The Demand for Credit at the Individual Level: The Credit Registry (RCC) Meets the National Household Survey (ENAHO)

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Abstract

This article examines the demand for credit at the individual level in Peru. It uses a unique database resulting from merging the Credit Registry (RCC) and the National Household Survey (ENAHO). The data allows for ideally identifying the amount of credit and the interest rate as well as the characteristics of each credit granted in the Peruvian banking system. It also includes indicators of the supply of each credit, which is key for the identification of demand. The elasticity of the demand for credit relative to the interest rate is estimated using a two-step procedure proposed by Heckman (1979) and is approximately –0.29. This value means that a rise in the market interest rate by 1% implies a reduction in the demand for credit by 0.29%. This elasticity is slightly lower than the one provided by international evidence and is highly heterogeneous throughout credit types and features of individual debtors.

Keywords: demand for credit, balance sheet effect, heterogeneity.
JEL classification: E21, E44, E51, E52.

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1. INTRODUCTION

Credit as a funding mechanism for firms and households is crucial to a country's economic development. Study of the fundamentals influencing borrowing by households and firms has received considerable attention from academics and economic policymakers during the years following the international financial crisis that broke out in 2008. The reason behind such increased interest has been the growing participation of individuals in the credit market, allowing them to receive the benefits of said market, and at the same time exposing them to financial fluctuations. This is the case, for instance, of the 2008 financial crisis, the effects of which have spread beyond the business sector, extending to the household segment. [1] This paper examines the characteristics of credit at the individual level in Peru while also estimating the demand for debt in this segment of economic agents. We believe the study is justified by the growing participation of households in Peru's formal credit market. Moreover, the Peruvian economy and its credit market have institutional and idiosyncratic characteristics, such as the dollarization of loans, its inflation targeting scheme and the economy's high level of exposure to external crises that make it different from others.

With respect to aggregate trends, household credit at the international level has been growing during recent decades (IMF, 2012), and Peru has seen a similar behavior.[2] Hence, between

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1 There is a large body of international literature on this subject suggesting business credit has positive effects on economic growth through higher investment and the resulting increased accumulation of physical capital. Meanwhile credit to households has a less clear impact on growth, functioning more as a mechanism that can improve households' wellbeing by the intertemporal smoothing of consumption during any adverse shocks they face (Hall, 1978).

2 Diverse factors have contributed to the expansion of credit, among which stand out: low inflation and interest rates, higher income and wages within a context of strong economic growth,

2001 and 2016 consumer credit grew at an average annual rate of 19%, increasing as a percentage of GDP from 4.2% in 2001 to 14.8% in 2016 (Figure 1). This significant growth in credit has been enough to change the composition of credit between consumers and firms. Thus, in 2001 consumer loans accounted for 18% of total credit and in 2016 this figure had increased to 37%. In this regard, international evidence suggests that the significant growth of consumer loans as a proportion of total credit could represent a source of vulnerability for this segment of the population during adverse events, both for the financial system and households themselves (BIS, 2006; IMF, 2016). The latter point is another reason to study and understand the characteristics of the determinants of household debt in Peru.

Another useful aspect of this study is an estimation of the elasticity of demand for credit, which under stable financial conditions allows for measuring the necessary adjustments in monetary policy rates aimed at correcting deviations in inflation with respect to price stability levels through the credit transmission channel in line with Bernanke and Blinder (1988). In general terms, this elasticity captures the transmission to households of shifts in the financial system (credit supply shocks) as a result, for instance, of changes in Reserva Federal's monetary policy and external financial crises propagated through international credit restrictions. The latter being the case of the 2008-2009 global financial crisis that marked the beginning of higher financing costs for small economies like Peru.

This paper reveals new evidence regarding the importance of dollarization in Peru's debt market. It should be remembered that dollarization has been one of the (greatest) vulnerabilities in the Peruvian economy since the beginning of the nineties. Dollarization of credit reached historically high levels in December 1999 when loans in dollars represented 81.7% of total

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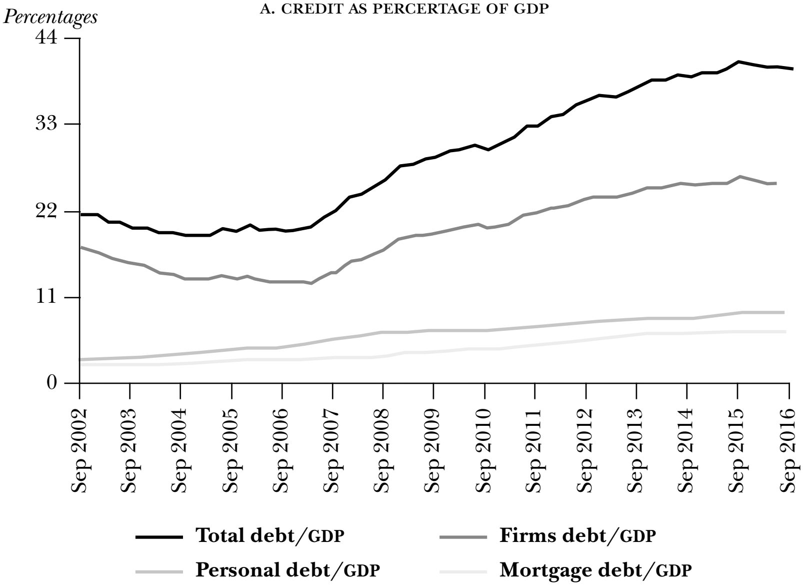
opening of capital markets, larger capital flows and improved credit offerings under an environment of positive macroeconomic performance reflected in low country-risk levels, etcetera.

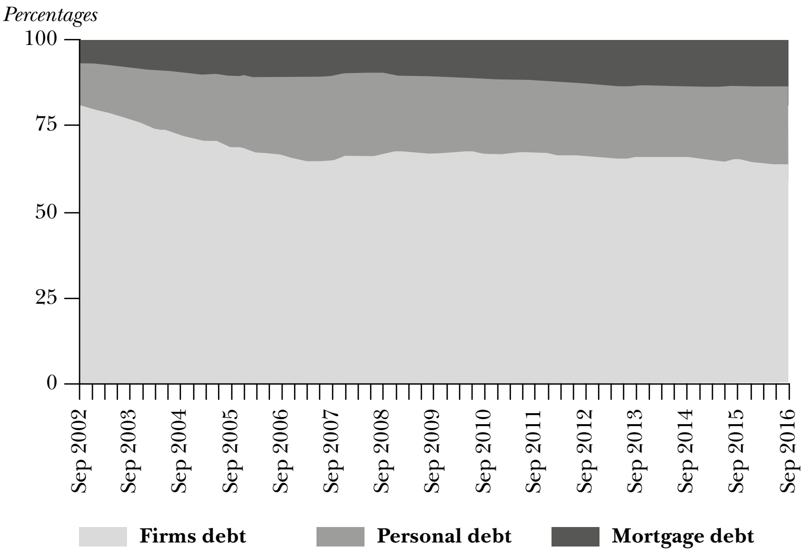
Figure 1

PERU: CREDIT EVOLUTION

A. CREDIT AS PERCERTAGE OF GDP



B. CREDIT COMPOSITION



Note: Credit (balances) of deposit entities to private is shown, by type of credit.
Source: Banco Central de Reserva del Perú.

credit.[3] Towards the end of 2015, and after a prolonged struggle in economic policy and macroeconomic stability terms, dollarization has fallen to around 30% of total credit. Given that dollarization is a phenomenon affecting only a small number of countries, empirical studies on foreign currency borrowing has been limited to a few particular cases [4] and no studies have been carried out for Perú.[5]

Literature examining credit dollarization at the individual level is very limited internationally, and in the case of Peru, non-existent. For instance, Beer et al. (2010) analyze the borrowing behavior of Austrian households and estimate the influence of household characteristics, which are divided into subjective factors (e.g. risk perception, financial literacy and level of education) and objective factors (e.g., sociodemographic).

[3] Corresponds to the dollarization ratio (%) of deposits firms to private banks (end of period).

[4] Internationally, there are several authors who study foreign currency borrowing at the aggregate level, while a smaller number of papers characterize the demand for credit among firms. For instance, Brown et al. (2011) and Cowan et al. (2005) include enterprise level features in a theoretical model examining the borrowing behavior of small firms. Those models emphasize the role of institutional infrastructure and compliance, imperfect bank information and the monetary composition of income. Brown et al. (2011) consider various micro-level determinants of borrowing among firms in Bulgaria (employing enterprise level data for loans between 2003 and 2007). Their model includes supply features (bank characteristics) and demand determinants (firm characteristics) of loans in foreign currency. Their findings demonstrate that comparatively larger and older firms, as well as those with lower bailout costs in case of default, demand more loans in foreign currency. Moreover, banks grant loans in foreign currency mainly for fixed investments and long-term projects.

[5] Data employed correspond to periods of high dollarization, even at the household credit level, meaning estimates from the study could be used to characterize the potential effects of external shocks on households' standards of living through the credit channel in domestic as well as foreign currencies.

According to their results, foreign currency borrowers tend to be risk seeking, older, financially literate and more affluent. Pellényi and Bilek (2009) present a study of survey data on foreign currency borrowing among households in Eastern Europe. They analyzed survey data collected in 2008 for Hungarian households and find that foreign currency borrowers tend to be less risk-loving and better aware of exchange rate risks.[6]

This paper studies the demand for loans among individuals using data disaggregated to the level of each loan. This procedure represents an advance in the literature on the credit market, especially in the case of Peru, for which no published papers are to be found on the subject.[7]

The study employs a unique database resulting from a merging of the National Household Survey (ENAHO) and the Credit Registry (RCC), which because it is an administrative registry allows for identifying without measurement errors the amount and interest rate of each individual bank loan by type of credit and currency, as well as the features of individual debtors. This consideration makes it possible to characterize the heterogeneity of credit according to the observable characteristics of individual debtors by currency type, age, income levels, region of residence, employment and informality, among others. After characterizing credit, we estimate the demand for credit at the individual level. This demand allows for identifying the sensitivity of credit to changes in interest rates after

[6] There is also some recent literature that examines credit demand using data at the individual level, such as that of Fidrmuc et al. (2013) which studies the determinants of foreign currency borrowing in nine Eastern European countries and finds that a lack of confidence in local currency stability among households is an important consideration when taking out loans in foreign currency.

[7] Papers on household credit in Peru include those of Cámara et al. (2013) and Alfageme and Ramírez-Rondán (2016), who use the ENAHO to perform a general study of the determinants of participation in the mortgage market.

controlling for the observable characteristics of demand and institutional features of credit supply. The estimation method consists of a two-step process (Heckman, 1979). In the first step, we estimate an equation for credit market participation and in the second an equation for credit demand that relates credit with interest rates and a group of relevant controls.

The results highlight a significant degree of heterogeneity of credit according to the observable features of individuals. One level of heterogeneity that stands out concerns an individual's income. Those with access to formal credit have high incomes. In line with the latter, credit in Lima is concentrated among middle-aged and better educated individuals, while informal workers are also seen to have access to formal credit. As for the elasticity of demand for credit relative to the interest rate, the estimation reveals that this is -0.29, figure heterogeneous according to several observable features of individuals such as the type of credit, the currency in which it is granted, geographic region and informality. Moreover, the average elasticity found is lower than those estimated by the literature employing similar quality administrative data, which is consistent with the existence of an inelastic and uncompetitive credit market.

The rest of the paper is organized as follows. Section 2 presents data sources and explains the methodology for constructing the data. Section 3 discusses the heterogeneity of credit according to different categories of individuals, and Section 4 presents the model that justifies the credit demand equation. Section 5 shows the econometric estimation and Section 6 summarizes the main findings.

2. DATA

Data is taken from two sources. Firstly, there is administrative data for each loan granted to individuals by financial entities registered in the Credit Registry (RCC). This information is collected each month by the Superintendence of Banking and

Insurance and the number of registries represents the whole population with loan obligations in the banking system. Information from the RCC corresponds to the credit balance of each individual by the banking institution. It is worth pointing out that this information discloses all loans held by an individual, identifying credit type and currency. The number of loans registered varies according to the month studied. Thus, in December 2014, for instance, 12.4 million loans were included, corresponding to a total of 5.7 million individuals with loans in the formal banking system.

The other source of information is the National Household Survey (ENAHO) conducted every year by the National Institute of Statistics and Information (INEI). This database collects information on diverse aspects, such as an individual's employment and personal data, that allow for identifying credit demand characteristics. The two databases are merged using the National Identity Document (DNI) and the names and surnames of each individual for data between 2008 and 2014 as common links, obtaining a total of 95 037 individuals in both databases. Considering that around 500 thousand individuals are registered in the ENAHO, the number with loans in the final sample during those years represents everyone in Peru that accessed formal credit in said period.

The credit sample in the final database is representative at the national level. This assertion is substantiated by comparing credit indicators estimated in the final database with those estimated in the RCC and the ENAHO. Hence, there is a similarity between the proportion of individuals reported in the final database and the corresponding value reported by the original data in the RCC (see Table 1). The RCC is used to estimate the share of individuals in the banking system with credit. As expected, the latter value is lower than the total share of individuals with credit in the banking system as well as other institutions (informal).

Table 1

CHARACTERISTICS OF CREDIT IN THE SAMPLE
Percentages

	RCC	*ENAHO and RCC*
Mortgage dollarization (no. of loans)	32.0	35.0
Mortgage dollarization (balances)	34.6	38.1
Consumer credit dollarization (no. of loans)	4.2	3.3
Consumer credit dollarization (balances)	7.7	5.9

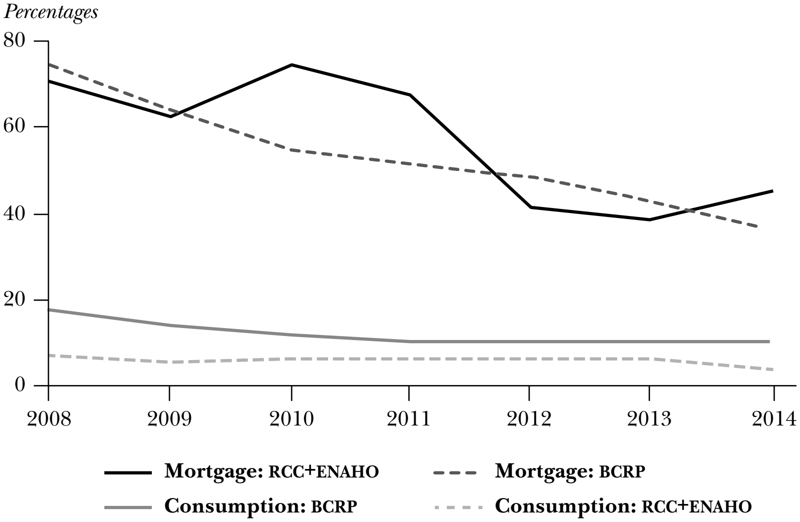
Notes: the second column (RCC) corresponds to 2014.
Sources: ENAHO, RCC, 2008-2014.

Another useful indicator for controlling the quality of data employed is aggregate credit dollarization information. The latter makes it possible to verify that household debt dollarization trends reported by the BCR are similar to those reported in the final database obtained by merging the ENAHO and the RCC (Figure 2).

Estimating the demand for credit requires indicators regarding the interest rates on each loan. Although no direct measure of interest rates is available, in this paper we estimate the implicit interest rate on each credit using the yields of the loans, which in practice correspond to the monthly interest charged (accrued) by financial institutions on the loans they grant. The indicator for average interest rates calculated in this way is closely related to the interest rates published by the SBS, thereby upholding the known stylized facts for said indicator, such as, for instance, mortgage rates are lower, consumer loans have lower rates and average interest rates during the study period have followed a downward trend.

Figure 2

DOLLARIZATION OF CREDIT FROM BCRP AND RCC–ENAHO DATA



Note: Percentage of credit balances in foreign currency to total of credit.
Sources: SBS, BCRP, ENAHO, and RCC, 2008-2014.

3. CHARACTERISTICS OF CREDIT AT THE HOUSEHOLD LEVEL

3.1 Descriptive Statistics

Credit and interest rates should be expressed in logs in the empirical model. This is particularly useful here because in order to guarantee the efficiency of model estimators. The first and second moments of the series employed must be well-defined. A casual inspection of the series suggests that these have a normal log distribution. The reason is that there is a considerable number of individuals with micro loans and a very small proportion with very large ones. Estimates for interest rates behave similarly, the use of logs, therefore, normalizes the series and guarantees stability in the variance of the estimators.[8] With this taken into consideration, the descriptive statistics correspond to the log series.

Credit heterogeneity is noteworthy at the level of its principle moments, meaning the estimation should control for those average effects. Average mortgage credit is larger than credit to small firms and consumer credit. Moreover, there are differences in terms of loans denominated in domestic currency and those in foreign currency. The data in Table 2 also reveal that there is heterogeneity with respect to the observable characteristics of individuals such as age, income, and region of residence, among others. This heterogeneity found regarding loan size is also seen in terms of estimated implicit interest rates as shown in Table 3. These two stylized facts suggest that the regression estimated to measure the elasticity of the demand for credit should be controlled for the heterogeneity of demand.

3.2 Correlation between Interest Rates and Credit

Aggregate data suggest the likelihood of a negative correlation between credit and interest rates as illustrated in Figure 3 for data between 1992 and 2016. Nevertheless, this aggregate correlation might not be correct in all the study periods. The correlation is positive, for instance, in the years between 2004 and 2008. Estimation of aggregate demand for credit should also be corrected for the influence of macroeconomic type variables. Furthermore, although it is not documented, estimation of the demand for credit might be susceptible to aggregation biases. With these considerations in mind, we take into account that estimation of the demand for credit among agents can properly identify the elasticity we aim to calculate.

8 A comparison of the distribution of credit in levels as well as logs reveals that the log series has an approximately normal distribution as illustrated in Figures A.1 to A.4 in the Annex.

Table 2

CHARACTERISTICS OF CREDIT BY INDIVIDUAL ACCORDING TO CREDIT TYPE AND CURRENCY

Size of credit in logs

	Type of Credit											
	Consumption				*Small firm*				*Mortgage*			
	DC		*FC*		*DC*		*FC*		*DC*		*FC*	
	$\bar{X}$	*SD*	$\bar{X}$	*SD*	$\bar{X}$	*SD*	$\bar{X}$	*SD*	$\bar{X}$	*SD*	$\bar{X}$	*SD*
Average	7.91	2.36	7.33	3.10	8.54	2.23	12.06	2.51	11.57	1.45	11.48	1.96
Quintiles												
I	8.07	2.43	7.02	2.87	8.38	2.30	13.26	1.79	12.15	2.12	11.67	1.59
II	8.20	2.51	9.14	3.65	8.50	2.28	12.22	2.74	10.78	1.56	13.42	2.59
III	7.99	2.43	7.52	3.87	8.53	2.22	11.76	2.35	11.01	1.06	12.44	2.15
IV	7.85	2.31	6.96	3.38	8.53	2.16	11.45	2.23	11.42	1.54	11.22	2.04
V	7.88	2.32	7.36	2.90	8.79	2.18	12.12	2.52	11.71	1.46	11.47	1.88
Age												
17 to 24	7.56	2.07	7.21	3.10	8.19	2.26	13.1	2.35	11.26	1.46	10.91	1.16
25 to 34	7.60	2.24	6.78	2.91	8.49	2.24	12.56	2.30	11.71	1.13	12.73	2.01
35 to 44	7.94	2.37	7.60	3.10	8.54	2.22	11.04	2.47	11.57	1.50	11.27	1.73

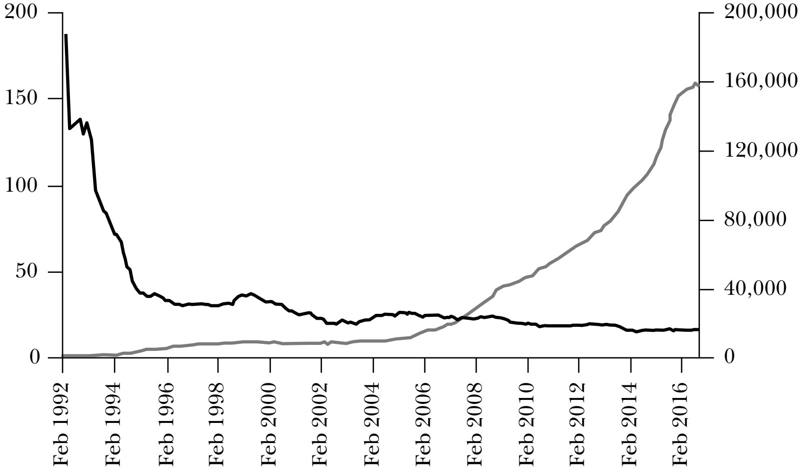
45 to 54	8.15	2.40	7.26	3.20	8.59	2.22	12.51	2.40	11.47	1.64	11.36	1.85
55 to 100	8.11	2.47	7.90	3.13	8.72	2.23	11.78	2.53	11.59	1.39	11.46	2.31
Region												
North Coast	7.80	2.25	7.04	3.49	8.18	2.12	11.09	1.91	11.26	1.31	11.41	1.78
Central Coast	7.73	1.99	6.68	3.24	8.29	2.03	10.97	3.00	10.39	0.88	10.93	1.77
South Coast	8.11	2.22	7.22	2.75	8.69	2.25	11.34	2.55	11.38	1.66	11.04	2.02
North Mountain Range	8.40	2.43	8.39	3.16	8.26	2.12	11.31	1.84	11.26	1.39	10.59	2.53
Central Mountain Range	8.13	2.15	7.81	3.99	8.34	2.17	12.04	1.97	11.54	1.33	11.98	2.01
South Mountain Range	8.18	2.47	7.08	2.96	8.78	2.29	12.03	2.54	11.31	1.41	12.18	2.20
Jungle	8.55	2.28	7.57	3.56	8.57	2.19	13.69	2.26	11.30	1.17	12.00	2.34
Lima metropolitan area	7.71	2.45	7.34	2.99	8.80	2.35	12.64	2.34	12.14	1.49	11.46	1.88
Without remittances	7.91	2.36	7.33	3.10	8.54	2.23	12.07	2.51	11.57	1.45	11.44	1.93
With remittances	8.07	2.45	6.74	3.22	8.92	2.40	10.85	–	–	–	15.44	0.29

Note: Shows the average $\overline{X}$ and standard deviation (SD) of credit per individual. DC denotes domestic currency and FC foreign currency. Note that the log average of credit is shown given that the distribution of credit is lognormal and in this case the use of logs better characterizes the series under consideration.
Source: ENAHO, RCC, 2008-2014.

Figure 3

CREDIT AND INTEREST RATE AT AGGREGATED LEVEL

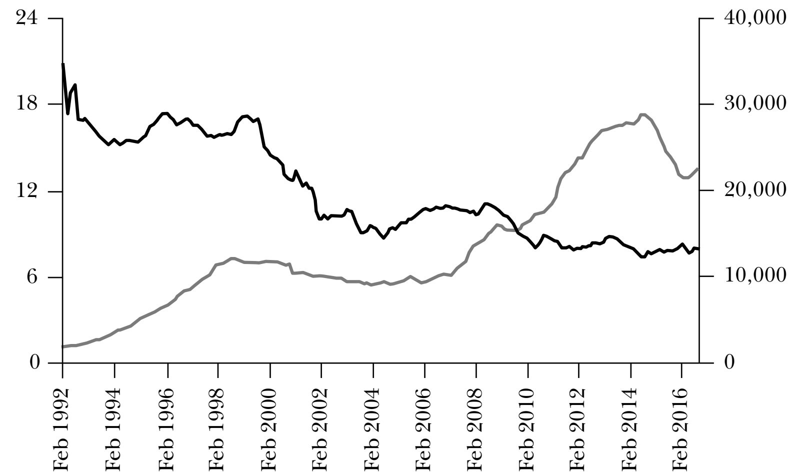
A. CREDIT AND INTEREST RATE IN NATIONAL CURRENCY



Lending interest rates of banking institutions in national currency

Banking system credit to private sector (end of period) – credit in national currency (millions of *soles*)

B. CREDIT AND INTEREST RATE IN FOREIGN CURRENCY



Average borrowing interest rates of banking entities in foreign currency

Banking system credit to private sector (end of period) – credit in foreign currency (millions of dollars)

Note: Identify the credit demand requires credit supply indicators. This identification is not possible at macro level.

Source: Banco Central de Reserva del Perú.

The correlation between credit and interest rates is difficult to identify using a scatter plot between credit and interest rates as seen in Figure 4. The latter shows the correlations for all loans considered (consumer, small business, mortgage), differentiating between the loan denomination currency. These five figures, together with the descriptive statistics presented, help to suggest that an estimation of the demand for credit requires the inclusion of additional controls on the supply as well as the demand side.

4. THE DEMAND FOR CREDIT MODEL

Credit demand compares the size of the loan with the interest rate through a reduced form that can be deduced from a household optimization equation. This equation is the simplest case where households decide the amount of credit based on their fundamentals with respect to sources of income and different preferences represented by an aversion indicator, their level of impatience, and the interest rate they face. Formally, we follow the representation of the consumption-savings intertemporal choice model of Hall (1978), whose household optimization equation is as follows:

$$\max \sum_{t=1}^{\infty} \beta^{t-1} U(c_t), \tag{1}$$

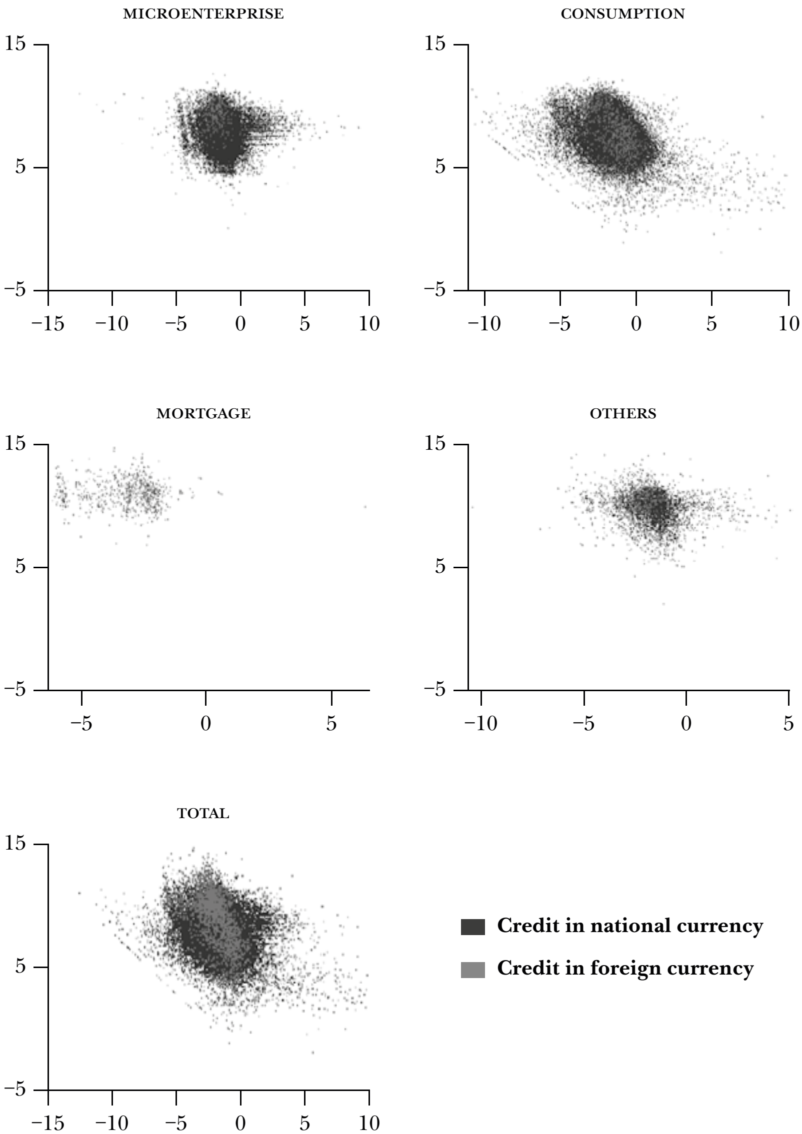
subject to:

$$c_t + b_t = y_t + (1 + r_t) b_{t-1}; \quad \forall t = 1, 2, \ldots \tag{2}$$

$$c_t \geq 0 \tag{3}$$

Figure 4

CORRELATION BETWEEN CREDIT AND INTEREST RATE



Note: Credit is on the y-axis, and the interest rate is on the x-axis. Variables are in logs.
Sources: RCC and ENAHO, 2008-2014.

4 $$\lim_{t\to\infty}\left[\frac{1}{1+r_t}\right]^{t+1} b_t \to 0,$$

where c_t is consumption and b_t a household's bond holdings in period t, with $b_t < 0$ representing the size of a household's credit. The preferences of each household at every moment, which for simplicity sake we assume has only one member, are described by the following utility function $u_t = \frac{c_t^{1-\sigma}}{1-\sigma}$. We include the usual assumptions $u_c(\cdot) > 0$, i.e., consumption generates positive utility in the individuals. The budget constraints families face in each period capture the equivalence between resource funds and uses, $c_t + b_t = y_t + (1+r_t)b_{t-1}$. Household income is y_t, r_t the interest rate, β the subjective discount factor, and σ the risk aversion parameter. The last two equations (3 and 4) represent the positive consumption constraint and the trasversality condition, respectively.

The solution to this problem is a set of optimum values for consumption and the amount of credit for every value of t=1, 2, ..., which take the following values after considering a constant interest rate over time and an initial amount of debt (b_0):

5 $$c_t = \{\beta(1+r)\}^{\frac{t}{\sigma}} \frac{\sum_{t=1}^{\infty}\left[\frac{1}{1+r_t}\right]^{t-1} y_t}{\sum_{t=1}^{\infty}\left[\frac{1}{1+r_t}\right]^{t-1} \beta^{\frac{t}{\sigma}}(1+r)^{\frac{t}{\sigma}-t+1}},$$

6 $$b_t = (1+r)^t b_0 + \sum_{j=1}^{t-1}(1+r)^{t-j}\{y_j - c_j\}.$$

In the equation above, credit corresponds to a representative individual and is defined by the measure of household risk aversion, level of impatience, interest rate and income. Nevertheless, the empirical section uses a reduced form for credit demand with different degrees of heterogeneity, which can be better justified if the heterogeneity of credit is explicit in the derivation of credit demand. To generate credit heterogeneity in the aforementioned equation it is only necessary to include the existence of different individuals with varying income levels. This idea can also be strengthened by including heterogeneity in the values for risk aversion and level of impatience, parameters that are considered heterogeneous by a large body of literature. Another item that can be used to generate heterogeneity is the interest rate.[9] The data employed suggest that individuals access the credit market at heterogenous rates that change over time, which captures risk profiles at the individual level from the perspective of credit granting institutions. The econometric estimation considers these different levels of heterogeneity by including observable features for individuals, their income and interest rates.

4.1 Reduced Form of the Demand for Credit

The previous expression represents the solution for each household under ideal credit conditions. It is easy to deduce from this sequence that credit depends negatively on interest rates for all individuals whose current income levels are below their corresponding consumption $\left(y_j > c_j\right)$. It can also be seen that said dependence is non-linear. Another characteristic that can be inferred from the equation is that other determinants of credit are present, such as risk aversion and level of impatience. We, therefore, summarize the equation into a reduced form that linearly relates the log of credit and the interest rate.

Empirical estimation of this reduced form requires prior consideration of some specific features of Peru's credit market. One such consideration is participation in the credit market. In

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[9] Among the first papers to estimate preference heterogeneity and risk aversion in particular are: Barsky et al. (1997), Kimball et al. (2008) and Kimball et al. (2009).

practical terms the sample of individuals who access the credit market might be different from those who do not. If this is the case, the estimated parameters of the demand for credit equation might contain so-called sample selection bias. This problem is solved by including a Heckman correction, which basically suggests that the demand for credit should be estimated using a two-step approach. The first step consists of estimating the credit market participation equation using the whole sample, while the second corresponds to estimating the intensive demand for credit considering only the sample of individuals with credit.

Credit Market Participation

Participation in the credit market is only observed for those who manage to obtain a loan, and this only takes place after a credit assessment process that is not observed in the data. The data only shows individuals who participate in the credit market, which is denoted by $I_{ijt} = 1$. This event is related to a continuous and latent variable I^* that is determined by a set of variables, grouped in x, that identify participation in the credit market through the equation

$$I^*_{ijt} = \delta x_{ijt} + \varepsilon_{ijt}.$$

We can see that the data registers credit market participation $\left(I_{ijt} = 1\right)$ only if the latent variable is positive $\left(I^*_{ijt} > 0\right)$, where i denotes each individual and t the period. With this in mind, and assuming a normal distribution of random component ε_{ijt}, the probability of participation in the credit market is expressed as follows:

7 $$Pr\left(I_{ijt}=1\right) = Prob(\delta x_{ijt} + \varepsilon_{ijt} > 0) = \Phi(\delta x_{ijt}),$$

where as usual Φ represents the normal distribution characterizing the probit model.

Intensive Demand for Credit

In the second stage, we define the amount of credit (b), that depends on a set of variables divided into demand-side and supply-side. The equation to be estimated is as follows:

8 $$b_{ijt}^{n} = \alpha + \beta_r R_{ijt} + \beta x_{ijt} + \theta z_{jt} + \delta T_t + \gamma \lambda_{ijt} + \nu_{ijt},$$

where b_{ijt} is the demand for credit in period t for household i in bank j, and R_{ijt} is the interest rate. x_{ijt} are the controls representing different levels of heterogeneity among individuals and z_{ijt} are the controls per bank (j), and T_t captures aggregate variables that are known to affect the credit market. ν is the error term that captures the determinants of credit that are not considered. The aforementioned specification includes the inverse Mills ratio λ_{ijt}, to correct the sample selection problem and also connect intensive demand with the estimation of extensive demand from the first stage.

The types of heterogeneity considered include observable features of individuals in terms of the level of education, age, and geographical region. We also include other less structural indicators for individuals captured in the type of employment (formal and informal) and by the shocks they experience, among which stand out employment, demographics, etc. Although there is only a small amount of literature on the subject, we believe the levels of heterogeneity employed capture probable differences in preferences (risk aversion, impatience, etc.) among households with respect to borrowing. This differentiation can be made according to the type of credit (consumer, mortgage) or the currency in which a loan is taken out, i.e. domestic or foreign. The latter separation allows for studying differences in the determinants of credit by type of currency.

One important aspect of the estimation is identifying the demand for debt achieved by including credit supply related variables measured for each credit granting institution in the estimation. The estimation contains identifiers of formal financial institutions using binary variables.[10]

It is also important to mention that, in the case of Peru, credit supply characteristics should include the potential role of exchange rate variations and their influence on the interest rates at which financial institutions offer loans. By including a binary variable at the level of the main banks and their interaction with time and loan currency, we are implicitly controlling for the expected devaluation such institutions incorporate into their loans. Besides expected changes in the exchange rate, this interaction effect also captures the institutional characteristics of Peru's banking system. Among the latter stand out, for instance, the high interest rates charged by small financial entities, while larger institutions report lower rates as mentioned in Céspedes and Orrego (2014).

5. RESULTS OF THE ESTIMATIONS

5.1 Credit Market Participation

Participation in the credit market is represented using a discrete choice probit model where the explanatory variable takes a value of one if an individual has a loan and zero if not. Among the variables that determine access to credit, we have a set of indicators commonly used in the literature to capture different aspects of participation. Hence, we consider the following.

- Property rentals: Individuals with property rentals have a regular flow of income they can use to ensure loan repayments. This variable identifies credit market participation in the data as illustrated in Panel A of Figure 5. The latter figure shows that access to credit for individuals with property rentals is clearly higher than that of individuals without such income, a fact sustained on average for all age groups considered.

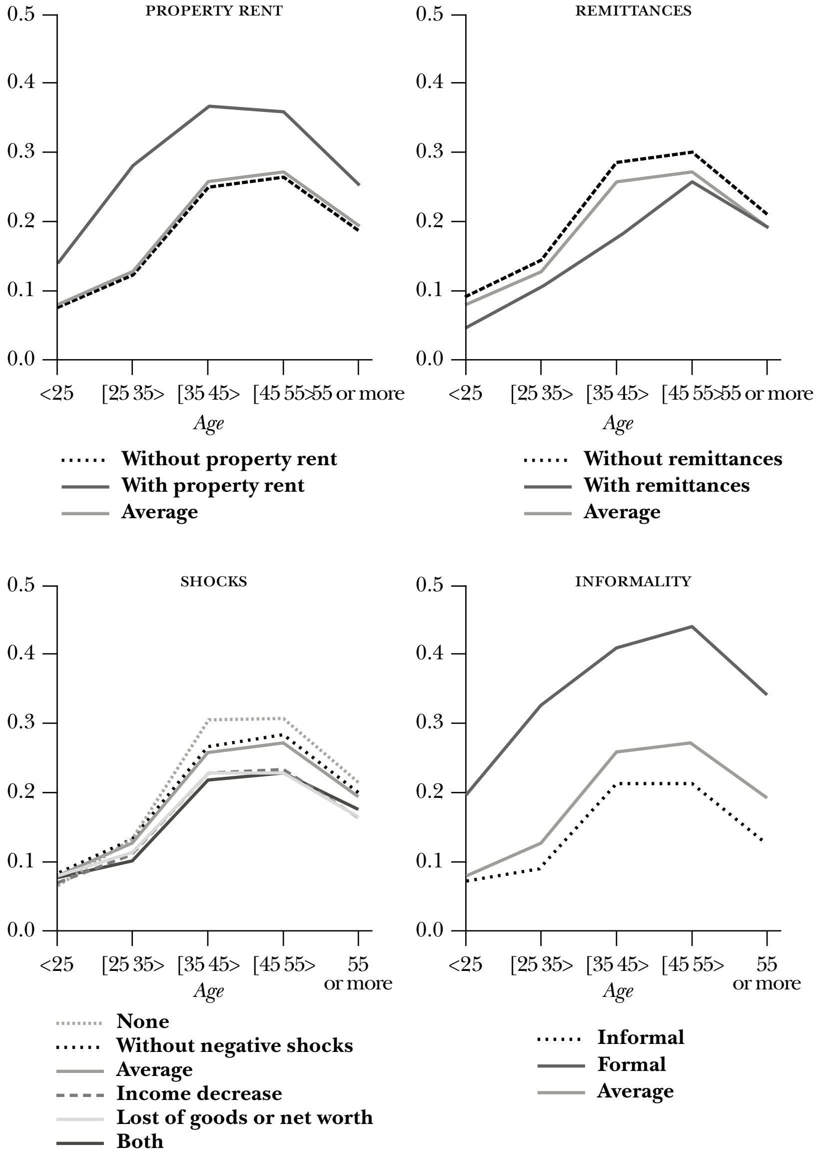
[10] It includes 26 artificial variables. The first 25 correspond to the largest financial institutions, while the remaining financial entities (small ones) are grouped into variable 26.

- Remittances: External remittances received by workers constitute a source of income that could be used as a mechanism for hedging loans, particularly those in foreign currency. This variable has been widely used in the literature on foreign currency borrowing, for instance: Fidrmuc et al. (2013) show the importance of external remittances in the demand for loans in Eastern European countries.
- Age and age-squared: The use of an individual's age as a variable to identify their participation in the credit market obeys the shape of inverted U of the age of participation in the credit market. Along the same lines, age-squared captures lower credit market participation among young and old-aged people, while the middle-aged participate more in said market.
- Shocks faced by households: This variable captures one characteristic of the credit theory as an insurance mechanism for responding to the shocks a household faces. According to this argument, households smooth consumption by using the credit market to face adverse events at the expense of future income. A set of shocks faced by households are considered such as, for instance: demographic shocks, employment shocks, natural disasters, etc. The reported index takes into account that an individual has been exposed to one of the shocks during the last 12 months.
- Informality: We consider that formal employment among workers identifies credit market participation basically using the characteristics of the credit database, which is limited to formal bank credit. In our data, formal workers access the credit market, while those in informal employment exhibit a much smaller access as shown in Panel D of Figure 5.

The participation equation estimated includes an additional set of controls such as gender, marital status, and region of residence. The estimation results provide a good fit in econometric terms as displayed in Table 3. Note that the variables identifying the selection are significant and also have signs consistent with that shown in Figure 3. These results are comparable to the estimates of Alfageme and Ramírez-Rondán (2016), and Cámara et al. (2013), although the size of the differences could be related to

Figure 5

PERSONS WHO HAVE A CREDIT
Percentage of the total population



Note: Participation in the credit market (percentage of persons with credit in each category).
Source: ENAHO and RCC, 2008-2014.

the inclusion of a set of variables identifying credit market participation, such as age, remittances, shocks and property rentals.

5.2 The Demand for Credit

The estimated elasticity of the demand for credit in Peru is −0.29. This figure is obtained after controlling for credit supply variables and Peruvian institutional characteristics as presented in Table 4. The latter table also presents estimated elasticities of the demand for credit using different specifications and estimation methods. This procedure highlights that the ordinary least squares estimator is not much different from the value estimated using Heckman's two-step method. The result that stands out is the fact that the elasticity of demand for credit is small, making it possible to conclude there is low credit market sensitivity among individuals during shocks channeled through interest rates. One of these events that occur relatively often are changes in Peruvian or US monetary policy. According to the results of this study, such changes would have had a modest impact on the demand for credit among individuals. International evidence on the value of this elasticity is mixed. On the one hand, Gross and Souleles (2002) use credit card records in the USA to find an elasticity of demand for credit of −1.3, which indicates a substantial reaction in credit demand (cards) to the interest rate. Meanwhile, another commonly referred to paper is that of Alessie et al. (2005), who use administrative data from a leading institution in Italy to find an elasticity of credit (instalment, revolving, personal loan) relative to the interest rate of −1.2 between 1995 and 1999. Nevertheless, this stance does not command full consensus because there is also literature suggesting a low elasticity of demand for credit. For instance, Ausubel (1991) includes one of the stylized facts most used for credit demand. This author employs administrative records and reveals that the demand for credit in the USA is rigid with respect to the interest rate and suggests that credit card holders rarely react to interest rate changes.

Table 3

CREDIT MARKET PARTICIPATION EQUATION

	Heckman selection equation	
	Coefficients	*z test*
Remittance (=0)	−0.0689[b]	(−2.68)
Property rentals	0.213[c]	(23.58)
Age	0.0842[c]	(101.10)
Age x age	−0.000870[c]	(−100.48)
Informal (=1)	−0.673[c]	(−138.24)
Married	−0.0320[c]	(−5.29)
Widowed	−0.171[c]	(−13.47)
Divorced	0.0150	(0.51)
Separated	−0.0378[c]	(−4.25)
Single	−0.178[c]	(−24.01)
Effect of shocks		
Reduced income	−0.0801[c]	(−13.09)
Loss of assets/wealth	−0.0374[b]	(−2.88)
Both	−0.0437[c]	(−3.59)
None	0.0127	(0.70)
Central Coast	−0.192[c]	(−20.58)
South Coast	0.0212[a]	(2.05)
North Mountain Range	−0.376[c]	(−31.63)
Central Mountain Range	−0.390[c]	(−47.53)
South Mountain Range	−0.0990[c]	(−12.14)
Jungle	−0.210[c]	(−27.77)
Lima metropolitan area	−0.249[c]	(−30.50)
Constant	−2.102[c]	(−101.87)
Mills (lambda)	−0.135[c]	(−5.97)
Rho	−0.10507	
Sigma	1.2845615	

Notes: corresponds to probit model estimates described in Equation 7. z statistic in parenthesis. [a] $p<0.05$, [b] $p<0.01$ and [c] $p<0.01$.
Source: ENAHO and RCC, 2008-2014.

The low elasticity of demand for credit could also be related to Peru's banking structure, which is characterized by being concentrated in a small number of financial entities (Céspedes and Orrego, 2014; and Jopen, 2013). In this regard, some literature suggests that the elasticity of demand for credit with respect to the interest rate should be high in a competitive market.

Table 4

CREDIT DEMAND ESTIMATES

	Dependent variable: log(credit)			
	MCO (1)	MCO (2)	Heckman (3)	Heckman (4)
Interest rate (log)	−0.362[a] (0.0066)	−0.295[a] (0.0057)	−0.307[a] (0.0034)	−0.294[a] (0.0035)
Demand characteristics				
Gender		✓	✓	✓
Age		✓	✓	✓
Age^2		✓	✓	✓
Education		✓	✓	✓
Parentage		✓	✓	✓
Marital status		✓	✓	✓
Economic sector		✓	✓	✓
Geographic region		✓	✓	✓
Supply characteristics				
Type of credit		✓	✓	✓
Type of currency		✓	✓	✓
Type of bank		✓	✓	✓
Year		✓	✓	✓
Type of bank×year×currency		✓		✓
Mills (lambda)			−0.233[a]	−0.135[a]
R^2	0.05	0.66		
Number of observations	84,394	78,889	543,358	543,353
Prob > F	0.0	0.0		
Prob > χ^2			0.0	0.0

Note: standard error in parenthesis.
Source: ENAHO and RCC, 2008-2014.

The elasticity of demand for credit could be an indicator of competition in Peru's market. The reasoning behind this lies in the capacity banks have to pass the shocks they face on to households by changing interest rates, and this capability depends on the elasticity of the interest rate. Under such interpretation, financial institutions maintain high rates because lowering them does not significantly increase the demand for credit.

The recent strong economic growth experienced by Peru could be important in explaining the low elasticity of credit with respect to the interest rate. The significant expansion of household credit seen between 2001 and 2014 mostly reflects the aggressive placement policies of financial institutions in an environment of higher employment and wages. The growth of placements basically takes place on the extension side, i.e., the number of new loans granted rather than average loan size. Such facts are consistent with the greater financial inclusion experienced by the economy in those years, with a larger amount of institutions offering credit such as rural savings banks and cooperatives, among others, that enabled previously unattended sectors to participate. These new loans are potentially riskier and reflect the participation of high-risk individuals with credit profiles that accept the high interest rates offered by the banks. In this context, banks have few incentives to lower (the high) interest rates on their products because this would not substantially increase the demand for credit given the corresponding low elasticity.

Another factor considered as possibly explaining the low elasticity is the greater financial inclusion being seen in the Peruvian economy (arriving at economic sectors that did not previously have access to credit). This phenomenon has been observed, for instance, in the marginalized areas of Lima, and generally in different regions of Peru where there were practically no banks in previous decades. However, the scenario has changed considerably and nowadays the network of agencies and agents offering loans (rural savings banks, municipal savings banks, savings, and credit cooperatives, major bank branches, etc.) has widened along with access to credit (new loans), which has followed a similar path.

5.3 Heterogeneity of the Demand for Credit

The demand for credit is heterogeneous and depends on the credit market supply and demand side characteristics. Moreover, the literature has found that heterogeneity is also present in the elasticity of demand for credit with respect to the interest rate. In this section, we consider several levels of heterogeneity basically related to the institutional order of Peru's economy that could sustain the heterogeneity of the transmission of interest rate shocks to household credit. This heterogeneity takes place according to the type of currency in which loans are granted, according to the region where they are granted and type of loan. We also consider the possibility that the elasticity of demand for credit changes over time.

Formally, Equation 8 is modified by including the effects of interaction between the interest rate and a set of artificial variables $\left(D_{ijt}^{l}\right)$ that take a value of one at each level of heterogeneity considered, the resulting equation is written as follows:

9 $$b_{ijt}^{n} = \alpha + \sum_{l=1}^{Q} \beta_r^l D_{ijt}^l \times R_{ijt} + \beta x_{ijt} + \theta z_{jt} + \delta T_t + \gamma \lambda_{ijt} + \nu_{ijt},$$

where Q levels of heterogeneity are considered. In this specification, indexes associated with interaction $\left(\beta_r^l\right)$ are the elasticities for each level of heterogeneity.

5.3.1 Heterogeneity by Type of Loan

The demand for credit is particularly heterogeneous according to the type of credit. The data allow for disaggregating up to three types of credit: consumer loans, mortgages, and credit to small and micro enterprises. The estimates suggest that the elasticity of the demand for credit differs according to the type of credit; consumer loans being the most elastic with an elasticity of close to −0.40, while mortgage loans are the least elastic.

5.3.2 Dollarization and Credit Demand

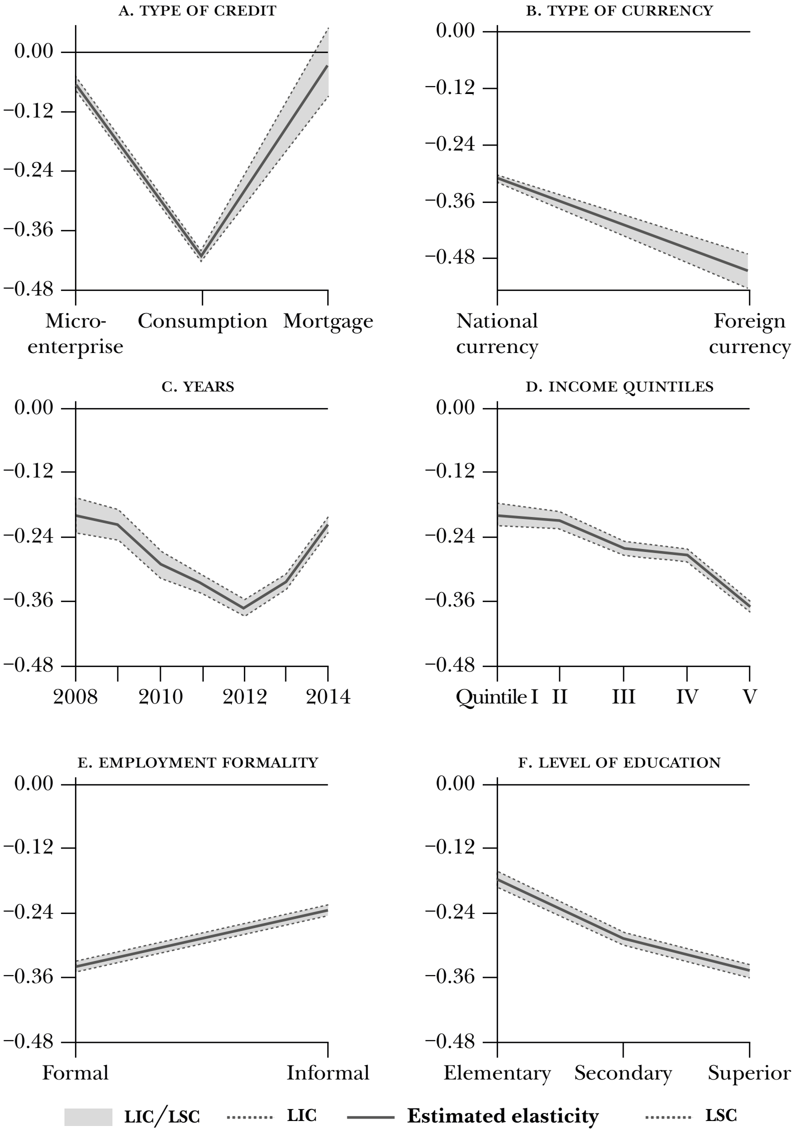
The type of currency can play an important role in the transmission of interest rate changes to credit. In this respect, dollarization of household credit in Peru's economy is around 30% and very heterogenous according to different observable categories among individuals such as income, age, and region of residence, among others, as documented in Céspedes (2017). The estimations in this section suggest that the elasticity of demand for credit is heterogeneous according to loan currency, those denominated in foreign currency being more elastic, while those in domestic currency are less so (Figure 6, Panel B).

The higher sensitivity of foreign currency borrowing could respond to a greater exposure of personal loans to interest rate movements. For instance, changes in international rates originating from, among other reasons, adverse global events could have a larger pass-through to households' foreign currency denominated credit, while such effects would be smaller in the case of loans in domestic currency.

However, the estimation methodology that has been implemented in this study might overestimate the sensitivity of interest rates to credit. This could be the case, for instance, of the exchange rate and the registration method used in the RCC by the SBS. In this regard, the RCC expresses loans in domestic currency using, in the case of loans in foreign currency, the official exchange rate at any given day (end-of-month for accounting purposes) for all loans and all financial institutions. Nevertheless, each financial entity uses a specific exchange rate that captures the expected exchange rate devaluation and is included in the interest rate they charge on loans, especially for individuals whose income is in domestic currency and have loans in foreign currency. The suggested overestimation would take place because the interest rate series employed has a lower variance by considering an average exchange rate and

Figure 6

ESTIMATED ELASTICITY OF CREDIT DEMAND BY DIFFERENT CATEGORIES



Note: The estimates of β_r^l from equation 9 are showed. There are also showed the confidence intervals. LIC is the lower limit of confidence of the credit demand elasticity, while LSC is the upper limit.
Source: ENAHO and RCC, 2008-2014.

a specific date, while interest rate variance would be larger if, ideally, it was possible to include the exchange rate used by each institution on the date loans are paid. Given that this volatility is not controlled in the regressions this would result in a larger elasticity of loans in foreign currency.

5.3.3 Changes in the Demand for Credit

By estimating the elasticity of demand for credit over time we find that this parameter increased in absolute value between 2008 and 2012 and exhibited a downward trend in 2013 and 2014 (Figure 6, Panel C). This result could be evidence that the pass-through of interest rate changes to credit has been related to the credit cycle, recalling that credit expanded at the highest rates between 2008 and 2012, and has slowed since 2012.

5.3.4 Credit Demand and Income

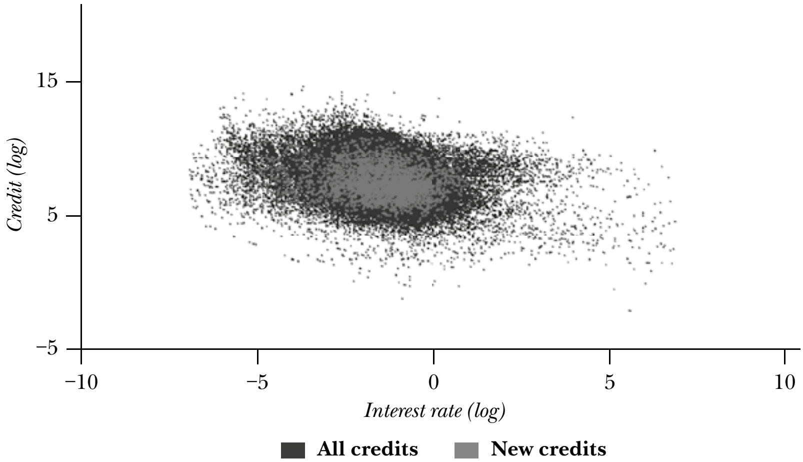
Participation in the credit market depends on the position in the income distribution. In this section, we have also found that the elasticity of the interest rate is lower in high income and better educated households, as well as among those with formal employment. These elasticities are statistically significant as illustrated in panels D, E, and F of Figure 6.

5.4 New and Old Loans

The demand for credit estimated in the previous section encompasses all loans registered in the RCC, while loan size corresponds to their balances. From the viewpoint of monetary policy, the loans that capture the transmission of changes in monetary policy would be new ones. We identify new loans using the credit panel in consecutive periods. To be specific, we distinguish the new loans in each month, identifying individuals with credit who did not have loans or were not registered in the RCC during the immediately preceding month. Note that individuals identified as having new loans might have had some type of credit in the past. We find that the new loans identified maintain a negative correlation with the corresponding interest rates, similar to that shown in Figure 4. Moreover, the new loans sample is small compared to the total sample, and said sample becomes even smaller if the different types of loan and individuals' characteristics are included, meaning the elasticity of demand for credit estimated for the previously mentioned categories (loan type, an individual's age, etc.) would only have high standard errors and be inaccurate with new loans. In light of the aforementioned considerations, the elasticity of credit is estimated with new loans and compared with the elasticities estimated using the full sample.

Figure 7

CREDIT AND INTEREST RATE OF NEW AND OLD CREDITS



Note: Credit is on the y-axis and the interest rate on the x-axis. Variables are expressed in logs.
Source: ENAHO and RCC, 2008-2014.

Credit demand for new loans is estimated using the same procedure described in the previous section, i.e., employing a binary variable that identifies new and old loans. As a result of this procedure, we find that the elasticity of demand for new loans is lower in absolute value (−0.17) than the elasticity reported for old loans (−0.30). This gap between the elasticity of new and old loans is similar using different methods (ordinary leas squares, Heckman). Furthermore, the elasticity increases when medium length loans and the oldest ones are included. The rationale of these outcomes lies in the particular characteristics of Peru's credit market, where interest rates on loans change over time even after being stipulated in a contract. Furthermore, there is a secondary market for purchasing debt, and each repo transaction qualifies as a new loan, although it would be difficult to identify them from RCC data. In sum, an important percentage of loans deemed to be old are in fact new ones and, therefore, the elasticity of demand for such loans in the secondary market should be higher.

6. CONCLUSIONS

Demand for credit at the individual level is an equation seldom estimated for an economy. The reason for this is that it is necessary to know credit and interest rates along with credit demand and supply features, but databases with this type of indicators are scarce at the international level. In this paper, we construct a new database that allows for observing the aforementioned variables by merging the National Household Survey with the Credit Registry for the period 2008-2014. The resulting database enabled us to examine 73,000 individual debtors.

Households' demand for credit is estimated using a two-step procedure proposed by Heckman (1979). The first step estimates extensive credit demand and the second intensive credit demand. The results highlight that participation in the credit market is determined by the number of property rentals households have, the remittances they receive, the size of the shocks they face, and their informality status. The latter characteristic is particularly important because it reveals a significant participation of informal individuals in formal bank credit. On this point, it is interesting to delve deeper into the reasons why informal workers participate in the formal credit market.

With respect to intensive demand for credit, it stands out that there is an elasticity of demand of approximately −0.29, figure slightly lower than that reported by the small number of international studies related to this paper.

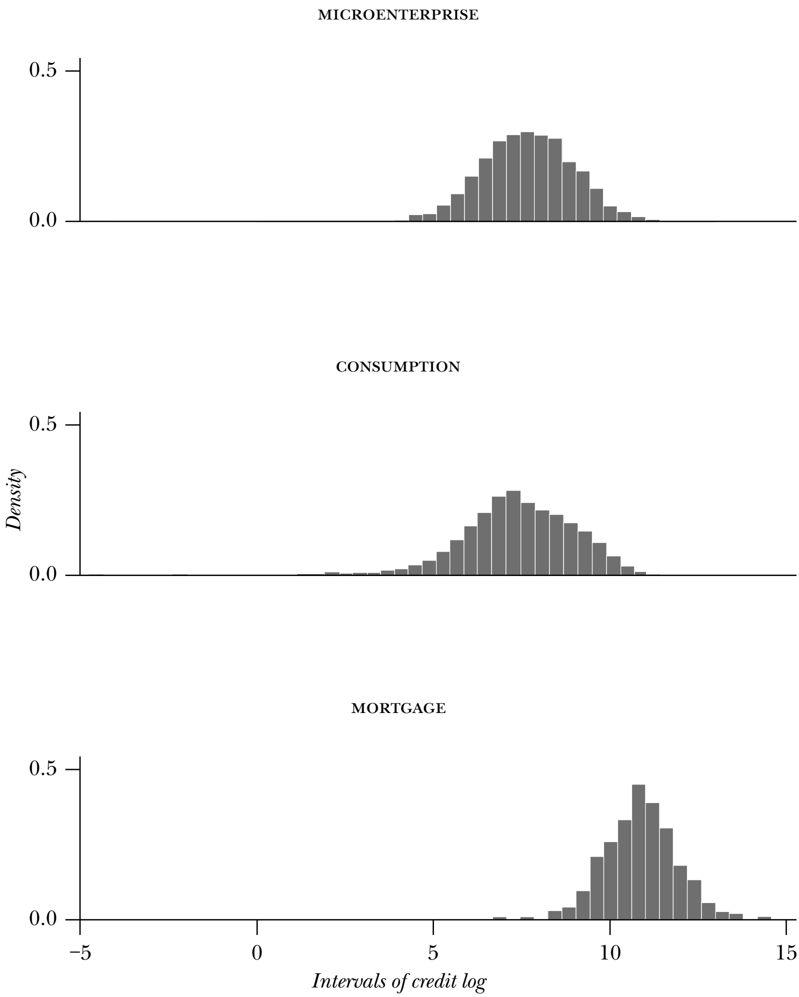
The elasticity of demand for credit is found to be heterogeneous in the estimation after controlling for the heterogeneity of credit demanders (individuals) and the heterogeneity of credit suppliers (banks). This evidence suggests that fixed effects at the individual and bank level not only impact average credit but also the elasticity of demand for credit. This heterogeneity is found according to loan type, currency denomination (domestic or foreign), individuals' income and level of education, among others.

Finally, it is important to highlight that the findings provide a first look at the heterogeneity of the demand for credit at the individual level in Peru. In general, the results of the study could be useful for assessing the transmission of the effects of the variables determining interest rates on individuals' credit and through the same channel on their consumption and standard of living. In particular, and considering the high and persistent dollarization in Peru's economy, the data shown in this article should be taken into account as arguments for explaining the pass-through of exchange rate shocks to credit at the individual level.

ANNEX

Figure A.1

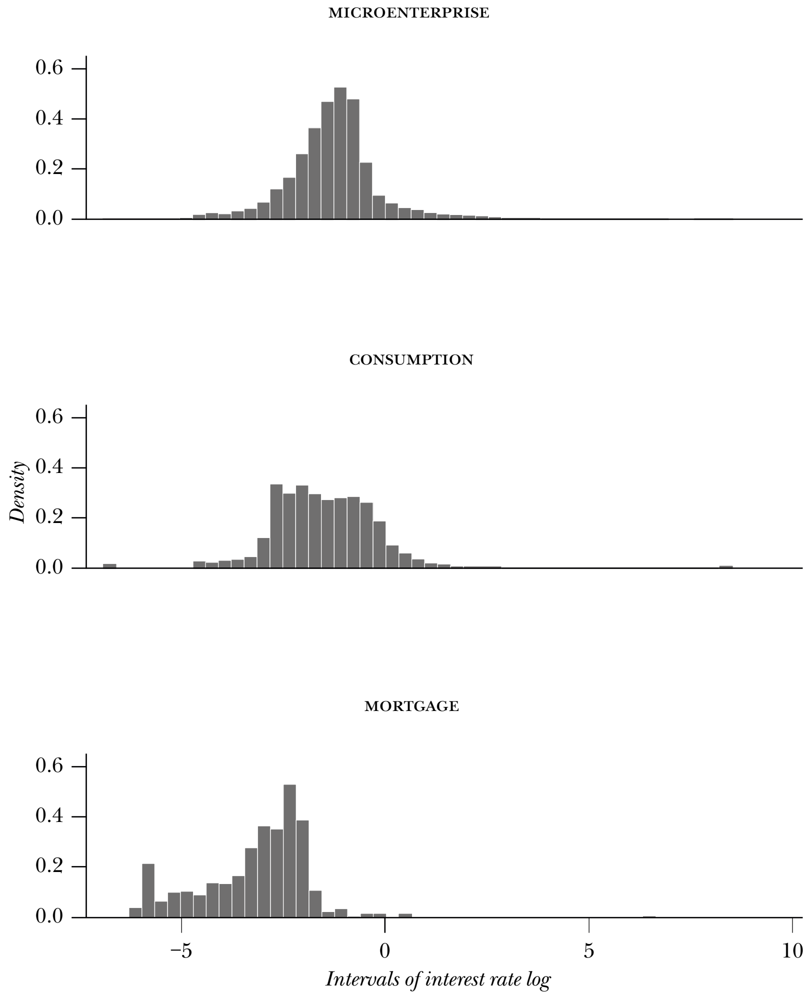
FREQUENCIES OF REAL CREDIT BY TYPE OF CREDIT



Source: ENAHO and RCC, 2008-2014.

Figure A.2

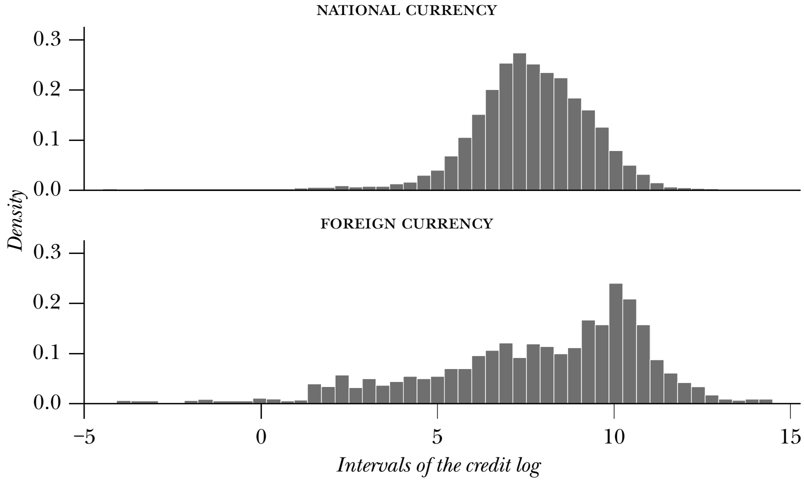
FREQUENCY OF INTEREST RATE BY TYPE OF CREDIT



Source: ENAHO and RCC, 2008-2014.

Figure A.3

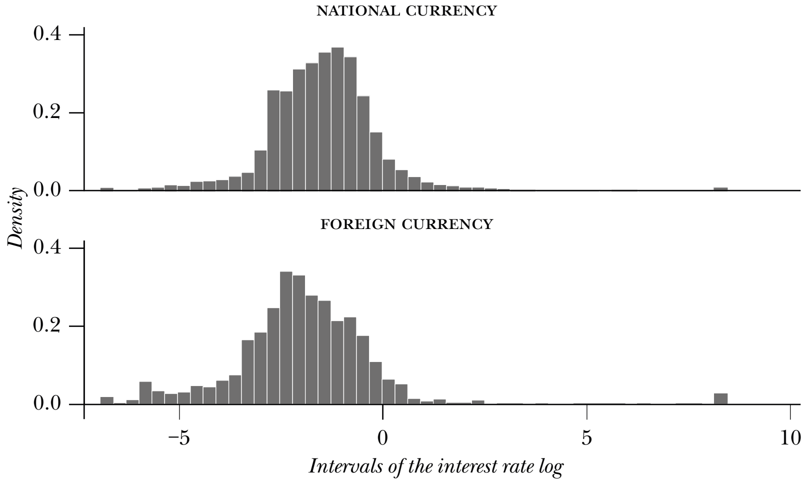
FREQUENCIES OF REAL CREDIT BY CURRENCY



Source: ENAHO and RCC, 2008-2014.

Figure A.4

FREQUENCY OF INTEREST RATE BY CURRENCY



Source: ENAHO and RCC, 2008-2014.

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