 6 complements the information presented in Table 5 by showing the marginal effects of an increment of one unit of each variable included in our logit estimations on the PD. The structure of the table is the same as Table 5, but effects considered as not significant at a 5% level are excluded. Since the variables of income and the amount of the loan are included in the model as natural logarithms, the marginal effects are computed considering an increment of one percent of each of these variables on the PD[6].

The maturity dummy variables show that short-term loans are associated with lower probabilities of default than medium-term loans, and medium-term loans have lower probabilities of default than long-term loans. This is also seen in the average PD of the models separated by terms, which is positively correlated with the maturity. This fact is supported by Flannery (1986) and Johnston et al. (2015) and by the fact that long-term loans are usually allocated in investment projects, which have an higher inherent risk than short-term expenses (such as working capital).

Moreover, considering the pooled model, the effects of the determinants of interest are in line with expectations. Holding an additional loan at an additional financial institution increases the probability of default by 2.0 percentage points (pp). This confirms that our hypothesis of using this variable as a measure of over-indebtedness seems to be accurate. It is important to note that our logit estimations control by company incomes; therefore, the number of bank-debtor relationships reflects only over-indebtedness issues and not the effects related to the size of the firms, as mentioned in Jiménez & Saurina (2004). Regarding the collateral, loans backed by guarantees have a PD lower in 0.71pp than not-collateralized loans. This evidence suggests that, regarding firms, the presence of collateral is associated with lower credit risk, and therefore, moral hazard problems are mitigated. The results are consistent even when separating the sample by loan maturity.

For our control variables, in most cases the effects are also in line with expectations. A higher income decreases the probability of default since the repayment ability improves. Loans granted by non-banking institutions are associated with higher probabilities of default especially in long-term loans. According to our MSME dummy, loans granted to these companies have a higher PD since almost none of wholesale companies have defaulted in our analysis period. However, the most important conclusion might be related to the signs of the amount of the loan, since we found evidence of a non-linear behavior of this variable (a U-inverted shaped form). Initially, the amount of the loan is related to increasing probabilities of default until a level on which the probability of default decreases as the amount of the loan increases. This behavior might be explained by the fact that loans involving large amounts are assessed thoroughly, and therefore, are associated to less-risky debtors.

[6]It is important to mention that these marginal effects are computed at the means of numerical variables and with dummy variables set as zero. For example, for the pooled model, these impacts are consistent to a wholesale firm based in Metropolitan Lima evaluated in 2014 who has more than two years in the financial system and with a long-term, not-collateralized loan in local currency in a bank.

Table 5: Determinants of the PD for firms
Dependent variable: default

	Short-term	Medium-term	Long-term	Pool
Variables of interest				
N of bank-debtor relationships	0.1832***	0.1696***	0.1136***	0.1711***
	(0.0011)	(0.0005)	(0.0033)	(0.0005)
Collateral	-0.0541***	-0.0690***	-0.0487***	-0.0614***
	(0.0044)	(0.0022)	(0.0138)	(0.002)
Short-term loan				-0.6209***
				(0.007)
Medium-term loan				-0.5753***
				(0.0066)
Controls				
Repayment ability				
Income	-0.0274***	0.0004	-0.0807***	-0.0105***
	(0.0019)	(0.001)	(0.0046)	(0.0008)
Loan conditions				
Interest rate	0.0066***	0.0108***	0.0023***	0.0087***
	(0.0001)	(0.0001)	(0.0006)	(0.0000)
Amount of the loan	0.1415***	0.4573***	0.4927***	0.3292***
	(0.0113)	(0.0082)	(0.0335)	(0.0062)
Squared amount of the loan	-0.0069***	-0.0201***	-0.0260***	-0.0145***
	(0.0006)	(0.0004)	(0.0015)	(0.0003)
Currency	0.0110***	0.2210***	-0.2129	0.0882***
	(0.0212)	(0.0088)	(0.0205)	(0.0075)
Non-banking loan	0.2262***	0.2311***	0.6552***	0.2299***
	(0.0047)	(0.0023)	(0.0147)	(0.002)
Debtor characteristics				
Province	-0.1518***	-0.1478***	-0.4084***	-0.1621***
	(0.0047)	(0.0024)	(0.0131)	(0.0021)
MSME loan	1.9192***	1.5715***	1.0599***	1.7837***
	(0.0749)	(0.0632)	(0.166)	(0.0462)
Year				
2012	-0.1113***	-0.0648***	-0.166	-0.0515***
	(0.007)	(0.0035)	(0.0259)	(0.0031)
2013	0.0392	0.0123***	-0.0133	0.0201***
	(0.0057)	(0.0031)	(0.0219)	(0.0027)
2015	-0.2901***	-0.2827***	-0.1439***	-0.2859***
	(0.0056)	(0.0028)	(0.0185)	(0.0025)
2016	-0.782	-0.8704	-0.2377	-0.8449
	(0.0066)	(0.0032)	(0.0199)	(0.0028)
Observations	1,277,393	5,151,173	115,279	6,543,845
Log- likelihood / P - value	71,213 / 0.0000	270,635 / 0.0000	7,860 / 0.0000	346,770 / 0.0000
Predicted probabilities (threshold = 0.5)	70.64%	72.28%	66.68%	71.80%
Pseudo R-Squared (McFadden)	0.0463	0.0448	0.0516	0.0448

1/ The coefficients are obtained after performing binomial logit estimations for each model. Standard errors are reported in parentheses. Each estimation includes a constant, which is not reported in the table. 2/ Income, amount of the loan and squared amount of the loan are included as natural logarithms.

Table 6: Marginal effects of the determinants of the PD for firms

	Short-term	**Medium-term**	**Long-term**	**Pool**
Variables of interest				
N of bank-debtor relationships	1.07	1.56	1.3	2.03
Collateral	-0.31	-0.62	-0.55	-0.71
Short-term loan				-5.85
Medium-term loan				-5.51
Controls				
Repayment ability				
Income	-0.16	*	-0.92	-0.12
Loan conditions				
Interest rate	0.04	0.1	0.03	0.1
Amount of the loan	-0.09	0.24	-2.38	0.12
Currency	0.06	2.22	*	1.08
Non-banking loan	1.46	2.33	9.44	2.96
Debtor characteristics				
Province	-0.83	-1.28	-4.02	-1.81
MSME loan	24.93	25.25	17.29	34.91

1/ The marginal effects in percentage points are obtained after performing binomial logit estimations for each model. These impacts are computed at means of continuous and discrete variables and at zero in dummy variables. 2/ Rows for income and amount of the loan show the marginal effect of a 1% increase in these variables. 3/* stands for not significant impact at 5% level of confidence. 4/ Results are controlled by temporal dummy variables for 2012, 2013, 2015 and 2016.

Following the same structure as the previous sub-section, Table 7 presents the results for the logit estimations applied to data of households from over the five year period studied. Our estimates show an acceptable rate of predicted probabilities, which is around 70%, considering a success threshold of 0.5. This is mostly due to the high number of observations (9,400,138).

Table 8 complements the information presented in Table 7; it shows the marginal effects of an increment of one unit of each variable included in our logit estimations. Our maturity dummy variables show that the PD and the loan maturity have a positive relationship, consistent with the firm's specifications.

At the pooled model, the effects of the determinants of our interest are in line with expected. The request for an additional loan at an additional financial institution increases the probability of default by 0.8pp. Regarding the collateral, loans backed by guarantees have a PD higher in 1.8 pp than loans which are not collateralized. This evidence goes in the opposite direction of our findings related to firms, but is in line with Jiménez & Saurina (2004). We discuss this issue in the following subsection, since there is also evidence that, according to our logit estimations for different maturities, the direction of the impact varies among the loan maturity.

Similarly to the case of firms, the effects of the control variables are mostly in line with expectations. However, an important difference with firm models is that loans granted by non-banking institutions are associated with a lower PD especially in long-term loans. This might be explained by the fact that, in the Peruvian financial system, there are small non-banking institutions that exhibit lower PDs than most banks in these segments in particular. Moreover, the most relevant conclusion might be related to the direction of the loan amounts impact, since we find evidence of a non-linear behavior of this variable but opposite in comparison to our firm results (a U-shaped form). We discuss this issue in the following subsection since there is evidence that this relation changes according to the maturity of the loan.

Finally, it is important to mention that debtors who have a consumer credit card and a consumer loan exhibit higher levels of probability of default, contrary to debtors who have a mortgage loan. These findings are in line with the idea that individuals holding mortgage loans tend to be more solvent, and thus more careful about their personal finances.

Table 7: Determinants of the PD for households
Dependent variable: default

	Short-term	**Medium-term**	**Long-term**	**Pool**
Variables of interest				
N of bank-debtor relationships	0.0407*** (0.0012)	0.0179*** (0.0005)	0.1022*** (0.001)	0.0362*** (0.0004)
Collateral	-0.0593*** (0.0054)	0.0876*** (0.0022)	-0.0780*** (0.0054)	0.0848*** (0.0019)
Short-term loan				-0.4304*** (0.0033)
Medium-term loan				-0.1161*** (0.0023)
Controls				
Repayment ability				
Income	-0.3572*** (0.0034)	-0.2893*** (0.0015)	-0.2733*** (0.0024)	-0.3058*** (0.0012)
Loan conditions				
Interest rate	0.0047*** (0.0000)	0.0077*** (0.0000)	0.0081*** (0.0002)	0.0065*** (0.0000)
Amount of the loan	-0.3441*** (0.0088)	-0.0268*** (0.0048)	0.1528*** (0.0109)	-0.1022*** (0.0034)
Squared amount of the loan	0.0252*** (0.0006)	-0.0002 (0.0003)	-0.0091*** (0.0006)	0.0042*** (0.0002)
Currency	-0.4421*** (0.0215)	-0.1503*** (0.0076)	0.0149** (0.006)	-0.1110*** (0.0044)
Non-banking loan	-0.0861*** (0.0046)	-0.0257*** (0.002)	0.1462*** (0.0055)	-0.0595*** (0.0017)
Debtor characteristics				
Age	-0.0165*** (0.0002)	-0.0141*** (0.0001)	-0.0110*** (0.0001)	-0.141*** (0.0001)
Woman	-0.1239*** (0.0043)	0.1166*** (0.0018)	-0.1571*** (0.0034)	0.1235*** (0.0015)
Province	-0.1997*** (0.0046)	-0.1259*** (0.0019)	-0.0925*** (0.0036)	-0.1146*** (0.0016)
MSME loan	-0.0170*** (0.0063)	-0.0444*** (0.0026)	0.1396*** (0.0077)	-0.0256*** (0.0022)
Credit card loan	0.3245*** (0.0051)	0.4845*** (0.0021)	0.3261*** (0.0044)	0.4391*** (0.0018)
Consumer loan	0.5594*** (0.0365)	0.1701*** (0.0157)	0.1957*** (0.0067)	0.2884*** (0.0058)
Mortgage loan	-0.2997*** (0.0123)	-0.2228*** (0.0051)	-0.2535*** (0.0053)	-0.2419*** (0.0034)
Year				
2012	0.3384*** (0.0072)	0.1864*** (0.0039)	0.0631*** (0.0073)	0.2428*** (0.003)
2013	0.2091*** (0.0065)	0.2102*** (0.0028)	0.1369*** (0.006)	0.2128*** (0.0023)
2015	-0.3342*** (0.0062)	-0.2289*** (0.0024)	-0.0383*** (0.0044)	-0.2037*** (0.0019)
2016	-0.6009 (0.007)	-0.6044 (0.0026)	-0.1687 (0.0045)	-0.5018 (0.0021)
Observations	1077428	6372874	1949836	9400138
Log- likelihood / P - value	85,660 / 0.0000	688,181 / 0.0000	83,193 / 0.0000	901,806 / 0.0000
Predicted probabilities (threshold = 0.5)	65.13%	66.59%	71.45%	67.22%
Pseudo R-Squared (McFadden)	0.0595	0.0802	0.0358	0.0725

1/ Coefficients are obtained after performing binomial logit estimations for each model. Standard errors are reported in parentheses. Each estimation includes a constant, which is not reported in the table. 2/ All revolving loans are considered as short-term loans and all mortgage loans are considered as long-term loans. 3/ Income, amount of the loan and squared amount of the loan are included as natural logarithms.

Table 8: Marginal effects of the determinants of the PD for households

	Short-term	**Medium-term**	**Long-term**	**Pool**
Variables of interest				
N of bank-debtor relationships	0.79	0.39	1.7	0.75
Collateral	-1.14	1.95	-1.27	1.78
Short-term loan				-8.05
Medium-term loan				-2.34
Controls				
Repayment ability				
Income	-6.96	-6.34	-4.54	-6.32
Loan conditions				
Interest rate	0.09	0.17	0.13	0.13
Amount of the loan	1.97	-0.87	-1.08	-0.5
Currency	-7.69	-3.2	0.25	-2.24
Non-banking loan	-1.64	-0.56	2.53	-1.21
Debtor characteristics				
Age	-0.32	-0.31	-0.18	-0.29
Woman	-2.34	-2.5	-2.49	-2.48
Province	-3.71	-2.7	-1.5	-2.31
MSME loan	-0.33	-0.97	2.41	-0.53
Credit card loan	6.78	11.36	5.92	9.81
Consumer loan	12.19	3.83	3.43	6.29
Mortgage loan	-5.42	-4.68	-3.9	-4.74

1/ The marginal effects measured in percentage points are obtained after performing binomial logit estimations for each model. These impacts are computed at means of continuous and discrete variables and at zero in dummy variables. 2/ All revolving consumer loans are considered as non-maturity loans and all mortgage loans are considered as long-term loans. 3/ Rows for income and amount of the loan show the marginal effect of a 1% increase in these variables. 4/ Results are controlled by temporal dummy variables for 2012, 2013, 2015 and 2016.

6.2 Overall analysis

Table 9 gathers all our estimations for firms and households and involves the main purpose of this paper. Although we are far from estimating models that effectively predict the probability of default, this analysis serves as a first view of the direction and magnitude of the impact for a set of limited determinants involving the loan maturity, the number of bank-debtor relationships for each debtor, and the presence of collateral, controlling by other factors such as repayment ability, loan conditions, debtor characteristics and macroeconomic factors.

From our results, it is clear that loans of longer maturities are associated with higher probabilities of default, as found in the previous sections. One of the reasons of this result might be the presence of informality in Peruvian financial debtors: since an important share of firms and households do not have formal documents to sustain their repayment ability, they require loans with longer maturities to have a lower debt-service-to-income ratio. Regarding the number of bank-debtor relationships, we observe that in all of our specifications it has a positive impact on the probability of default, which is greater for long-term loans.

As for the collateral, the results are mixed. For firms, it is clear that collateralized loans exhibit lower PDs, for any maturity. However, in the case of households and considering the pool estimation, having collateral increases the PD, with the exception of long-term loans (which are mostly mortgages). Since firms have usually a better power of negotiation than households, this negative relationship might show that these agents prefer to pledge collateral in order to have a lower interest rate [Stiglitz & Weiss (1981), Bester (1985), Chan & Kanatas (1985), Besanko & Thakor (1987 a, b), and Chan & Thakor (1987)]. In the case of households, the relationship seems to be positive since this power of negotiation is lower and financial entities usually require collateral to riskier borrowers.

Nevertheless, long-term collateralized household loans are associated with lower PDs, as in the case of firms. This can be explained by the value of the collateral that is considered for this kind of loans (mainly mortgage loans). It is more likely that a debtor adjusts her financial behavior in order to meet the loan payment and avoid losing a valuable asset. As for the case of credit card holders, they are characterized by very heterogeneous credit risk profiles. In that sense, the value of the collateral is also heterogeneous and thus do not always serve as a tool to mitigate moral hazard problems.

Another important and interesting result involves the original amount of the loan. There is evidence of a non-linear behavior in both firms and households but in opposite directions. As for firms, the non-linear behavior has a U-inverted shape form, since loans involving large amounts are assessed thoroughly, and therefore, is associated with less-risky debtors.

However, in households, the relationship between the amount of the loan and the PD has a U-shape form because entities prefer lending lower amounts to riskier borrowers. Nevertheless, the presence and significance of the non-linearity recognize the impact of over-indebtedness risk, by having a positive impact on the probability of default after a certain point (excessive credit).

Table 9: Determinants of the probability of default
Dependent variable: default

	Firms				**Households**			
	ST	MT	LT	Pool	ST	MT	LT	Pool
Variables of interest								
N of bank-debtor relationships	(+)	(+)	(+)	(+)	(+)	(+)	(+)	(+)
Collateral	(-)	(-)	(-)	(-)	**(-)**	(+)	**(-)**	(+)
Short-term loan				(-)				(-)
Medium-term loan				(-)				(-)
Controls								
Repayment ability								
Income	(-)	*	(-)	(-)	(-)	(-)	(-)	(-)
Loan conditions								
Interest rate	(+)	(+)	(+)	(+)	(+)	(+)	(+)	(+)
Amount of the loan	(+)	(+)	(+)	(+)	(-)	(-)	**(+)**	(-)
Squared amount of the loan	(-)	(-)	(-)	(-)	(+)	(+)	**(-)**	(+)
Currency	(+)	(+)	**(-)**	(+)	(-)	(-)	**(+)**	(-)
Non-banking loan	(+)	(+)	(+)	(+)	(-)	(-)	**(+)**	(-)
Debtor characteristics								
Age					(-)	(-)	(-)	(-)
Woman					(-)	(-)	(-)	(-)
Province	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
MSME loan	(+)	(+)	(+)	(+)	(-)	(-)	**(+)**	(-)
Credit card loan					(+)	(+)	(+)	(+)
Consumer loan					(+)	(+)	(+)	(+)
Mortgage loan					(-)	(-)	(-)	(-)

1/ * stands for not significant impact at 5% level of confidence. 2/ Results are controlled by temporal dummy variables for 2012, 2013, 2015 and 2016. 3/ Significant shifts in the direction of the impact for long-term loans are marked in bold red.

7 Conclusions and pending agenda

This paper analyzes the impact of a limited set of credit risk drivers (collateral and number of bank-debtor relationships) for long-term loans, and evaluates the effect of loan maturity on the probability of default. In our estimations, we treat households and firms separately and include variables that reflect repayment ability, debtor characteristics, loan conditions, and macroeconomic factors as controls.

We use a huge dataset of more than twenty-six million observations from the Financial Regulatory Authority's Credit Report of Debtors and two other large datasets compiled for in-situ and extra-situ supervisory procedures. Therefore, the results of our estimations do not rely on specific samples but on a loan-by-loan analysis, which assures the efficiency of parameters estimation. The focus is on ex-post credit risk, for which the debtors included in the analysis are those who were not in a situation of default at the beginning of a one-year evaluation window.

The correlation between loan maturity and the probability of default appears as positive for both firms and households, meaning that long-term loans are riskier than loans with shorter maturities. As mentioned in previous section, one of the reasons of this result might be the presence of informality in Peruvian financial debtors. Furthermore, the impact of some credit risk drivers varies when differentiating loans by their maturity. For instance, collateralized household loans tend to show a higher PD, contrary to the case when considering only long-term loans. On the other hand, the number of bank-debtor relationships has the same positive impact on the PD among all models estimated. This result suggests that holding loans granted by many different institutions, could be a sign of over-indebtedness, and thus, of higher credit risk.

Regarding the control variables, their impact is in most cases in line with economic theory. A particularly interesting result is the non-linear effect that the loan amount appears to have on the PD, which varies between firm and household loans. These findings are useful as a supervision tool for in-situ procedures, and can ultimately result in policy actions to mitigate the scarcity of long-term loans in the country.

Two important considerations should be included in following versions. The first one is related to the inclusion of debtors who are in default at the beginning of the twelve-month evaluation window. This will imply that our dependent variable would change to a measure of credit risk downgrade instead of a measure of default. This specification could be defined as a recovery from default and we might expect to obtain the opposite results compared to the first specifications (probability of default) in order to validate the robustness of the models. The second one is related to the robustness analysis of the number of bank-debtor relationships by including instead of this variable, an alternative over-indebtedness measure, such as a debt-service-to-income ratio.

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9 Annexes

Annex 1. Definition of the probability of default

With information provided by the Credit Report of Debtors, the probability of default is computed as:

$$PD_t = \sum_{i=1}^{N_{t-12}} D_{i,t-12} \times I(a_{i,t} > 60 \mid 60 \geq a_{i,t-12}) / \sum_{i=1}^{N_{t-12}} D_{i,t-12} \times I(60 \geq a_{i,t-12})$$

Where:

- PD_t : Ratio of default in month t.
- D_{it} : Debt of individual i in month t.
- a_{it} : Days past due of individual i in month t.
- $I(.)$: Characteristic function, 1 if the argument is true; 0 otherwise.
- N_{t-12}: Number of individual in the financial system in month $t-12$.

This ratio indicates the proportion of individuals who were in a situation of delay in their payments of less than 60 days in t-12 went to a situation of delay in their payments greater than 60 days, 12 months after this situation. For example, if the probability of default in January 2011 was 10%, this indicates that of 100 soles that were in a situation of delay in their payments of less than 60 days in January 2011, ten of these migrated to a situation of delay in their payments greater than 60 days in January 2011.

Annex 2: Structure of loans by type

	Debtors		Size of portfolio		Average	Average
	Number	%	US$ Million	%	interest rate (%)	maturity (months)
Firms	**2,228,189**	**35.9**	**53,859**	**65.3**	**46.2**	**17**
Corporates	654	0.01	17,522	21.3	5.2	21
Big-sized companies	2,781	0.05	11,800	14.3	7.7	22
Medium-sized companies	29,740	0.48	13,597	16.5	12.6	29
Small-sized companies	423,613	6.82	7,896	9.6	29.5	27
Micro-sized companies	1,784,387	28.73	3,044	3.7	49.5	14
Households	**4,613,542**	**74.2**	**28,590**	**34.7**	**63.8**	**42**
Revolving loans	2,878,864	46.36	5,723	6.9	68.7	-
Non-revolving loans	3,064,405	49.35	10,522	12.8	49.4	37
Mortgages loans	234,549	3.78	12,344	15	10.3	186
Total	**6,209,854**	**100**	**82,449**	**100**	**59.5**	**32**

Source: SBS

Annex 3: Main stats of loans by type and maturity

2016

	Share of portfolio (%)			Average interest rate (%)			Average maturity (months)		
	ST	**MT**	**LT**	**ST**	**MT**	**LT**	**ST**	**MT**	**LT**
Firms	**26**	**62**	**12**	**61.2**	**40.1**	**21.3**	**7**	**19**	**74**
Corporates	38	54	7	5.1	5.2	5.8	5	28	75
Big-sized	26	62	12	7.6	7.8	8.4	5	29	78
Medium-sized	25	53	22	12.3	13.1	11.8	5	30	88
Small-sized	5	84	11	40.7	29.1	22	7	16	75
Micro-sized	11	88	1	66.6	45.5	32.4	7	26	73
Households	**1**	**22**	**77**	**67.6**	**55.6**	**15**	**7**	**28**	**116**
Non-revolving	2	53	45	67.7	55.7	17	7	27	85
Mortgages	0	2	98	10.9	13.9	10.3	4	42	189
Total	**23**	**45**	**32**	**64**	**48.7**	**15.3**	**7**	**24**	**114**

2012

	Share of portfolio (%)			Average interest rate (%)			Average maturity (months)		
	ST	**MT**	**LT**	**ST**	**MT**	**LT**	**ST**	**MT**	**LT**
Firms	**31**	**63**	**7**	**60.7**	**46.6**	**25.5**	**8**	**18**	**70**
Corporates	47	47	5	4.9	5.1	4.3	6	24	80
Big-sized	41	51	8	7	7.5	7.6	5	26	75
Medium-sized	25	53	22	12.3	14.7	13.2	6	27	79
Small-sized	9	83	8	32.4	30.5	22.1	7	26	68
Micro-sized	13	86	1	65.2	51.1	40.2	8	16	76
Households	**17**	**33**	**49**	**47.6**	**48.8**	**16**	**6**	**23**	**90**
Non-revolving	19	48	43	48.9	50.2	17.6	6	23	70
Mortgages	15	30	55	9.8	10.9	11	6	33	150
Total	**28**	**52**	**20**	**53.8**	**47.4**	**16.7**	**7**	**20**	**88**

Annex 4: Initial amount of the loan by type of loan and maturity

(USD thousand)

	Short-term	Medium-term	Long-term	Total
Firms	**46**	**21**	**176**	**28**
Corporates	14,313	17,741	167,391	16,170
Big-sized companies	1,467	2,866	4,044	2,352
Medium-sized companies	329	508	711	474
Small-sized companies	10	14	31	15
Micro-sized companies	1	2	4	2
Households	**3**	**3**	**24**	**6**
Revolving Consumer	3	0	0	3
Non-revolving Consumer	1	3	11	5
Mortgage	90	33	56	55
Total	**6**	**11**	**31**	**10**

Source: SBS