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Consumer credit in an emerging economy: Demand, supply, and liquidity restrictions

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ABSTRACT

Using a rich set of microdata from a credit union in Colombia, we estimate the factors behind the consumer credit demand and provide evidence of credit constraints from different perspectives including the lack of response of low-income customers to the interest rate. We also show the different ways in which the credit union implements additional rationing such as denying and trimming down the credit requests. For this, the credit union uses the scores and indebtedness of individuals. Finally, we estimate the supply of consumer credit where the interest rate, income, scores, and indebtedness are fundamental.

1. Introduction

Most studies of consumer credit have focused on developed countries, with little evidence presented for emerging economies. [1] In this paper, we aim to address this shortcoming by examining the determinants for the demand and supply of consumer credit using a dataset of the trade operations of a credit union in Colombia. [2] In doing so, we present evidence of the determinants for both the demand and the supply of consumer credit as well as for the liquidity constraints faced by consumers, and we discuss the way in which this financial institution implements credit rationing.

After the publication of the stochastic version of the life cycle–permanent income hypothesis (LC–PIH), the theory of liquidity restrictions emerged as an important alternative hypothesis not only with respect to the consumption behaviour and consumer credit of households (see, e.g., Zeldes, 1989; Runkle, 1991; Ludvigson, 1999; Crook, 2006; Attanasio et al., 2008), but also with respect to

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[1] Notable exceptions that refer to this part of the world are Ruiz-Tagle and Vella (2016) and Garmaise and Natividad (2017). Using aggregate data for a sample of 16 countries, Haque and Montiel (1989) show that Ricardian equivalence would hardly hold in developing countries. Gan et al. (2016), among many others, present evidence for the case of credit cards in China. Bertola et al. (2006) present an ample number of contributions to this area, most for developed countries. Durkin et al. (2014) offer an interesting and useful combination of theory, functioning description, statistics, and remarkable results in the literature of demand and supply of consumer credit in the United States.

[2] This is one of the five credit unions supervised by the financial authority in Colombia.

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stabilization policies (Hubbard and Judd, 1986), the economic growth (Jappelli and Pagano, 1994), and so on. [3]

In this paper, we first examine the determinants of the demand for consumer credit. In contrast to previous research, based on surveys (e.g., Jappelli, 1990; Cox and Jappelli, 1993; Duca and Rosenthal, 1993; Magri, 2002, 2007; Ruiz-Tagle and Vella, 2016), [4] we use a unique administrative dataset containing all the non-collateralized instalment credit records of a credit union [5] located in Medellín, which is the second largest city in Colombia, and in ten further municipalities in the surrounding area. As Alessie et al. (2005) do, we use the amounts requested by customers. In addition, we control for liquidity constraints and other key selectivity aspects by introducing suitable identifying assumptions along the lines of Cox and Jappelli (1993), Duca and Rosenthal (1993), and Crook (2006). Then, we delve into the credit supply of this credit union and how it implements additional credit rationing. [6] For this, we consider a set of variables that are used by the lender to grant credit and to determine the disbursed amounts. These variables include the credit score assigned to each customer, the indebtedness rate (i.e., the proportion of current income assigned to repay debts) and, finally, their current debt performance across the financial market.

The dataset used in this study comes from a single local credit union, which accounts for 0.5% of the total consumer credit market in Colombia (the representativeness of these data is discussed in Section 2). [7] The data comprise monthly information from 222,977 credits requested by 103,965 different individuals between July 2007 and March 2014. The information also includes the amounts of credit granted and disbursed or whether the credit request is turned down, the interest rate of the month in which the credit is conceded, the credit's maturity, the amount of monthly instalments of current debt relative to an individual's income, etc. It also contains the characteristics of individuals, such as age, education, current income, and marital status, among others.

Taking advantage of this dataset where these non-collateralized instalment credit operations meet the legal definition of consumption credit in Colombia, [8] this paper aims to establish the determinants of the demand for consumer credit in Colombia, where no previous investigation of this type has been carried out. [9] By using all this information and other complementary datasets, we introduce two selection corrections (Maddala, 1983, 1992) to alleviate some of the challenges in identifying the determinants of consumer credit demand, at least in this credit union. One such correction – related to credit-constrained and discouraged individuals – is statistically significant and has the expected sign. These estimations correspond to years 2009 and 2010, which are very close to the slowdown of the Colombian economy in 2008. According to the results, the sensitivity of consumer credit demand with respect to the interest rate is high (over -0.03). When we consider the whole sample period and stop controlling for selection phenomena, we find that the elasticity of consumer credit demand with respect to current income is about 0.65, the semi-elasticity with respect to the real interest rate is around -0.015, and the coefficient of the credit maturity is about 0.04, while the coefficient of the indebtedness is close to 0.135. Other variables, such as education, age, house ownership, etc., are also some of the factors behind of credit consumer demand. These results were found by using instrumental variables given the potential endogeneity of variables such as the interest rate, maturity if credits and labour income. Ruiz-Tagle and Vella (2016) analyse not only consumer debt but also mortgage debt. [10] They estimate that the elasticity of consumer debt to income is 1.47, more than twice our estimate.

We analyse some other aspects of the liquidity constraints, as introduced by Juster and Shay (1964) and more recently also verified by Attanasio et al. (2008). Accordingly, more restricted customers are less responsive to the interest rate than unrestricted customers. We find that customers who have labour income below the 10th percentile do not respond to the interest rate, while those below the median are less responsive than those above the 75th percentile. Along this line of analysis, Arango and Quevedo-Rocha (2022) also present evidence of liquidity constraints by using information about the use of credit cards in Colombia. They show that more restricted customers are those who have used a higher proportion of their credit card limits.

[3] There is ample evidence of credit constraints. Agarwal et al. (2007) find that, given tax rebates, individuals increase expenditure, which goes against the LC–PIH and the Ricardian equivalence (see also Shapiro and Slemrod, 2003, 2009). Sullivan (2008) shows that households with very low assets do not borrow in response to periods of unemployment that result in income shortfalls, and the reason for this seems to be credit restrictions (see also Keys et al., 2018). Scholnick (2013) tests the "magnitude hypothesis" and, by using information for individuals who are making final mortgage payments, provides evidence against consumption smoothing (see also Jappelli and Pistaferri, 2017, p. 149). Bazzi et al. (2015) find no consumption response to transitory cash transfers, a result that may be compatible with consumption smoothing behaviour. However, given the negative consumption shock associated with delayed disbursements, they interpret that the null treatment effects of receiving the full set of disbursements in a timely manner suggest some degree of precautionary savings behaviour driven by borrowing constraints (see also Gross et al., 2014). In contrast, Herkenhoff (2019) shows statistics according to which unemployed individuals go into debt to compensate for falls in income that result from periods of unemployment. He points out that the access of the unemployed to unsecured credit has grown significantly since 1970, which allows them to soften their consumption.

[4] Alessie et al. (2005) also use a database containing financial operations instead of a survey.

[5] Because we do not wish to identify this financial institution, hereafter we refer to it as the "Credit Union".

[6] Ramcharan et al. (2016) study the effects of the 2007–2009 financial crisis in the credit supply by using an extensive dataset of credit unions in the United States.

[7] Similar to Einav et al. (2013), who use data from a company specialized in low-income and high-risk customers.

[8] The criteria used by the credit union to classify an active operation as "consumer credit" are consistent with the definition used by the Office of the Financial Superintendent (i.e., the Financial Supervisory Authority in Colombia) as the credit granted to natural persons, with no commercial purposes, intended for the acquisition of consumption goods or the payment of services. See Chapter II of the External Normative 100 of 1995 issued by the Financial Supervisory Authority.

[9] The work of Arango et al. (2021), analyses the determinants of the value of purchases with credit card rather than consumer credit.

[10] Their analysis is based on the Chilean Survey of Household Finances, carried out in 2007, and they face similar problems related to selection and endogeneity of variables. Nevertheless, the kind of data and the solutions implemented are different.

However, we go beyond credit demand and the analysis of liquidity constraints from this point of view. In fact, step-by-step we examine the determinants for the supply of consumer credit, and we look at how further stages of credit rationing operate. Given that we have access to the credit score assigned to each customer by an external credit bureau, [11] we can estimate the probability of the credit being granted or not. We find this probability is determined not only by the credit score, but also by the current income, the repayment as a payroll deduction and the indebtedness of the customer. We also provide evidence that the level of indebtedness of individuals as well as their current credit performance (internal score) appear as determinants of the lender's decision to reduce, the amounts requested. Further, the empirical specification of the credit supply – based on the amounts granted – includes, apart from the customer's income (or the determinants of income, such as age, educational attainments, strata, etc.), the interest rate, the score, the credit performance, and the indebtedness of the individual. The estimates suggest that the credit supply increases with the interest rate (possibly linked to the fact that a higher amount of credit conveys higher risk for the credit union), score, income, and credit payment through the monthly payroll. By contrast, the negative sign of the coefficient of the indebtedness rate is highly informative.

Apart from the richness of the data, in this paper we are able to put together a consistent story of consumer credit by looking at both sides: demand and supply. We provide robust results for the determinants of demand and supply by emphasizing liquidity constraints and the way in which they appear. These results, based on administrative microdata on consumer credit, are ground-breaking for Colombia and, possibly, Latin America; not only the financial industry but also the monetary authorities can learn lessons from these results that show that not all individuals in an economy react to changes in the interest rate, which might affect the results of some monetary interventions. Also, given the relevance of the indebtedness rate for both the demand and supply of consumer credit, as proposed by Ruiz-Tagle and Vella (2016), it is important to study the relaxing of liquidity constraints mainly for low-income households. It would also help to reduce some of the adverse effects, cited above, experienced by these consumers.

The rest of the paper is organized as follows. In Section 2, we present some facts about consumer credit in Colombia, as well as in the credit union, and we describe the data. In Section 3, we describe the theoretical and empirical approaches that guide the specifications used and the interpretation of the results. In Section 4, we show and examine the results on the determinants of demand for consumer credit, controlling for some sources of credit restrictions and selection bias. In Section 5, we introduce factors such as the applicant's scores, their current credit performance, and the indebtedness rate. The purpose of this is to establish the factors that affect the credit union's decision regarding the rejection, or reduction, of the amount requested. We also present and analyse the consumer credit supply of this credit union, which, as stated above, follows normal practices, and is supervised by the financial authority in Colombia. Finally, we draw some conclusions in Section 6.

2. Data description

Before presenting the data used to conduct the analysis in this work, using information from the Global Findex Database, we give a brief overview of the use of the financial system by individuals in Colombia and, for comparison, three other countries: Chile, Mexico, and the United States. The proportion of people who borrowed from financial institutions is lower in Mexico (8%) than in Chile (12%), Colombia (14%), and the United States (24%). If the variable is defined as the proportion of people who borrowed from financial institutions or used a credit card, Mexico still has the lowest value (15%), but now Chile (31%) has a higher percentage than Colombia (21%) while the United States (66%) shows the highest proportion. According to this information, there are important differences between the countries in how closely individuals relate to the financial system. Individuals in the United States exhibit, by far, the highest familiarity with it. Interestingly, Chile also reports significant numbers of individuals who are familiar with such system, mainly with regards to credit cards, while individuals in Colombia and Mexico show much less prevalence for using this payment method. It is important to keep this in mind in the following.

The data used in this work correspond to consumer credit transactions between a private credit union and its affiliated customers located in Medellín and its surrounding municipalities from January 2007 to March 2014. The number of credit applications with valid information during the 7 years was about 222,977, [12] which corresponds to 103,965 individuals. During this period, the financial institution granted around 206,143 loans, for about 6.8 million Colombian pesos (COP) each, on average, in real terms for December 2012. As mentioned previously, the consumer credit under analysis is paid in monthly instalments. It is important to emphasize that the customers who receive credit from this credit union must leave in a savings account a deposit corresponding to 10% of the credit granted; thus, the customers can access 90% of the amount of credit granted.

Apart from the characteristics of individuals, such as age, education, current income, number of dependents, individuals active in the labour market at home (employment status), and homeownership, the information also includes the credit amounts requested by them, the requests turned down, the amounts granted and disbursed, the interest rate for the month in which the credit is granted, the credit's maturity, the amount of monthly instalments of all outstanding debts relative to an individual's income, and whether the credit

[11] Although we do not focus on informational and risk problems of the customers as Einav et al. (2013) do, our work uses three variable that contain traces of possible moral hazard and asymmetric information, such as the credit score, the indebtedness rate, and the current debt performance of customers across the financial market. Durkin et al. (2014, chapter 5) presents a comprehensive review of the score (see Mester, 1997). Jappelli and Pagano (2006) also explain the role of this variable in the consumer credit environment. Garmaise and Natividad (2017) analyse the effects on credit rating of a currency shock and its persistence.

[12] The total number of individuals who approached the credit union was about 264,000; however, we exclude individuals who represented individual business, and those individuals at either the top 0.1% or the bottom 0.1% of the credit demand. A similar procedure was applied for the individual's income, with the aim of reducing outliers. Thus, we end up with 222,977 observations.

is paid in person at the credit union or directly as a payroll deduction. [13] Fig. 1 presents the evolution of the average amount (per credit operation) of credits requested, credits approved, and credits turned down, between 2007 and 2014. The figure shows that, on the one hand, the average amount of consumer credits requested increased since 2009, reaching a value of COP 8.6 million by the end of 2014, and, on the other hand, the average amount of rejected credits is higher than the amount approved, suggesting, at first glance, the existence of credit constraints. Moreover, this difference increased since mid-2009. In general, however, the average amounts granted are not far from those requested.

Table 1 reports some descriptive statistics by gender and age groups. Among individuals demanding credit at the credit union, 54% are men and, among these men, those aged over 65 request more credit compared with other age groups; in comparison, women aged between 56 and 65 request more credit. The distribution of the credit demand is not homogeneous, with older individuals requesting credit more frequently but for amounts below the average. [14] In Table 2, we observe that credit is requested mainly by less-educated individuals. In fact, 76% of applicants had only secondary, or lower, levels of education. It is important to note that the amount of credit increases monotonically with individuals' levels of education and income, even though the population under study has an average monthly wage below COP 1 million. [15]

In terms of the external validity of this study, we can start by saying that the credit provided by this credit union is about 0.5% of the consumer credit in Colombia. In the best scenario, our results might be extrapolated to a similar population to the one served by this credit union (i.e., low- and middle-income households). To move in such a direction, we can observe how the people in our sample compare to individuals who apply for credit at other financial institutions. In this sense, we exploit the administrative records of all individuals who hold credit in the country and the financial institution that concede this credit. For this, we use the administrative records of customers from all banks and other financial institutions in Colombia from form 341 provided by the Financial Supervisory Authority.

Given the lack of demographic information for credit holders at other financial institutions, with the aim of having some individual characteristics, we merge the credit data with the demographic information contained in the System of Potential Beneficiaries of Social Programs in Colombia (SISBEN is the Spanish acronym), which is a survey that characterizes more than 60% of the whole population in the country, focusing mainly on low-income households. [16] Apart from some identifiers, this dataset contains variables such as education, number of household members, employment status of household members, access to health services, housing quality (materials used to build the house), etc. The survey is designed to classify the population into six different levels (strata) according to their socio-economic information, where stratum 1 identifies the most disadvantaged households. [17]

The average figures reported in Table 3 suggest that individuals from the credit union under study are not statistically different from those demanding credit at other financial institutions in the dimensions of gender composition, age, and marital status. Some differences are found in the case of the average amount of credits, education (the customers of the credit union are less educated), and strata composition (the customers of the credit union are more vulnerable, given the higher proportion living in strata 0, 1 and 2). Thus, regardless of these differences, we could still consider that our results are representative of consumer credit demand and consumer credit supply in Colombia.

3. Theoretical guide and empirical specification of consumer credit demand

Frequently, the analysis of an individual's decision about the amount of debt to hold is framed within the LC–PIH according to which the demand of consumer debt is the result of an agent optimization problem where individuals maximize their expected lifetime utility with time-separable preferences, subject to an intertemporal budget constraint. Thus, credit demand depends on individuals' time preference, the intertemporal elasticity of substitution, current asset holdings, the present value of expected future income, and the interest rate at which the market allows the intertemporal transference of resources. In this framework, saving (borrowing) is determined by the difference between the current level of income and the optimal level of consumption.

Assuming that the interest rate, r, is constant over time and across consumers, allowing time to go to infinity and introducing the equilibrium condition $(1+r)\beta = 1$, where β is the discount factor, we arrive at the familiar expression of an individual's debt, $D_{i,t}$:

$$D_{i,t} = E_{i,t} \sum_{j=0}^{\infty} \frac{w_{t+j}\left(1 - l_{i,t+j}\right) + x_{i,t+j}}{(1+r)^{j+1}} - \frac{c_{i,t}}{r}. \tag{1}$$

[13] This type of credit repayment, which comes directly from an individual's wage, is called *libranza* and it requires the credit union to have an agreement with the individual's employer.

[14] Crook (2006, p. 66) shows that people aged between 40 and 49 in Japan, the Netherlands and the United States are the most indebted, while in Canada, Germany, Italy, and the United Kingdom this characteristic corresponds to households aged between 30 and 39.

[15] In contrast, Crook (2006, p. 66) shows that households in the lower-income percentiles are less indebted than those in the upper-income percentiles.

[16] The SISBEN survey is collected every three or four years; nevertheless, there are updates, which include individuals who asked to be interviewed with the aim of being beneficiaries of different programmes. In the case of Antioquia (the province whose capital city is Medellín), which has 6,221,817 inhabitants, the SISBEN 2009–2010 interviewed 3,956,890 individuals (about 64% of the total population).

[17] This is a socioeconomic stratification system used in Colombia to classify the urban population depending on socioeconomic characteristics. The system classifies areas on a scale from 1 to 6. Of these, strata 1, 2, and 3 correspond to areas with fewer resources while strata 5 and 6 correspond to areas with the greatest economic resources.

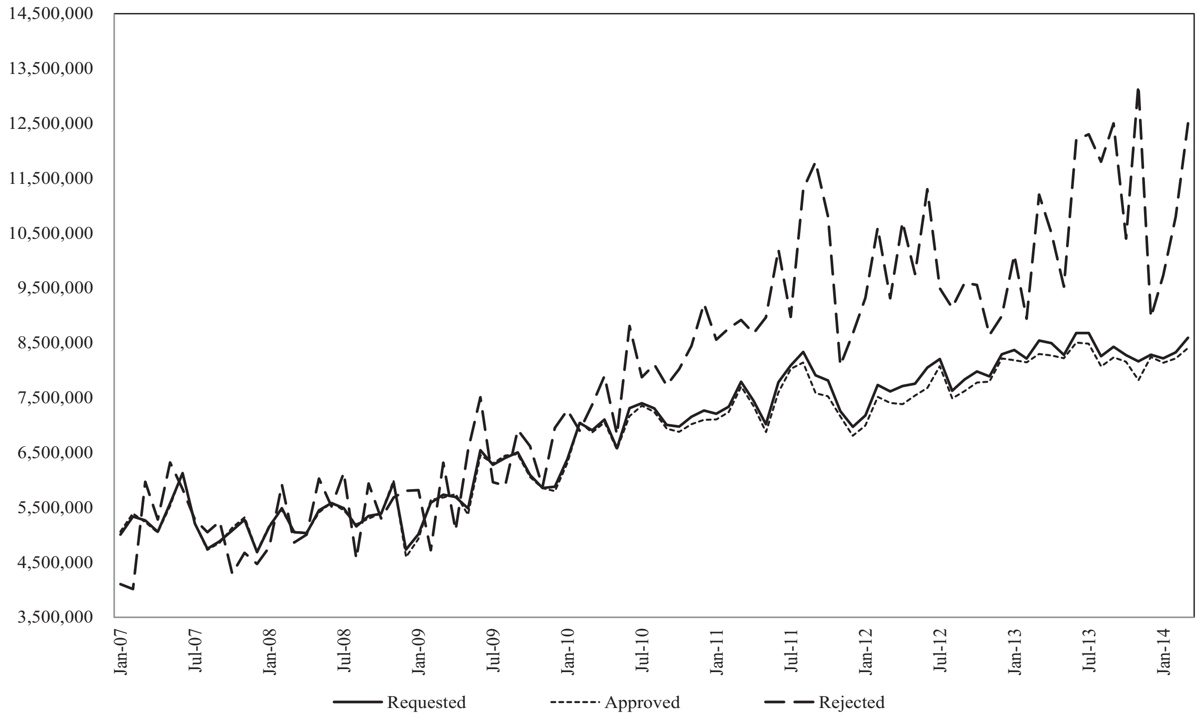

Fig. 1. Average nominal amounts of consumer credits: 2007–2014.
Note: The *y*-axis shows the amount in COP.
Source: Credit Union; authors' calculations.

Table 1
Consumer credit requests by gender and age.

Age range	Number	Average amount of credit (million COP)
Women		
Whole sample	103,704	6.7
Age 18–25	8073	4.5
Age 26–35	19,850	6.4
Age 36–45	18,654	7.2
Age 46–55	16,645	8.1
Age 56–65	22,916	6.7
Age 66+	17,501	6.3
Men		
Whole sample	123,303	6.8
Age 18–25	10,689	4.2
Age 26–35	23,617	6.2
Age 36–45	22,148	7.4
Age 46–55	20,565	8.0
Age 56–65	21,083	7.3
Age 66+	25,091	6.3

Note: For women, there were 65 credits without a reported age, while for men there were 110.
Source: Credit Union; authors' calculations.

Here, $E_{i,\ t}$ represents the expectations operator, conditional on the information set available for individual i at period t, $c_{i,\ t}$ represents consumption, $l_{i,\ t}$ is leisure, $x_{i,\ t}$ is the non-labour income, and w_t is the real wage. According to Eq. (1), the current debt of an individual is the present value of the expected labour and non-labour income in excess to the present value of smoothed consumption.

As we can observe, the life-cycle model yields this solution only under very restrictive circumstances, such as when the agent faces no credit limits (e.g., there is no need for collateral) or when the borrowing and lending interest rates are equal. Thus, it is convenient to consider the case in which liquidity constraints arise.

Attanasio et al. (2008) give some insight into the demand for credit in the presence of such friction under two situations. In the first

Table 2
Consumer credit requests by education and income of individuals.

	Number of observations	Percentage distribution	Average amount of credit (million COP)
Education			
None	822	0.4%	4.4
Primary	73,462	32.4%	5.6
Secondary	97,967	43.2%	6.1
Technical and technological	29,729	13.1%	8.0
College	21,492	9.5%	11.6
Postgraduate	1015	0.4%	16.2
Missing	2520	1.1%	5.2
Labour income range (COP)			
< 1000,000	146,397	65.0%	4.7
1000,001–2,000,000	59,599	26.5%	8.8
2,000,001–3,000,000	11,362	5.0%	13.5
3,000,001–4,000,000	4092	1.8%	15.7
4,000,001–5,000,000	1556	0.7%	20.3
> 5,000,000	2101	0.9%	24.8

Note: There were 1900 credits with no reported income. Source: Credit Union; authors' calculations.

Table 3
Statistics from the credit union and other financial institutions (2004–2014).

Variable	Average of other financial institutions overseen by the Office of the Financial Superintendent	Credit union
Value of credit	COP 3,044,349	COP 4,088,623
Proportion of male customers	0.526	0.539
Average age (years)	42.9	43.7
Primary education	0.540	0.550
Secondary education	0.128	0.061
Technical and college education	0.092	0.065
Strata 0 and 1	0.081	0.106
Stratum 2	0.452	0.558
Stratum 3	0.463	0.333
Stratum 4	0.004	0.003
Proportion married or cohabiting	0.574	0.533
Proportion separated	0.075	0.065
Proportion widowed	0.056	0.084
Proportion single	0.295	0.318
Proportion of workers in labour force	0.956	0.946
Observations	304,174	49,820

Note: The statistics proceed from the matching between SISBEN and form 341.
Source: Office of the Financial Superintendent; SISBEN; authors' calculations.

case, individuals cannot borrow as much as they want to finance current consumption using future earnings or income (see Jappelli and Pistaferri, 2017, chapter 5). In the second situation, individuals are liquidity-constrained if the interest rate at which they can borrow resources from the market is greater than the interest rate at which they can lend. The limited amount of liquid assets of these individuals has a high subjective yield that makes it extremely costly for them to liquidate such assets to acquire consumer goods. Along the lines of Juster and Shay (1964), for Attanasio et al. (2008) rationed borrowers should be more responsive to maturity changes in credit than unrationed borrowers. Also, the demand for credit of the rationed borrowers will be less sensitive to interest rates than that of unrationed borrowers. The latter, with relatively high levels of savings and liquid assets that have, consequently, subjective yields substantially lower than restricted borrowers are unwilling to pay high interest rates for new loans.

In the case of car loans, Attanasio et al. (2008) split the non-liquidity-constrained consumers into two categories. The first category comprises those for which it is optimal never to finance goods for consumption. These individuals will never exhibit sensitivity to either the interest rate or the credit maturity. The second category includes unconstrained households who will find it optimal to finance consumption. These customers will show high sensitivity to the interest rate, but less sensitivity to the loan's maturity. [18] Credit-constrained individuals are also those who are either precluded or prevented from applying for credit (see Crook, 2006, and references therein); one reason for this discouragement might be the amount of instalments they have to pay monthly during the loan term.

Liquidity constraints are introduced into our analysis from different perspectives. First, we consider that agents are liquidity-

[18] We use this argument to invoke the endogeneity of the loan's maturity that we consider below (see Durkin et al., 2014, chapter 3). However, given the amount of the loan, we regard the interest rate and the maturity of the loan as highly collinear with each other.

constrained if they are discouraged to apply for a loan or if their credit request is rejected. These cases have already been documented (see Jappelli, 1990; Crook, 2006; Ruiz-Tagle and Vella, 2016). Second, agents are regarded as constrained when their credit demand at the credit union is not responsive to the interest rate, as in Juster and Shay (1964) and Attanasio et al. (2008), because the subjective yield of assets is high or, in complement, they have less credit options for funding some expenditures (see also Arango and Quevedo-Rocha, 2022). Finally, from the point of view of credit supply, we illustrate and provide evidence of the way in which the credit union operates additional rationing; in particular, we consider those cases when the amount requested by potential customers is denied or reduced by the credit union (i.e., when the demand for debt is positive and greater than the credit supplied).

Thus, we add to our previous theoretical description an upper borrowing limit $\overline{D}_{i,t}$, imposed by any financial institution. Following Ludvigson (1999), we define

$$C_{i,t} \equiv \overline{D}_{i,t+1} - \left(1 + r_{i,t+1}\right)D^{o}_{i,t} + \left[w_t\left(1 - l_{i,t}\right) + x_{i,t}\right],$$

which includes some elements of the empirical specification that we use below. Here, $C_{i,\,t}$ (different from the desired consumption, $c_{i,\,t}$) is the level of consumption in the presence of credit limits while $D^{o}_{i,\,t}$ is the observed level of debt. [19]

Another concept of debt is the desired level for consumer i in period t, $D_{i,\,t}$, which is not always observable for all individuals. By ignoring this fact, we might be able to generate estimates of the demand for credit that would suffer from selectivity bias. Under the current framework, we face different types of selections: an individual's decision to hold positive debt, an individual's decision to request credit from a financial institution and, finally, the credit restrictions imposed by the financial institution but not always observed by the econometrician. These problems, familiar in this strand of the literature, can be addressed with censored models. As noted by Maddala (1983, p. 5; 1992, p. 341), an accurate procedure should allow us to model all the decisions that produce different demand outcomes, including, in our case, zero demand at the credit union. Our empirical specification of credit demand follows Cox and Jappelli (1993), Duca and Rosenthal (1993) and Crook (2001). We start with the individual's demand for credit.

The desired level of debt is a function of some observable characteristics, $X_{i,\,t}$, plus a random term, $\mu_{i,\,t}$:

$$D_{i,t} = X_{i,t}\gamma + \mu_{i,t}. \tag{2}$$

As previously stated, $D_{i,\,t}$ is not always observed. Individuals might not need credit or are not pushed by their preferences to hold a positive amount of debt at the current interest rate. To account for this, we define the dummy variable $\widehat{D}_{i,t}$, which takes the value of 1 if the individual holds a positive amount of debt, and 0 otherwise. This variable depends on the latent variable $\widehat{d}_{i,t}$, which is determined by a set of individual variables $\widehat{X}_{i,t}$ and a random term $\widehat{\mu}_{i,t}$:

$$\widehat{d}_{i,t} = \widehat{X}_{i,t}\widehat{\gamma} + \widehat{\mu}_{i,t}. \tag{3}$$

Thus, $\widehat{D}_{i,t}$ will be observed (equal to 1) when $\widehat{d}_{i,t} > 0$ and will be zero otherwise. Once this decision to have positive debt has been made, the agents might be discouraged or face liquidity constraints in financial institutions, other than the credit union under analysis, that restrict their desired level of debt; in this case, $\overline{D}_{i,t} = 0$.[20] To account for this, a dummy variable for not being constrained or not discouraged, $\widehat{D}^{U}_{i,t}$, is defined, as well as the latent variable $\widehat{d}^{U}_{i,t}$, which is determined by some individual characteristics $\widehat{X}^{U}_{i,t}$ as[21]

$$\widehat{d}^{U}_{i,t} = \widehat{X}^{U}_{i,t}\widehat{\gamma}^{U} + \widehat{\mu}^{U}_{i,t}. \tag{4}$$

The absence of credit constraints $\left[\widehat{D}^{U}_{i,t} = 1\right]$ is observed when $\widehat{d}^{U}_{i,t} > 0$. Once an individual has decided to demand credit and is neither constrained nor discouraged, the third decision they make is to choose the financial institution to request credit from. We define a dummy variable, $\widehat{D}^{C}_{i,t}$, which takes the value of 1 if the individual chooses the credit union from this analysis, and 0 otherwise. As before, this decision is determined by an underlying latent variable $\widehat{d}^{C}_{i,t}$, which depends on some individual characteristics, $\widehat{X}^{C}_{i,t}$ and the error term $\widehat{\mu}^{C}_{i,t}$:

$$\widehat{d}^{C}_{i,t} = \widehat{X}^{C}_{i,t}\widehat{\gamma}^{C} + \widehat{\mu}^{C}_{i,t}. \tag{5}$$

[19] In this case, the first-order condition of the problem is given by $u_c'(c_{i,\,t}, l_{i,\,t}) = \max\ [u_c'(C_{i,\,t+1}, l_{i,\,t+1}), \beta_i E_{i,\,t} u_c'(c_{i,\,t+1}, l_{i,\,t+1})(1 + r_{i,\,t+1})]$. Complementary to this framework, Jappelli (1990) develops an empirical model where a consumer is classified as liquidity-constrained when $c_{i,\,t} - x_{i,\,t} - w_t(1 - l_{i,\,t}) - (1 + r_{i,\,t+1})D^{o}_{i,\,t} > \overline{D}_{i,t+1}$.That is, when the desired consumption – once the resources available are subtracted – is greater than the level of debt available for the individual. This accounts for the first definition of liquidity constraint of Attanasio et al. (2008).

[20] Given the nature of the data we have obtained to introduce the selectivity corrections, we cannot account for more general liquidity constraints such as when $c_{i,\,t} - x_{i,\,t} - w_t(1 - l_{i,\,t}) - (1 + r_{i,\,t+1})D^{o}_{i,\,t} > \overline{D}_{i,t+1}$; that is, when the desired consumption – once the resources available are subtracted – is greater than the level of debt available for the individual.

[21] Apart from individuals constrained by the banks, credit unions, etc., there are people who do not even go to the financial system for consumer credit because they presume that the application would be denied. Unfortunately, we do not have explicit data on these discouraged potential customers. This is another source of self-selection within the problem at hand (see, e.g., Jappelli, 1990).

The decision about whether to choose the credit union, $\widehat{D}^{C}_{i,t}$, will be observed (equal to 1) when $\widehat{d}^{C}_{i,t} > 0$, and 0 otherwise. Note that $\widehat{X}$, $\widehat{X}^{U}$ and $\widehat{X}^{C}$ might share some elements.

The following six possible situations emerge from the realizations of the latent variables, $\widehat{d}_{i,t}$, $\widehat{d}^{U}_{i,t}$, and $\widehat{d}^{C}_{i,t}$:

$$\widehat{D}_{i,t} = 1, \widehat{D}^{U}_{i,t} = 1, \widehat{D}^{C}_{i,t} = 1;$$

$$\widehat{D}_{i,t} = 1, \widehat{D}^{U}_{i,t} = 0, \widehat{D}^{C}_{i,t} = 1;$$

$$\widehat{D}_{i,t} = 1, \widehat{D}^{U}_{i,t} = 1, \widehat{D}^{C}_{i,t} = 0;$$

$$\widehat{D}_{i,t} = 1, \widehat{D}^{U}_{i,t} = 0, \widehat{D}^{C}_{i,t} = 0;$$

$$\widehat{D}_{i,t} = 0, \widehat{D}^{U}_{i,t} = 1, \widehat{D}^{C}_{i,t} = 0;$$

$$\widehat{D}_{i,t} = 0, \widehat{D}^{U}_{i,t} = 0, \widehat{D}^{C}_{i,t} = 0.$$

Here, the latter two are observationally equivalent as the individual is deciding not to hold any level of debt. [22] This leaves us with only five situations.

Following Cox and Jappelli (1993), consistent estimates of the consumer credit demand can be obtained from the full sample of observable customers of the credit union ($\widehat{D}_{i,t} = 1$, $\widehat{D}^{U}_{i,t} = 1$, $\widehat{D}^{C}_{i,t} = 1$) by addressing other sources of bias. Assuming that each error term in expressions (3)–(5) is normally distributed with mean equal to zero and constant variance, [23] and also that $\sigma_{\widehat{\mu}} = \sigma_{\widehat{\mu}^{U}} = \sigma_{\widehat{\mu}^{C}} = 1$, [24] estimates of $\widehat{\gamma}$, $\widehat{\gamma}^{U}$, and $\widehat{\gamma}^{C}$ will be consistent. Accordingly, when considering the demand for consumer debt, the positive demand for debt, the selection of the credit union and the existence of credit constraints should be considered. This can be expressed as

$$D_{i,t} = X_{i,t}\gamma + \sigma\widehat{\rho}\frac{\phi(\widehat{d})}{\Phi(\widehat{d})} + \sigma\widehat{\rho}^{U}\frac{\phi(\widehat{d}^{U})}{\Phi(\widehat{d}^{U})} + \sigma\widehat{\rho}^{C}\frac{\phi(\widehat{d}^{C})}{\Phi(\widehat{d}^{C})} + \mu_{i,t}, \tag{6}$$

where $\widehat{\rho}$, $\widehat{\rho}^{U}$ and $\widehat{\rho}^{C}$ are the cross-correlations between $\mu_{i,t}$ and $\widehat{\mu}_{i,t}$, between $\mu_{i,t}$ and $\widehat{\mu}^{U}_{i,t}$, and between $\mu_{i,t}$ and $\widehat{\mu}^{C}_{i,t}$, respectively. These cross-correlations are crucial in identification because if they are all zero, the credit demand will be determined only by observed individual characteristics, $X_{i,t}$, and $\mu_{i,t}$. Because $\phi(.)$ and $\Phi(.)$ are the unit normal density and distribution functions, $\phi(.)/\Phi(.)$ is the inverse of the Mills ratio, which corresponds to the selection correction terms (see Heckman, 1979; Maddala, 1983, chapter 6).

To obtain estimates of $\sigma\widehat{\rho}$, $\sigma\widehat{\rho}^{U}$, and $\sigma\widehat{\rho}^{C}$, we merge data from the country's credit records (form 341) and the SISBEN. From 1,309,393 individuals located in the relevant geographical area where the credit union operates (i.e., Medellín, its metropolitan area, and some other small municipalities), 505,224 were found in the credit records. [25] Table A1 in the Appendix shows the probit model estimates used to mitigate the selection biases of the demand for credit. We estimate the probability that an individual with a low to middle income would demand credit for consumption purposes. Specifications in Columns (1) and (2) include age, gender, educational attainments, ownership of home appliances (e.g., television, cable connection, heating, oven, etc.) and marital status, among others. The estimates suggest that the probability of requesting consumer credit is affected by whether an individual is working, the gender of the head of the household, the education attainments, the presence of home appliances, and the household's strata. In other words, the probability of requesting consumer credit increases with the economic conditions of the individual. The exclusion restrictions are having home appliances and the number of unemployed people at home. That is, we are assuming that both affect the probability of requesting consumer credit but not the amount of credit requested at the credit union. [26]

[22] Arguably, two more cases could arise: $\widehat{D}_{i,t} = 0$, $\widehat{D}^{U}_{i,t} = 1$, $\widehat{D}^{C}_{i,t} = 1$; and $\widehat{D}_{i,t} = 0$ $\widehat{D}^{U}_{i,t} = 0$, $\widehat{D}^{C}_{i,t} = 1$. However, the decision not to hold positive debt makes the decision to have the debt with the credit union irrelevant.

[23] We are also assuming that the error terms are not jointly distributed. That is, we are assuming that being willing to have a positive debt, not being constrained, and accepting credit from the credit union are independent events. Otherwise, the equations for $\widehat{D}_{i,t}$, $\widehat{D}^{U}_{i,t}$, and $\widehat{D}^{C}_{i,t}$ should be estimated jointly by maximum likelihood, as in Einav et al. (2012).

[24] That is, all these unobserved elements of the decisions are equally important.

[25] From these 505,224 people, 13,738 were found in the credit union and 491,486 in other financial institutions.

[26] Notice that in Table A1, individuals looking for a job (unemployed) increase the probability of requesting a consumer credit. Tables 4 and 5 include, as controls, the number of individuals at home who are active in the labour market. However, these were not significant, both with and without the selection corrections. Sullivan (2008) presents evidence that very low-asset households do not borrow in response to unemployment episodes that bring about income shortfalls. However, other low-asset households do. Herkenhoff (2019) documents and addresses the decision of the unemployed to hold a positive non-collateralized debt to smooth out consumption in a labour market in which there is an important unemployment insurance, a situation that is very different in Colombia. Nevertheless, this finding of Herkenhoff means that our exclusion assumption should be considered with some caution.

The outcome of the probit model in Columns (1) and (2) of Table A1 in the Appendix corresponds to the estimate of the joint probability that an individual observed in the credit records (form 341) and SISBEN database decides to hold a positive debt and *ex ante* is neither discouraged nor restricted in financial institutions other than the credit union from this analysis. Thus, instead of having separate estimates for $\sigma\widehat{\rho}$ and $\sigma\widehat{\rho}^{U}$, in Eq. (6), we would have only $\sigma\widehat{\rho}^{U'}$; the associated Mills inverse ratio is $\phi\left(\widehat{d}^{U'}\right)/\Phi\left(\widehat{d}^{U'}\right)$ where $\widehat{d}^{U'}$ is the latent variable linked to the process of a dummy variable $\widehat{D}_{i,t}^{U'}$ that takes the value of 1 when the individual holds a positive debt and is neither constrained nor discouraged, and 0 otherwise. The underlying latent variable, determined by some individual's characteristics, $\widehat{X}_{i,t}^{U'}$, can be expressed as

$$\widehat{d}_{i,t}^{U'} = \widehat{X}_{i,t}^{U'}\widehat{\gamma}^{U'} + \widehat{\mu}_{i,t}^{U'}. \tag{7}$$

Thus, an individual holding positive debt $\left[\widehat{D}_{i,t}^{U'} = 1\right]$ will be observed when $\widehat{d}_{i,t}^{U'} > 0$, and 0 otherwise. In this case, Eq. (6) for the demand of credit becomes [27]

$$D_{i,t} = X_{i,t}\gamma + \sigma\widehat{\rho}^{U'}\frac{\phi\left(\widehat{d}^{U'}\right)}{\Phi\left(\widehat{d}^{U'}\right)} + \sigma\widehat{\rho}^{C}\frac{\phi\left(\widehat{d}^{C}\right)}{\Phi\left(\widehat{d}^{C}\right)} + \mu_{i,t}. \tag{8}$$

The third element on the right-hand side of Eq. (8), corresponds to the probability that an individual requests debt from the credit union from this analysis. The coefficients of the model in Columns (3) and (4) of Table A1 in the Appendix are different from those in Columns (1) and (2), respectively. Being retired, making contributions to the social security system, the level of education and home appliances are important determinants of the decision to hold debt at this credit union. Such a model includes, apart from the same variables of the model in Columns (1) and (2), a dummy variable that takes the value of 1 if there are people older than 60 living at home; this is the exclusion restriction used in this case. [28] This variable, statistically significant, was considered based on the information of Tables 1 and 3, according to which the customers of the credit union are older. Given that retired people are an important demographic for this credit union, as we observe in Table 1, the probability of requesting credit is affected by this variable.

4. Determinants of consumer credit demand

The above corrections, aimed at addressing selection issues, allow us to move in the direction of having unbiased estimates of the consumer credit demand at this credit union. The first estimates focus on years 2009–2010 when SISBEN and the demographic characteristics of people not demanding credit are available; that is, for this subsample, we can undertake the corrections that are made explicit in eq. (8). In addition, the estimates correspond to the amounts requested by individuals demanding credit for the first time at the credit union (i.e., the continuous line in Fig. 1).

Table 4 shows the ordinary least-squares (OLS) estimates of the determinants of consumer credit demand, including the sample selection correction terms as expressed in Eq. (8). The dependent variable is the amount, in logarithms, of the first-time credit requested by the customers. The use of individuals requesting first-time credits allows us to consider the two corrections more neatly than for people who have previously shown a preference for debt at this credit union. The models in Columns (1), (3), and (5) include the interest rate charged to the customers by the credit union in percentage terms, the maturity of credits in months, the log of the real income of customers, indebtedness (i.e., the proportion of current income assigned to repay debts), gender (a dummy variable that takes the value of 1 if the credit operation corresponds to a female, and 0 otherwise), type of house (dummy variables that, each in turn, take the value of 1 when the customer lives in a family house or their own house, and 0 otherwise; the reference is a rented house), other controls, and the selection correction terms, denominated Mills inverse ratios.

To avoid some collinearity, instead of current income, models in Columns (2), (4), and (6), include its determinants such as the variables linked to the human capital theory (age, squared age, and educational attainments) and strata. Educational attainments are included as dummy variables that, each in turn, take the value of 1 when the credit operations correspond to individuals who have achieved high school, technical and technological, and college education, and 0 otherwise; the reference is elementary education. By the same token, strata are modelled as dummy variables, leaving stratum 1 as the reference.

Columns (1) and (2) in Table 4 include both the interest rate and credit maturity. Because some collinearity might exist between the interest rate and maturity, Columns (3) and (4) exclude maturity, while the last two models exclude the interest rate. For Attanasio et al. (2008), these two are the key variables to distinguish constrained from unconstrained individuals (on the collinearity of the interest rate and the maturity, see also Durkin et al., 2014, chapter 3).

Both selectivity correction terms are significant in all specifications except in Column (3). Accordingly, these sources of bias might

[27] Crook (2006) shows some empirical findings for the United States and Italy based on two methodologies: sample selection and disequilibrium methods. While, with the first approach, the equations for positive debt and credit constraints of the households are jointly estimated, with the second method, it is necessary for the credit demand to be greater than the supply of credit, the former being positive (Grant, 2007). Thus, some exclusion restrictions are needed to identify the model.

[28] The exclusion restriction is people older than 60 living at home. Given that retired people are an important demographic for the credit union, we believe that the probability of requesting credit there is affected by this variable, as indeed it is, according to the results in Table 4.

Table 4
Determinants of consumer credit demand (first credits): 2009–2010, OLS estimates.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Real interest rate (r)	−0.019***	−0.020***	−0.053***	−0.052***		
	(0.005)	(0.005)	(0.008)	(0.009)		
Maturity in months	0.044***	0.046***			0.044***	0.046***
	(0.001)	(0.001)			(0.001)	(0.001)
Log of real labour income	0.537***		0.830***		0.539***	
	(0.021)		(0.030)		(0.021)	
Indebtedness rate	0.170***	0.203***	0.701***	0.797***	0.193***	0.229***
	(0.032)	(0.036)	(0.049)	(0.054)	(0.032)	(0.036)
Gender (Female = 1)	0.053***	−0.005	0.127***	0.007	0.053**	−0.004
	(0.014)	(0.015)	(0.025)	(0.027)	(0.014)	(0.016)
Age		0.012***		0.049***		0.012***
		(0.003)		(0.005)		(0.003)
Age^2		−0.000***		−0.000***		−0.000***
		(0.000)		(0.000)		(0.000)
High school		0.059***		0.069**		0.062***
		(0.019)		(0.031)		(0.019)
Technical		0.255***		0.465***		0.258***
		(0.031)		(0.049)		(0.031)
College		0.440***		0.631***		0.441***
		(0.043)		(0.065)		(0.043)
Family house	−0.025	−0.026*	−0.182***	−0.197***	−0.023	−0.024
	(0.019)	(0.020)	(0.035)	(0.036)	(0.019)	(0.021)
Homeownership	0.069***	0.101***	0.102***	0.072**	0.071***	0.102***
	(0.016)	(0.018)	(0.027)	(0.030)	(0.016)	(0.018)
Other house	0.238	0.308***	0.691***	0.673***	0.177	0.254*
	(0.179)	(0.151)	(0.197)	(0.179)	(0.176)	(0.150)
Mills inverse ratio: probability of requesting credit	−0.073***	−0.157***	−0.188***	−0.294***	−0.069***	−0.152***
	(0.019)	(0.022)	(0.033)	(0.035)	(0.019)	(0.022)
Mills inverse ratio: probability of requesting credit from the credit union	0.070**	0.301***	−0.065	0.497***	0.068**	0.307***
	(0.029)	(0.042)	(0.046)	(0.062)	(0.029)	(0.042)
Constant	6.203***	12.572***	4.445***	13.089***	5.850***	12.185***
	(0.287)	(0.153)	(0.410)	(0.248)	(0.272)	(0.112)
Controls for other active people at home	Yes	Yes	Yes	Yes	Yes	Yes
Controls for strata	No	Yes	No	Yes	No	Yes
Controls for marital status	Yes	Yes	Yes	Yes	Yes	Yes
Controls for number of dependent people at home	Yes	Yes	Yes	Yes	Yes	Yes
Controls for labour participation condition	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4548	4548	4548	4548	4548	4548
Adjusted R^2	0.757	0.718	0.304	0.235	0.756	0.717
VIF	1.23	4.60	1.22	4.65	1.25	4.70

Notes: Standard errors in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.
Source: Credit Union; authors' calculations.

be controlled for, or at least mitigated. The sign of the first correction term, $\sigma\widehat{\rho}^{U'}$, suggests that there is a negative correlation between the unobservable variables for the probability of being unrestricted, not discouraged and having preferences for positive credit and demand for credit. [29] In other words, unobservable factors that reduce the demand for credit also increase the probability of being unrestricted or not discouraged while having preferences for positive credit. Given the significance of the coefficient, it could be the case that some individuals with low to middle income are credit-constrained: unobservable variables that make people more likely to demand credit are also making them more restricted or discouraged. Related to the coefficient $\sigma\widehat{\rho}^{U'}$ is the fact that, as we will see below, the coefficients of indebtedness rate are positive and significant in all models of Table 4, suggesting that the higher the indebtedness, the higher the demand for credit. This first-time credit customers have shown taste for debt in the past.

The estimate of $\sigma\widehat{\rho}^{C}$ indicates the existence of a positive correlation between unobservable factors that explain the probability of requesting credit from the credit union and the amount of debt desired. That is, unobservable factors that increase the probability of requesting credit from the credit union also increase the desired amount of debt.

The model of Column (1) shows that, after controlling for the liquidity constraints associated with the selectivity correction ($\sigma\widehat{\rho}^{U'}$), the real interest rate, [30] credit maturity, current income, gender, and homeownership are still significant determinants of consumer credit demand. These latter three variables positively affect the demand for credit. In the case of the interest rate, an increase of 100

[29] Moreover, indebtedness is one of the determinants used in the empirical model specification of consumer credit demand of first-time credit customers at the credit union.

[30] Unlike Cox and Jappelli (1993) and Duca and Rosenthal (1993), who used Survey of Consumer Finance information and kept the interest rate as a constant term, we can use our estimates to exploit the time variation of the interest rate.

basis points reduces the demand for consumer debt by 1.9%, suggesting that individuals care about the credit price when asking for credit. [31]

Credit maturity is also a determinant of the demand for credit. This can be understood by the fact that, ceteris paribus, monthly instalments become smaller as the maturity becomes longer: one additional month in the credit maturity increases the amount demanded by 4.4%. Similarly, an increase of 1.0% in income increases the demand for credit by about 0.54%. [32] Also, the higher the proportion of current income assigned to repay debts (i.e., the indebtedness rate) is, the higher the demand for consumer credit. This might indicate that, once individuals are indebted, as a signal that credit rationing is less than full, they demand more debt to smooth out consumption. Some rationale about the sign of this coefficient might suggest that these borrowers have a higher taste for debt or that individuals could have some diffuse information about their debt limits when acquiring new debt. In terms of other characteristics, higher levels of experience (age) and education are also linked to higher amounts of debt requested, as we can observe in the model of Column (2). In this case, as occurs in models where current income is not included, gender is not significant.

Specifications in Columns (3) and (4) exclude credit maturity while Columns (5) and (6) exclude the interest rate. This is to observe the results in case of any potential collinearity between them. With respect to the coefficients presented in Columns (1) and (2), in Columns (3) and (4) we can observe numerical changes in the coefficients but not in the signs. This is the case for the interest rate, income, indebtedness rate, age, and educational attainments. Being a homeowner is positive and significant. The fit of the models is rather low in contrast to the others in Columns (1)–(2) and (5)–(6). The models of Columns (5) and (6), which exclude the interest rate, have coefficients like those of Columns (1) and (2) in quantitative and qualitative terms.

Even though we have found that credit maturity explains the amount of credit demanded by an individual, the maturity could also be the result of an agreement between the customer and the financial institution given the amount of credit and the interest rate. If this reverse relationship exists, then the OLS estimate of maturity in Table 4 might be biased. This would add to the potential bias originated by unobservable exogenous factors, simultaneously explaining the requested amount of credit, [33] the interest rate, the current income, and the credit maturity. An example of this situation would be an aggregate shock that generates changes in the individual's (transitory) income and inflationary pressures; this situation might impulse the monetary authority to intervene in the money market with ulterior effects in the set of market interest rates.

Thus, in some cases, a rise in the requisitions for credit could be accompanied by changes in the interest rate, current income, and credit maturity. Hence, the unobservable term in expression (8), $\mu_{i,\,t}$, would comprise two elements, $\mu_{i,\,t} = \nu_t + u_{it}$, where the former corresponds to the current shocks while the latter corresponds to a well-behaved individual heterogeneity.

Table 5 reports estimates of consumer credit demand following an instrumental variables approach. We do this to account for the potential endogeneity of the interest rate, current income, and loan's maturity, and also the simultaneity (reverse relationship) of the latter. The list of instruments for models in Columns (1)–(4) include: the sixth lag of the monthly interbank interest rate (as a proxy for the intervention interest rate) [34] and the third lag of an indicator for the presence of the El Niño phenomenon (both aimed at instrumenting the interest rate), age, squared age, educational attainments, the sixth lag of unemployment rate and the twelfth lag of confidence index (used to instrument the income and the maturity of credits). The instruments used to estimate the models in Columns (5)–(8) are: the 3-month lagged indicator of the precipitation regime (aimed at instrumenting the interest rate), and lags three, six and twelve of the indices of economic conditions and expectations of consumers (used to instrument the income and the interest rate).

The instruments are valid under the assumption that they affect the interest rate, the income, and credit maturity without affecting the amount of credit demanded. Any of these two sets of instruments is intuitively related to the market interest rate after a few months and, depending on the timing or the nature of the variables, they can be considered as systematically unrelated to $\mu_{i,\,t}$. Moreover, the lags of the real interest rate correspond to the months ahead in which the current movement of the intervention interest rate is expected to influence the market interest rates (see Becerra and Melo, 2009). The statistics related to the instruments suggest these are reliable.

For the 2009–2010 subsample, the inverse of the Mills ratios become not significant in the models of Columns (1) and (3). This would suggest that there is no correlation, on the one hand, between the unobservable variables for the probability of having preferences for positive debt, not being discouraged or being unrestricted and the demand for credit and, on the other hand, between the unobservable variables for the probability of having debt at the credit union and the amount of the consumer credit demand. These results contrast with those in the models of Columns (5) and (7) where the ratios are statistically significant. The point estimates of the Mills inverse ratios and the interest in the model of Column (5) are all estimated with high precision given the standard errors.

The coefficients of income and maturity exhibit similar magnitudes as those in Table 4, but higher for the interest rate. For this, we

[31] Ponce et al. (2017) analysed the situation for Mexico and provide evidence that consumers do not seem to pay enough attention to contractual interest rates when making purchases. They find that, on average, consumers have a higher proportion of debt on credit cards that have a higher interest rate. Recently, Arango et al. (2021) found that different interest rates are determinants of credit limits, probability of use and value of purchases with credit cards in Colombia. They explain the channels through which monetary policy affects the demand credit used to purchase semi-durable and non-durable goods.

[32] Our estimates of the demand function are higher than those of Grant (2007) who found that the income elasticity is 0.2. He also studied "unsecured" debt.

[33] For Mian and Sufi (2018), credit demand shocks are linked to "changes in household permanent income, demographics, or beliefs". Arango et al. (2021) show that both permanent and transitory components of income are determinants of the credit limits of credit cards and the value of monthly purchases.

[34] The interbank interest rate is very close to the intervention rate but, given the constant variability, is more convenient than the intervention interest rate, which remained constant during some months of the sample period.

Table 5
Determinants of consumer credit demand (first credits): 2009–2010, instrumental variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Real interest rate (r)	−0.034**	−0.034**			−0.031***	−0.029***		
	(0.014)	(0.014)			(0.009)	(0.009)		
Maturity in months	0.049***	0.050***	0.050***	0.051***	0.024**	0.026**	0.070***	0.069***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.010)	(0.010)	(0.012)	(0.012)
Log of real labour income	0.699***	0.664***	0.695***	0.655***				
	(0.071)	(0.042)	(0.071)	(0.042)				
Indebtedness rate	0.064	0.052	0.093***	0.084**	0.484***	0.485***	−0.112	−0.092
	(0.048)	(0.044)	(0.0467)	(0.042)	(0.142)	(0.142)	(0.168)	(0.176)
Gender (Female = 1)	0.055***	0.052***	0.054***	0.051***	0.004	−0.012	−0.010	−0.016
	(0.017)	(0.016)	(0.017)	(0.016)	(0.019)	(0.019)	(0.020)	(0.019)
Age					0.030***	0.032***	−0.008	−0.006
					(0.009)	(0.009)	(0.010)	(0.011)
Age^2					−0.000***	−0.000***	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)
High school					0.063***	0.118***	0.054**	0.079***
					(0.022)	(0.023)	(0.024)	(0.026)
Technical					0.350***	0.442***	0.141**	0.188**
					(0.061)	(0.070)	(0.066)	(0.080)
College					0.524***	0.673***	0.334***	0.409***
					(0.066)	(0.079)	(0.072)	(0.091)
Mills inverse ratio: probability of requesting credit	0.009		0.021		−0.255***		−0.096*	
	(0.030)		(0.029)		(0.045)		(0.049)	
Mills inverse ratio: probability of requesting credit from the credit union	−0.031		−0.031		0.426***		0.211***	
	(0.048)		(0.048)		(0.067)		(0.079)	
Constant	4.298***	4.667***	3.718***	4.180***	12.662***	13.252***	12.196***	12.555***
	(0.878)	(0.584)	(0.836)	(0.543)	(0.203)	(0.206)	(0.140)	(0.094)
Control for other active people at home	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for strata	No	No	No	No	Yes	Yes	Yes	Yes
Controls for property of house	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for number of dependent people at home	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for labour participation conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen test p-value	0.418	0.381	0.193	0.178	0.747	0.664	0.365	0.373
Sargan statistic p-value	0.345	0.296	0.1458	0.135	0.740	0.670	0.370	0.379
Underidentification test (Kleibergen–Paap LM statistic)	111.339	163.837	115.242	179.218	15.133	15.712	14.051	12.831
Underidentification p-value	0.000	0.000	0.000	0.000	0.019	0.015	0.003	0.005
Cragg–Donald Wald F-statistic	17.665	26.339	14.860	28.881	2.202	2.287	4.563	4.200
Stock–Yogo weak ID test critical values								
5% maximal IV relative bias	13.95	13.95	18.3	18.3	16.88	16.88	13.91	13.91
10% maximal IV relative bias	8.50	8.50	10.43	10.43	9.92	9.92	9.08	9.08
20% maximal IV relative bias	5.56	5.56	6.22	6.22	6.16	6.16	6.46	6.46
30% maximal IV relative bias	4.44	4.44	4.69	4.69	4.76	4.76	5.39	5.39
Observations	4547	4547	4547	4547	4547	4547	4547	4547
Adjusted R^2	0.743	0.742	0.740	0.740	0.615	0.620	0.578	0.584

Notes: Standard errors in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The instruments for models in columns (1)–(4) include: the sixth lag of the monthly interbank interest rate (as proxy of the intervention interest rate), the third lag of an indicator for the presence of El Niño phenomenon (both aimed to instrument the interest rate), age, squared age, educational attainments, the sixth lag of unemployment rate and the twelfth lag of confidence index (used to instrument the income and the maturity of credits). The instruments used to estimate the models in Columns (5)–(8) are: the 3-month lagged indicator of the precipitation regime (aimed to instrument the interest rate), and lags three, six and twelve of indexes of economic conditions and expectations of consumers (use to instrument the income and the maturity).
Source: Credit Union; authors' calculations.

should recall that the estimates correspond to first-time credits and that the economy was leaving a slowdown that lasted for over a year. For gender and indebtedness rate, the situation is also different. While gender is not significant when income is not included explicitly in the empirical model (Columns (5)–(8)), the estimate of indebtedness rate has changes not only in the magnitude but also in the significance and the sign.

Importantly, in the models in Columns (5)–(6) and Columns (7)–(8), which contain and do not contain the Mills corrections, respectively, regardless of being significant when they are included, we can observe that the most relevant coefficients do not change in any major way. Together with the lack of significance of the Mills corrections in the specifications of Columns (1) and (3), this would allow us to continue the estimation process of demand for consumer credit without such corrections. Recall that the models of Table 5 were estimated for years 2009–2010 when the SISBEN database including demographic characteristics of people not demanding credit was available to build the two $\phi(.)/\Phi(.)$ ratios. Thus, the lack of data to introduce selectivity corrections, made explicit in eq. (8), for the whole sample period (2007–2014) should not prevent us from producing reliable estimates of the determinants of credit demand. Consequently, we report next the estimates of our model using the whole sample (2007–2014) without the Mills inverse ratios. In addition, the models estimated so far do not allow us to assert whether is there any form of liquidity restriction in the sense of Juster and Shay (1964) and Attanasio et al. (2008) during the sample period. Thus, the models below will include both interest rate and maturity, regardless of any possible collinearity between these two variables.

Table 6 shows the estimates of credit demand using all credit requests between 2007 and 2014 with the pooled sample. The first column shows the OLS estimates, whereas Column (2) shows instrumental variables (IV–2SLS) results under the assumption that interest rate, income and maturity are endogenous. In both cases, the interest rate and credit maturity are significant. The IV–2SLS estimates have good properties in terms of the signs and significance of the coefficients as well as the statistics that validate the instruments.

In the specification of the consumer credit demand in Column (1), all the coefficients have the expected sign and sensible magnitudes. These are close to those of Column (2) where the estimated parameters and significance of the interest rate (−0.015), the credit maturity (0.040) and the income (0.648) allow us to maintain that the estimate corresponds to a demand function for consumer credit. However, regardless of the significance of the coefficients for interest rate and maturity in the model of Column (2), we still cannot distinguish which is more prevalent – credit-constrained or unconstrained customers. Indebtedness rate also has a positive coefficient; thus, a higher proportion of income devoted to payment of outstanding debts generates a higher demand for credit. This variable also conveys the information according to which individuals could previously access to credit.

As we stated above, an individual can demand new consumer credits either after the previous credit has been completely settled or while paying the current debt. In the latter case, part of the new credit is used to pay the outstanding amount. To consider this, we can take advantage of the panel structure of the data to conduct a fixed effects estimation, which appears in Column (3) of Table 6. In the fixed effects (FE) specification, the semi-elasticity of the interest rate is similar, in size, to the precedent (pooled sample) models. This is also the case for the coefficients of indebtedness and maturity but not for the labour income, which is about a half. This is a very important result as, once we consider former customers, labour income variations have less traction in the estimation of the demand for credit.

We continue the analysis of the factors behind the consumer credit demand by dividing the credit operations depending on the percentile of the income and indebtedness of the customers. Based on the claims of Juster and Shay (1964) and Attanasio et al. (2008), this exercise has the purpose of observing the statistical significance of semi-elasticities of the interest rate and the credit maturity.

Table 6
Determinants of consumer credit demand: 2007–2014.

Variable	OLS	2SLS-IV	Panel-FE
	(1)	(2)	(3)
Real interest rate (*r*)	−0.016***	−0.015***	−0.018***
	(0.001)	(0.003)	(0.001)
Maturity in months	0.041***	0.040***	0.037***
	(0.000)	(0.001)	(0.000)
Log of real labour income	0.532***	0.648***	0.268***
	(0.003)	(0.012)	(0.012)
Indebtedness rate	0.148***	0.135***	0.105***
	(0.006)	(0.008)	(0.010)
Female	0.038***	0.047***	
	(0.003)	(0.003)	
Constant	6.453***	4.918***	10.293***
	(0.047)	(0.180)	(0.160)
Controls for other active people at home	Yes	Yes	Yes
Controls for strata	No	No	No
Controls for educational attainments	No	No	No
Controls for property of house	Yes	Yes	Yes
Control for marital status	Yes	Yes	Yes
Control for number of dependent people at home	Yes	Yes	Yes
Controls for labour participation conditions	Yes	Yes	Yes
Time fixed effects	Yes	Yes	
Hansen test *p*-value		0.914	
Sargan statistic *p*-value		0.911	
Underidentification test (Kleibergen–Paap LM statistic)		3797.8	
Underidentification *p*-value		0.000	
Cragg–Donald Wald *F*-statistic		814.122	
Stock–Yogo weak ID test critical values 5% maximal IV relative bias		9.53	
Observations	210,050	187.162	210,050
R^2	0.736		
Adjusted R^2		0.701	0.708
VIF	1.45	7.34	11.83

Notes: Standard errors in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The set of instruments used in the model of Column (2) are: 9-month lag of interbank interest rate (as a proxy of the intervention interest rate), 6-month lag of indicator of the El Niño phenomenon, 6-month lag of precipitation (rain) regime, age and squared age. The models include neither educational attainment nor strata because these are considered to be highly related to labour income and, in some models below, are used as instruments for labour income.
Source: Credit Union; author's calculations.

According to these authors, restricted consumers are not sensitive to the interest rate but are to changes in the loan's maturity, while unrestricted individuals are responsive to the interest rate.

To check for this hypothesis, we divide the customers into different categories depending on labour income and their indebtedness. We estimate credit demand models for individuals with labour income equal to or lower than the 10th, 25th and 50th percentiles and greater than the 75th and 90th percentiles of the labour income distribution (see Table 7).

However, to be more rigorous with the test for liquidity constraints, we select customers in each income quantile with different levels of indebtedness to check the hypothesis that these individuals have different responses to the interest rate depending not only on their income but also on the proportion of income devoted to repaying outstanding debts. [35] Thus, except for the median, we also estimate consumer credit demand functions for customers in each of these percentiles in combination with indebtedness equal to or lower than the 25th percentile of the indebtedness distribution and greater than the 75th percentile.

As we can observe, as long as we move from the left to the right across income percentiles, the response of customers to changes in the interest rate increases in absolute value: −0.004 for the 10th percentile, −0.017 for the 25th percentile, −0.015 for the median, −0.030 for the 75th percentile, and − 0.038 for the 90th percentile, where the former coefficient is not only the lowest but also not statistically significant. When we observe the responses to the interest rate depending on the income and indebtedness percentiles, the pattern is less clear as the difference in responsiveness within each income percentile is not significant. Thus, the dominant variable in the definition of constrained customers is labour income.

The coefficients linked to maturity do not exhibit sizeable changes across consumer credit demand functions. Thus, we retain just the results with respect to the interest rate to identify rationed customers; this is still compatible with the prediction of Attanasio et al. (2008) in the case of car loans.

Although the responses to income are more heterogeneous, the coefficients linked to indebtedness – mainly of individuals with this indicator lower than the 25th percentile – are notoriously higher (1.345, 2.335, 1.613 and 1.707) than those with indebtedness higher than the 75th percentile. Apparently, customers with this indicator lower than the 25th percentile exhibit a greater appetite for debt.

5. Two further steps of credit constraints and the supply side

According to our findings so far, there is a likelihood that a number of individuals are liquidity-constrained given the significance of the Mills inverse ratio in the estimates corresponding to the period 2009–2010. In addition, given the lack of response to the interest rate while there is a response to credit maturity, there is another group of customers of the credit union who are probably liquidity-constrained.

Further, customers can also be constrained when the credit union does not grant the exact amount of credit that they request. In fact, the credit union might either reject the request completely or grant a proportion of the original request, depending on the customer's default probability and, possibly, some other considerations.

These additional restrictions imposed by the credit union occur in two stages. In the first stage, based on the external score, the known measure of the customers' risk – computed by external *credit bureaus* with the help of automated information systems – the credit union decides whether the amount requested will be granted or not. To compute the score, the external rating agency uses information of an individual's credit payment history, previous debts and other information. [36] In short, the external credit score is a risk evaluation device that maps specific information about individuals into their probability of defaulting; the higher the score, the lower the probability that a customer will default. In the second stage, the credit union decides on the amount to be granted, taking the amount requested as a starting point.

The credit limits imposed by the credit union are determined by the external score, $S_{i,\,t}$. In this case, an individual's payment habits and credit history determine the amount of debt: $D^o_{i,t} \leq \overline{D}_{i,t} = F\left(D^o_{i,t-1} \leq \overline{D}_{i,t-1}\right)$. [37] Once we include this information in the model, two possible scenarios arise: (1) the score assigned to an individual is below threshold $\overline{S}$ and the credit supply is equal to zero; (2) an individual receives a score above such a threshold. That is,

$$\begin{cases} \overline{D}_{i,t} = 0 < D_{i,t} \text{ if } S_{i,t} \leq \overline{S} \\ 0 < D^o_{i,t} \leq \overline{D}_{i,t} \leq D_{i,t} \text{ if } \overline{S} < S_{i,t} \end{cases}, \tag{9}$$

where $\overline{D}_{i,t}$ represents the credit supply, as before, $D_{i,\,t}$ is the desired level of debt and $D^o_{i,\,t}$ is the observed debt amount.

The individual's credit score takes a value between 0 and 1000 points and it can be defined as the latent variable driving the credit

[35] This exercise is in line with Arango and Quevedo-Rocha (2022) who present evidence of liquidity constraints for individuals who have used a high percentage of the credit limit on their credit cards. The value of purchases is inelastic to the interest rate for these customers, whereas the response is sizable for customers who are less restricted.

[36] These cost-effective devices are based on credit history, payment history, delinquencies, open accounts, lines of credit, etc. Durkin et al. (2014, p 209) point out that the score models make it possible to identify, to a certain extent, good borrowers from bad ones in the process of loan origination; thus, score-type models are used by financial institutions to support the decision to grant credit or not.

[37] Of course, the score depends on many other observable determinants, which are included in the model; however, for ease of exposition, we focus on these two main determinants of the score.

Table 7

Determinants of consumer credit demand depending on income and indebtedness: 2007–2014; IV-2SLS.

Variables	$y \leq 10$	$y \leq 10$ & $d \leq 25$	$y \leq 10$ & $d > 75$	$y \leq 25$	$y \leq 25$ & $d \leq 25$	$y \leq 25$ & $d > 75$	$y \leq 50$	$y > 75$	$y > 75$ & $d \leq 25$	$y > 75$ & $d > 75$	$y > 90$	$y > 90$ & $d \leq 25$	$y > 90$ & $d > 75$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Real interest rate (r)	−0.004	0.000	0.015	−0.017***	−0.018**	−0.023	−0.015***	−0.030***	−0.041***	−0.037*	−0.038***	−0.071***	−0.108***
	(0.007)	(0.020)	(0.016)	(0.004)	(0.007)	(0.020)	(0.003)	(0.008)	(0.011)	(0.019)	(0.014)	(0.021)	(0.034)
Maturity in months	0.044***	0.037***	0.056***	0.047***	0.034***	0.066***	0.046***	0.070***	0.050***	0.074***	0.038***	0.051***	0.057***
	(0.002)	(0.004)	(0.005)	(0.001)	(0.002)	(0.006)	(0.001)	(0.008)	(0.008)	(0.007)	(0.006)	(0.008)	(0.009)
Log of real labour income	1.053***	1.029***	0.379	1.095***	1.171***	1.516	1.197***	0.799***	0.636***	0.744***	1.378***	0.650***	0.660***
	(0.188)	(0.241)	(0.332)	(0.232)	(0.289)	(1.171)	(0.148)	(0.058)	(0.077)	(0.051)	(0.175)	(0.116)	(0.102)
Indebtedness rate	0.224***	1.345***	0.083	0.158***	2.335***	−0.115	0.069***	−0.052	1.613***	0.407***	0.155***	1.707***	0.299***
	(0.047)	(0.220)	(0.137)	(0.022)	(0.175)	(0.105)	(0.019)	(0.049)	(0.413)	(0.082)	(0.031)	(0.344)	(0.096)
Constant	−0.687	−0.615	7.446*	−1.086	−2.379	−7.062	−2.507	1.694***	4.605***	2.195**	−5.537**	4.791***	5.339***
	(2.508)	(3.171)	(4.330)	(3.066)	(3.812)	(15.331)	(1.991)	(0.931)	(1.000)	(0.911)	(2.707)	(1.681)	(1.845)
Controls for other active people at home	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for strata	No	No	No	No	No	No	No	No	No	No	No	No	No
Controls for educational attainment	No	No	No	No	No	No	No	No	No	No	No	No	No
Controls for marital status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for number of dependents at home	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for labour participation condition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen test p-value	0.725	0.557	0.538	0.103	0.141	0.916	0.026	0.075	0.109	0.210	0.795	0.291	0.112
Sargan statistic p-value	0.732	0.479	0.484	0.109	0.118	0.900	0.023	0.080	0.117	0.221	0.782	0.325	0.126
Underidentification test (Kleibergen–Paap LM statistic)	102.471	60.269	36.699	166.442	90.311	22.597	320.102	33.913	20.018	51.761	70.568	24.406	28.857
Underidentification p-value	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.003	0.000	0.000	0.000	0.000
Cragg–Donald Wald F-statistic	38.915	11.991	4.980	44.528	17.211	3.733	54.203	4.855	2.468	5.948	10.044	2.922	3.824
Stock–Yogo weak ID test critical values													
5% maximal IV relative bias	9.53	9.53	15.18	12.2	13.95	15.18	13.95	16.1	15.18	16.1	13.95	15.18	15.18
10% maximal IV relative bias	6.61	6.61	9.01	7.77	8.5	9.01	8.5	9.37	9.01	9.37	8.5	9.01	9.01
20% maximal IV relative bias	4.99	4.99	5.69	5.35	5.56	5.69	5.56	5.78	5.69	5.78	5.56	5.69	5.69
30% maximal IV relative bias	4.3	4.3	4.46	4.4	4.44	4.46	4.44	4.46	4.46	4.46	4.44	4.46	4.46
Observations	14,967	4725	3285	45,754	12,693	6733	94,710	44,720	11,328	16,234	18,243	4525	7899
Adjusted R^2	0.705	0.661	0.671	0.718	0.714	0.433	0.704	0.395	0.630	0.335	0.416	0.543	0.485

Note: Standard errors in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. In the different columns y denotes labour income while d denotes indebtedness. All models are estimated by 2SLS-IV. The instruments vary from model to model depending on the statistics. In general, the instruments are: 9-month and 6-month lag of interbank interest rate (as a proxy of the intervention interest rate), 6-month and 3-month lag of indicator of the El Niño phenomenon, 6-month and 3-month lag of the precipitation (rain) regime, age and squared age, educational attainment, strata, and different lags of the consumer confidence index and its components.

Source: Credit Union; authors' calculations.

union's decision whether to grant a credit or not. [38] Fig. 2(a) and (b) show the density of individuals' scores for credits granted and rejected, respectively. As can be observed in Fig. 2(a), there is an important mass of individuals' scores at 600 points. The density of the score of granted credits is, as expected, skewed to the left (the higher the score, the higher the probability of being approved). Fig. 2(b) shows how the score density is almost uniformly distributed for rejected applications. Fig. 2(c) superimposes the score distributions of rejected and granted credits.

The score is the main instrument of the credit union for granting or denying credit requests. From the raw data, our estimates indicate that 16,103 credit requests, out of 222,977, were turned down; that is, for 7.2% of credit requests the amount supplied was zero, $\overline{D}_{i,t} = 0$. These are borrowers who are unable to smooth out consumption as they would want. This proportion might be higher if we consider the potential restricted customers that we approach in the previous section that gave rise to the selectivity problems that we attempt to attenuate when studying the demand for consumer credit. Hall and Mishkin (1982) estimated that about 20% of households are constrained, similar to the figures found by Hubbard and Judd (1986), Mariger (1987) and Jappelli (1990). Grant (2007) found that the proportion of constrained households was close to 30%. Ruiz-Tagle and Vella (2016), using the Chilean Survey of Households Finances of 2007, identify that 17% of the sample corresponded to constrained consumers. [39]

As mentioned above, we assume that, at least, part of the difference in the proportion of constrained individuals observed for developed countries and those found in this study, is the result of the presence of discouraged individuals and those rejected by other financial institutions, who do not even approach the credit union, but were captured by the selection corrections in Tables 4 and 5. Using the 1983 Survey of Consumer Finances (SCF), Jappelli (1990) estimated that discouraged borrowers composed 34% of the total number of credit-constrained individuals.

Table A2 in the Appendix reports some Credit Union characteristics by the status of the credit (rejected and granted). The preferred maturity of loans is between 2 and 4 years, followed by 5 years or more. The average age of a credit holder is around 49 while the average age of a rejected customer is around 39. This estimate matches that of Jappelli (1990), who finds that restricted people are younger.

Table A2 shows the economic conditions of people demanding credit at the credit union. More than 90% of the credits are requested by people living in strata 1, 2 and 3, with monthly earnings of less than COP 1000,000 (about twice the minimum wage during the sample period). Among customers who have their requests approved, 52% are homeowners, while among individuals who are denied credit, this figure is only about 24%. Importantly, 74% of approved credits are repaid through monthly wages (payroll deductions). In the case of rejected applications, this proportion is only 14%. This supports the idea that even in the case of unsecured credits, the credit union prefers credit holders with a good history of repayment and with the possibility of repayments through their monthly wage. An important finding is that people with rejected applications allocate, on average, a high proportion of their income (61%) to repay current debts, while customers with approved applications allocate, on average, half of their monthly income to this purpose.

Using the income, the (external) score, the dummy variable that informs whether the customer will repay the debt from their monthly wage (payroll deduction), and the indebtedness rate, we estimate the probability that a credit request will be granted. The results of probit models estimated by maximum likelihood (ML) are shown in Table 8; given the inclusion of labour income of customers and its potential endogeneity, the models in Columns (1) and (2) show the coefficients estimated by instrumental variables. The difference between the two models is the inclusion in Column (2) of the indebtedness rate. According to the results, the income is significant only in the model of Column (1); in Column (2), that variable is not significant. The coefficients of the score are both significant and with the expected sign as well as those of the payment through the monthly wage. Interestingly, the higher the proportion of the income devoted to repaying debts (indebtedness rate), the lower the probability that the credit requested will be granted. It is important to note at this stage that, given the information used to build the score by credit bureaus, mentioned at the beginning of this section, we regard this variable as exogenous.

According to the Wald tests of exogeneity, we can estimate standard probit models by maximum likelihood. The results in Columns (3) and (4) correspond to the marginal effects where we observe that all derivatives have the expected signs that match with methods used by the credit union to grant or deny consumer credit requests. Note that we differ from many other authors (e.g., Grant, 2007), who instead of the individual's score use demographic and socio-economic characteristics to provide evidence for the probability of restricting a customer. Rather, we directly use one of the most important variables that the credit union employs to make this decision. The importance of the significance of this variable lies in its content on potential opportunistic behaviour and moral hazard by customers.

Once we have also identified liquidity-constrained individuals as those whose applications have been turned down by the credit union, we move to a further step of credit rationing: the difference between the amount requested by the customer and the amount conceded by the credit union. As we have stated above, an individual who has been approved for credit might obtain an amount less than that requested; this is the second step in the process of the restriction carried out by the credit union.

It is important to recall, at this point, that the amount disbursed by the credit union considers that customers must leave a deposit of at least 10% of the amount approved in a saving account at the credit union; this is a condition for membership of the credit union. This deposit, as well as a difference between the amount requested and the amount disbursed higher than 10%, might be indicative of

[38] It is important to mention that a small percentage of individuals who are below the threshold are not exempted from receiving consumer credit in this credit union.

[39] The questions used in the survey to identify the restricted/unrestricted consumers are: How many credit applications have you filled out in the last two years? (Including refinancing); How many credit applications have been rejected? Why did you not apply for credit?': 1. Don't need it; 2. Don't like to apply for credit; 3. Could not pay back; 4. They would not grant it; 5. Already have a credit; 6. Other reason.

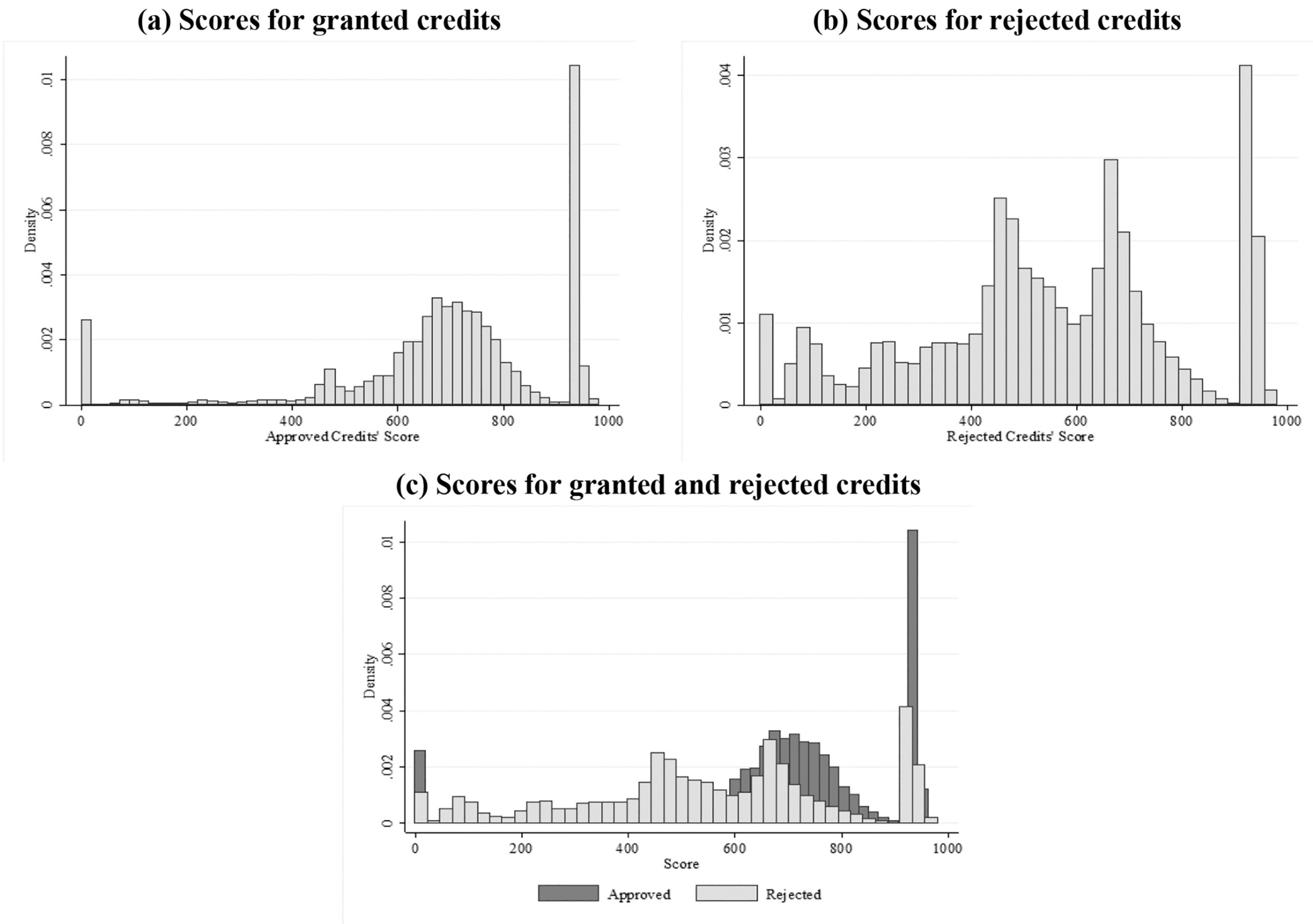

Fig. 2. Distribution of consumer credit scores.
(Source: Credit Union; authors' calculations.)

Table 8
Probability that a credit is granted. 2007–2014.

Variable	ML IV probit		ML probit (marginal effects)	
	(1)	(2)	(3)	(4)
Income	0.118***	0.045	0.006***	0.002***
	(0.017)	(0.030)	(0.001)	(0.000)
(External) Score	0.860***	0.718***	0.058***	0.030***
	(0.011)	(0.124)	(0.001)	(0.001)
Payment through monthly wage (payroll deduction)	1.469***	1.503***	0.181***	0.139***
	(0.012)	(0.015)	(0.002)	(0.002)
Indebtedness rate		−0.335***		−0.014***
		(0.026)		(0.001)
Fixed time effects	Yes	Yes	Yes	Yes
Observations	211,578	201,713	211,578	201,713
Pseudo-R^2	0.273	0.280	0.278	0.282
Wald test of exogenity	2.95	0.03		
p-value of Wald test of exogeneity	0.0857	0.8642		

Note: robust standard errors in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Instruments used in model of Column (1) are: age, age^2, educational attainments (high school, technical school, college, and postgraduate). Instruments used in model of Column (2) are: social strata (stratum 2, stratum 3, and strata 4, 5, and 6).
Source: Credit Union; authors' calculations.

further rationing. This latter situation might reflect the presence of borrowers who are regarded as high-risk customers.

Before discussing the results of this process of restriction, it is also important to mention that some customers who request a new credit but have a current one and still have the 10% deposit corresponding to it in a saving account in the credit union, may use this deposit to complete the 10% deposit for the new credit. In such cases, the difference between the amount requested and the amount disbursed might be less than 10%.

To decide the amount to be disbursed with respect to the amount requested, this financial institution uses the internal score, instead of the external one (as in Table 8). This variable, which corresponds to a risk grade of the individual, is produced by the credit union based on the customer's performance with regards to all her/his outstanding debts in the financial market. If there is any delinquency or default with any of the individual's credits, the internal score is reduced. Thus, this internal credit grade or internal score is understood as the "alignment" of the agent with the financial system. This variable has three types of performance: excellent, good, and bad, each modelled as a dummy variable.

The whole difference is modelled as a function of the individual's labour income, the internal credit grade (internal score) awarded by the credit union for the credit request, payment through the payroll (*libranza*), and the individual's indebtedness rate. The estimates of the difference between the amounts requested and disbursed are shown in Table 9; we present the results of the OLS and 2SLS–IV models, the latter given the potential endogeneity of the individual's income. Columns (1) and (2) correspond to the difference of all credits including those denied; Columns (3) and (4) show the results when the difference between the demand and the disbursement is only for granted credits, while Columns (5) and (6) correspond to differences of less than 10% between those amounts.

The evidence suggests that, as expected, income, internal score, and the payment through monthly wage (payroll deduction) reduce the difference while an individual's indebtedness rate increases it, at least in the models of Columns (1) and (2) in the case of the latter variable.

The coefficient for the income of individuals is negative and significant for any difference in the amounts (Columns (1)–(4)) and is smaller in magnitude for those with a difference of less than 10% (Columns (5) and (6)). Thus, the higher the income of the customer, the smaller the difference between the amount requested and the amount disbursed. Something similar occurs with the grade of individuals. The better the performance of individuals with regards to outstanding debt, the less reduction there is in the requested amounts. An interesting result is related to the method used to repay the debt. When this is done through the monthly payroll, the restriction (the difference) is lower for the models of Columns (1) and (2); however, the sign is positive, increasing the restriction when the difference is computed only for credits granted or for smaller differences. We emphasize the significance and the sign on the indebtedness rate. Accordingly, the higher the level of indebtedness, the higher the difference between the amount requested and the amount disbursed.

Tables 8 and 9 show evidence of further rationing imposed by this financial institution. Thus, using the information provided by the credit union, we are now able to estimate the determinants of the amounts effectively supplied; that is, information about granted resources, including zero amounts, for those whose request was completely denied. Our fully fledged specification to predict the amounts effectively supplied by the credit union to customer i, $\overline{D}_{i,t}$, accounting for possible moral hazard, opportunistic behaviour, and asymmetric information, is [40]

[40] Puri et al. (2011), using a difference-in-difference approach, estimate demand and supply effects of the 2008 financial crisis in Germany. Ramcharan et al. (2016) study the way in which the financial crisis affected the credit supply of credit unions in the United States. They find that the credit supply decreased, especially for those credit unions with weaker capitalization.

Table 9
Determinants of the difference between amounts requested and disbursed.

Variable	Any difference between the requested and disbursed amounts				Credits with differences between 0% and 9.99%	
	All credits requested		Only granted credits		Only granted credits	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Income	−0.031***	−0.068***	−0.030***	−0.066***	−0.001***	−0.016***
	(0.002)	(0.005)	(0.001)	(0.004)	(0.000)	(0.003)
(Internal score) Grade “excellent”	−0.512***	−0.513***	−0.001***	−0.005***	−0.001*	−0.003*
	(0.006)	(0.006)	(0.007))	(0.007))	(0.000)	(0.000)
(Internal score) Grade “good”	−0.428***	−0.433***	−0.082***	−0.090***	−0.002***	−0.007***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.000)	(0.000)
Payment through monthly wage (payroll deduction)	−0.356***	−0.359***	0.212***	0.205***	0.018***	0.015***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.000)	(0.001)
Indebtedness rate	0.021***	0.028***	0.047***	0.052***	0.005***	0.006***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.000)	(0.000)
Constant	1.090***	1.599***	0.471***	0.962***	0.024***	0.023***
	(0.021)	(0.067)	(0.020)	(0.062)	(0.001)	(0.037)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Interaction between internal scores and payment from the labour income	Yes	Yes	Yes	Yes	Yes	Yes
Observations	209,999	209,999	198,812	198,812	98,845	98,845
Adjusted R^2	0.095	0.092	0.156	0.153	0.457	0.164
Hansen J statistic (p-value)		0.063		0.130		0.2076
Kleibergen- Paap Underidentification test p-value)		0.000		0.000		0.000

Note: robust standard errors in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Instruments used in model of Column (2) and (4) are: lags six and twelve of economic situation index and strata 4, 5, and 6. Instruments used in model of Column (6) are: lag three of occupation rate of Medellín and Metropolitan area, and lag six of consumer confidence index.
Source: Credit Union; authors' calculations.

$$\overline{D}_{i,t} = \pi_r r_t + \pi_m m_{i,t} + \pi_S S_{i,t} + Z_{i,t}\pi_Z + X_{i,t}\gamma_S + \mu^S_{i,t}, \tag{10}$$

where r_t is the interest rate, [41] $m_{i,\,t}$ is maturity, $S_{i,\,t}$ is external score, $Z_{i,\,t}$ denotes other financial characteristics of the customer i, such as the internal score, indebtedness rate, and so on, and $X_{i,\,t}$ denotes other observable characteristics. We assume that the interest rate and the labour income of individuals also collect some macroeconomic information relevant for the credit supply.

Tables 10 reports the OLS and IV–2SLS estimates of Eq. (10). We estimate the model of the amounts supplied by the credit union including the zero amounts. The model in Column (1) does not include the variables of indebtedness rate, the (external) score, the (internal scores) grades “excellent” and “good”, which aim to capture any traces of opportunistic behaviour and asymmetric information of the customers. The purpose of omitting these variables is to observe the magnitude, sign, and significance of the coefficient linked to the interest rate; we expect to obtain a negative response that would be interpreted as the portion of the credit supply with a negative slope. However, as we can observe, the coefficient is zero; the credit union does not react to changes in the interest rates. The payment through the monthly wage becomes relevant for the credit union; although this is a non-collateralized credit, living in one's own house increases the amount supplied. Technical, college, and postgraduate education increase the amount supplied with respect to primary education while high school education reduces the amount of credit supplied.

The models in Columns (2) and (3) include the indebtedness rate, the (external) score, and the (internal scores) grades “excellent” and “good” and interchange the determinants of labour income by the income itself. In both columns, the interest rate has a positive sign, suggesting that, once we control for such variables, all significant and with the expected signs, the credit supply increases with the interest rate; that is, the credit supply corresponds to the portion of the positively sloped function. Given that the credit union has denied some credits and reduced some other credit requests, it is now in position to take a higher risk as long as the interest rate is higher. Maturity is also positive and significant, as well as the labour income. In the latter case, when the economy is booming, the credit supply increases. Thus, the behaviour of the supply that we are capturing might well fit the credit-driven household demand channel of Mian and Sufi (2018).

As before, given the potential endogeneity of the interest rate, maturity of credits and labour income, the models in Columns (4) and (5) are estimated by 2SLS–IV. The instruments used in the model of Column (4) are the 12th lag of the overnight interbank interest rate, the 6th lag of the El Niño phenomenon, the 6th lag of the rain regime, and the 12th lag of the economic situation component of the consumer confidence index. Instead of the latter instrument, the model of Column (5) includes a dummy variable for stratum 2, and the 12th lag of the employment rate of Medellín and its metropolitan area.

In Columns (4) and (5), the coefficient of the interest rate is positive. As in models of Columns (2) and (3), the indebtedness rate is

[41] Possibly, instead of the interest rate, a more appropriate variable would be the difference between active and passive interest rates; however, this variable, also called spread, was not available for this research.

Table 10
Determinants of consumer credit supply at the credit union: 2007–2014.

Variable	OLS			2SLS–IV	
	(1)	(2)	(3)	(4)	(5)
Real interest rate	0.000	0.013***	0.010***	0.013*	0.031***
	(0.004)	(0.003)	(0.003)	(0.007)	(0.007)
Maturity in months	0.010***	0.022***	0.021***	0.100***	0.030***
	(0.000)	(0.000)	(0.000)	(0.014)	(0.010)
Log of real labour income			0.600***		0.369***
			(0.013)		(0.074)
Indebtedness rate		−1.586***	−1.537***	−2.717***	−1.665***
		(0.348)	(0.034)	0.205	(0.148)
(External) Score		0.418***	0.405***	0.383***	0.414***
		(0.024)	(0.024)	(0.026)	(0.025)
(Internal score) Grade “excellent”		1.039***	1.031***	1.296***	1.033***
		(0.034)	(0.034)	(0.058)	(0.047)
(Internal score) Grade “good”		0.882***	0.889***	1.350***	0.912***
		(0.038)	(0.039)	(0.092)	(0.074)
Payment through monthly wage (payroll deduction)	1.412***	0.423***	0.446***	0.011	0.362***
	(0.020)	(0.013))	(0.013)	0.074	(0.063)
Age	0.065***	0.037***		0.000	
	(0.003)	(0.002)		(0.007)	
Age^2	−0.001***	−0.000***		−0.000***	
	(0.000)	(0.000)		(0.000)	
High school	−0.135***	0.177***		0.139***	
	(0.016)	(0.024)		(0.016)	
Technical	0.206***	0.462***		0.266***	
	(0.027)	(0.021)		(0.042)	
College	0.542***	0.776***		0.551***	
	(0.031)	(0.025)		(0.048)	
Postgraduate	1.291***	1.360***		1.231***	
	(0.118)	(0.091)		(0.104)	
Family house	−0.155***	−0.075***	−0.081***	0.070**	−0.071***
	(0.021)	(0.017)	(0.017)	(0.032)	(0.024)
Homeowner	0.313***	0.209***	0.103***	0.227***	0.124***
	(0.018)	(0.014)	(0.014)	(0.016)	(0.017)
Other house	−9.612***	−13.761***	−13.809***	−14.284***	−13.916***
	(0.066)	(0.037)	(0.028)	(0.096)	(0.083)
Constant	13.394***	9.779***	2.736***	8.797***	5.160***
	(0.145)	(0.177)	(0.254)	(0.220)	(0.921)
Controls for other active people at home	Yes	Yes	Yes	Yes	Yes
Controls for gender	Yes	Yes	Yes	Yes	Yes
Controls for age and educational attainments	Yes	Yes	No	Yes	No
Controls for strata	Yes	Yes	No	Yes	No
Controls for number of dependent people at home	Yes	Yes	Yes	Yes	Yes
Controls for labour participation conditions	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Hansen test p-value				0.479	0.525
Underidentification test p-value (Kleibergen–Paap)				0.000	0.000
Cragg–Donald Wald F-statistic				47.380	57.145
Stock–Yogo weak ID test critical values 5% maximal IV relative bias				11.04	9.53
Observations	221,862	201,439	201,439	201,430	201,430
Adjusted R^2	0.301	0.512	0.511	0.399	0.508
VIF	3.86	3.89	1.61		

Notes: Robust standard errors in parentheses. *, **, and *** correspond to 10%, 5.0% and 1.0% levels of significance, respectively. The instruments used in model of Column (4) are: the 12th lag of the interbank interest rate (as a proxy for the intervention interest rate), 6-month lag of indicator of the El Niño phenomenon, 6-month lag of precipitation (rain), and the 12th lag of the economic situation component of the consumer confidence index. The instruments in Column (5) are: the 12th lag of the interbank interest rate (as a proxy for the intervention interest rate), 6-month lag of indicator of the El Niño phenomenon, 6-month lag of precipitation (rain), stratum 2, and 12th lag of the occupation rate of Medellín and its metropolitan area.
Source: Credit Union; authors' calculations.

significant and negative. Thus, for customers who dedicate a higher proportion of their monthly income to repay debts, the credit supply is less.

Arguably, the coefficients in Table 10 are biased as we are treating the supply of strictly positive values in the same way as the supply equals to zero (denied credits). To verify the robustness of the findings, the model for credit is also estimated using the concept of censoring that arises when the credit union completely rejects a credit application and supplies a zero amount; this situation recalls the Tobin (1958) problem. Table 11 shows the estimates with a Tobin approach to account for such censoring.

As in Table 10, Columns (1)–(3) do not consider the possible endogeneity of the interest rate, the maturity, and the labour income, while Columns (4) and (5) do. The model in Column (1) ignores the scores, grades, and indebtedness rate to observe the response to the interest rate. In this case, although the coefficient is negative as we would expect, it is not significant; thus, the supply function would be the portion negatively sloped when the variables linked to the risk of the customers are ignored.

The evidence in the rest of models suggests that the higher the interest rate, the higher the supply of credit. As before, the sign of this coefficient is possibly related to the fact that a higher amount of credit conveys a higher risk for the credit union. However, it is willing to assume such a risk because other risk sources, associated with the indebtedness rate and the internal and external scores, are being controlled for. The amount supplied also increases with the income of the customer, the age, the educational attainments, homeownership, and repayment through the monthly payroll.

The models in Column (5) of Table 11 best represent, in our view, the credit supply function of this credit union, which follows normal practices and is supervised by the financial authority in Colombia.

6. Conclusions

This paper presents a coherent and stitched empirical development of the determinants of consumer credit demand and supply using information from a credit union that follows normal practices and is supervised by the financial authorities in Colombia. Of course, the interpretation of results is solely our own. We estimate the determinants of consumer credit demand and supply using monthly microdata from this credit union between 2007 and 2014, accounting for credit constraints and the ways in which these are implemented. This document is the first to present evidence on consumer credit for the case of Colombia by using this type of microdata.

The richness of the data allows us to observe some features of the trade, such as the amounts requested, amounts granted (disbursed), credit requests turned down, interest rates, credit maturity, labour income, an individual's indebtedness rate, the scores assigned by an external credit bureau to credit applicants, internal scores (a variable generated by observing the performance regarding all outstanding debts that individuals have in the financial market), and the demographic characteristics of borrowers. The information is homogeneous in terms of the final use of the credit (consumption).

The number of non-collateralized credit operations (over 220,000) gives robustness to the results and provides evidence about liquidity constraints and rationing in different ways. First, we control for people who do not show any preference for having a positive debt or who are discouraged, or credit constrained. Complementary databases are used to introduce Heckman-type corrections to account for these liquidity constraints in the estimation of the consumer's demand for credit for period 2009–2010. Depending on the specification, these corrections are statistically significant and one of them is interpreted as the first evidence of rationing.

The results for the whole sample show that the real interest rate, the credit maturity, current income, educational attainments, homeownership, and age, among other variables, determine the demand for consumer credit. The elasticity of current income is about 0.648, while the semi-elasticity of the real interest rate is around −0.015%. The semi-elasticity of credit maturity is 0.04 while the coefficient of the indebtedness is around 0.135. Individuals with higher educational attainments demand more consumer credit. A highly robust result is the one related to the indebtedness rates of individuals. Accordingly, a higher proportion of monthly income allocated to pay previous debts increases the demand for credit; however, this result is clearer for customers with indebtedness rate lower than the 25th percentile of the indebtedness distribution.

We also provide evidence of differential semi-elasticities of the interest rate for individuals depending on the quantile of the income distribution to which their income belongs. Customers with income below the 10th percentile of the income distribution are not responsive to the interest rate, which is interpreted as evidence that these individuals have a higher likelihood of being credit-constrained. These customers with limited liquid assets that have high subjective yields find it extremely costly to liquidate such assets to acquire consumer goods. They are, however, responsive to maturity. In addition, it can also be noted that these customers have less alternative credit sources to finance purchases. This lack of possibilities to smooth consumption for these agents affects their well-being and takes weight off the permanent income theory. On the other extreme of the income distribution are customers who are highly responsive to the interest rate. The higher coefficients are estimated for individuals whose income is greater than the 90th percentile and 75th percentile.

In this study, we also analyse the determinants of credit restrictions imposed by the credit union that take place in, at least, two further stages. In the first stage, the financial institution uses the score and other variables, such as income, repayment method and indebtedness rate, to determine which applications are rejected and which are accepted. In the second stage, the rationing occurs when the credit union decides to trim down the amount of some requested credits, after considering the indebtedness rate of the customer and other indicators, such as the internal score or grade. The results allow us to conclude that liquidity constraints do exist in Colombia under the assumption that this credit union follows common practices.

We also estimate the determinants of the amounts supplied (disbursed) by the credit union. The evidence shows that credit supply increases with the interest rate. This finding is possibly related to the fact that a higher amount of credit conveys higher risk for the credit union, but this financial institution is willing to assume it because other risk sources, linked to the indebtedness rate and the internal and external scores, are already accounted for. [42] The credit supply increases with the income of individuals, maturity of the

[42] Maybe, instead of the interest rate, a more appropriate variable would be the spread (difference between active and passive interest rates); however, this variable was not available for this research.

Table 11
Determinants of consumer credit supply at the credit union: 2007–2014.

Variable	Tobin			2SLS–IV Tobin	
	(1)	(2)	(3)	(4)	(5)
Real interest rate	−0.001	0.018***	0.014***	0.029***	0.045***
	(0.005)	(0.003)	(0.003)	(0.009)	(0.008)
Maturity in months	0.009***	0.022***	0.021***	0.094***	0.026**
	(0.000)	(0.000)	(0.000)	(0.013)	(0.010)
Log of real labour income			0.626***		0.352***
			(0.016)		(0.075)
Indebtedness rate		−1.611***	−1.573***	−2.644***	−1.632***
		(0.038)	(0.038)	(0.198)	(0.152)
(External) Score		0.517***	0.499***	0.487***	0.518***
		(0.029)	(0.029)	(0.022)	(0.020)
(Internal score) Grade “excellent”		1.130***	1.126***	1.362***	1.102***
		(0.040)	(0.039)	(0.053)	(0.041)
(Internal score) Grade “good”		0.991***	1.003***	1.417***	0.985***
		(0.044)	(0.044)	(0.086)	(0.070)
Payment through monthly wage (payroll deduction)	1.547***	0.461***	0.478***	0.084	0.411***
	(0.024)	(0.016)	(0.015)	(0.073)	(0.064)
Age	0.071***	0.039***		0.005	
	(0.004)	(0.003)		(0.007)	
Age^2	−0.001***	−0.000***		−0.000***	
	(0.000)	(0.000)		(0.000)	
High school	−0.183***	0.185***		0.150***	
	(0.020)	(0.015)		(0.018)	
Technical	0.175***	0.483***		0.304***	
	(0.032)	(0.025)		(0.041)	
College	0.522***	0.807***		0.601***	
	(0.037)	(0.029)		(0.047)	
Postgraduate	1.303***	1.394***		1.278***	
	(0.132)	(0.097)		(0.096)	
Family house	−0.167***	−0.076***	−0.082***	0.057*	−0.081***
	(0.024)	(0.018)	(0.018)	(0.031)	(0.024)
Homeowner	0.322***	0.207***	0.093***	0.223***	0.124***
	(0.021)	(0.016)	(0.016)	(0.017)	(0.017)
Other house	−11.205***	−19.568***	−19.633***	−20.093***	−19.766***
	(0.095)	(0.236)	(0.237)	(0.152)	(0.147)
Constant	13.513***	9.000***	1.626***	7.908***	4.619***
	(0.125)	(0.210)	(0.295)	(0.199)	(0.931)
Variance	12.050***	6.249***	6.262***		
	(0.103)	(0.073)	(0.073)		
Controls for other active people at home	Yes	Yes	Yes	Yes	Yes
Controls for gender	Yes	Yes	Yes	Yes	Yes
Controls for age and educational attainments	Yes	Yes	No	Yes	No
Controls for strata	Yes	Yes	No	Yes	No
Controls for number of dependent people at home	Yes	Yes	Yes	Yes	Yes
Controls for labour participation conditions	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	221,862	201,439	201,439	201,430	201,430
Censured observations	15,840	10,787	10,787	10,785	10,785
Pseudo R^2	0.070	0.148	0.148		
Wald test of exogeneity				138.88	90.84
Wald test of exogeneity (*p*-value)				0.000	0.000
Wald test				43,570.45	42,487.97
Wald test (*p*-value)				0.000	0.000

Notes: Robust standard errors in parentheses. *, **, and *** correspond to 10%, 5.0% and 1.0% levels of significance, respectively. The instruments used in model of Column (4) are: the 12th lag of the interbank interest rate (as a proxy for the intervention interest rate), 6-month lag of indicator of the El Niño phenomenon, 6-month lag of precipitation (rain), and the 12th lag of the economic situation component of the consumer confidence index. The instruments in Column (5) are: the 12th lag of the interbank interest rate (as a proxy for the intervention interest rate), 6-month lag of indicator of the El Niño phenomenon, 6-month lag of precipitation (rain), stratum 2, and 12th lag of the occupation rate of Medellín and its Metropolitan Area.
Source: Credit Union; authors' calculations.

credit and the scores (internal and external). The sign of the indebtedness rate and the size of its coefficient are more revealing: an increase in the latter reduces the credit supply.

Some implications of these results arise. The monetary authority and the financial supervisory authority, on the one hand, and the financial industry, on the other, should always pay attention to the existence of both restricted and unrestricted consumers to achieve their objectives regarding the behaviour of household's consumer credit, consumption, and welfare as well as the economy in general. The monetary authority, when intervening in the money market, should be more assertive and cautious of not overreacting –for example, increasing excessively the policy interest rate– trying to obtain "an expected" response of inflation expectations and consumption since some agents will not respond to the interest rate changes. By the same token, when monitoring the performance of a particular institution and the consumer credit market, the financial supervisory authority should consider that some demographic groups are unresponsive to the interest rate. This could be the case when, for example, we have a dynamic demand for credit together with high interest rates; the decoupling of these two variables should be interpreted considering the existence of liquidity restrictions. Finally, the financial industry might implement differential mechanisms aimed at increasing the access to consumer credit and the welfare of customers who are more credit constrained. To make the right decisions, all these institutions should know the income distribution, the indebtedness rate, the scores, as well as the demographic characteristics of both actual and potential customers.

Credit author statement

My coauthor, Lina Cardona-Sosa, and I jointly designed the research for our paper, "Consumer credit in an emerging economy: demand, supply, and liquidity restrictions". Lina and I were involved in each stage of the project, from conception to completion. We jointly oversaw data curation and the management of software, made the estimations, and validated the results. We also carried out the analysis of the results, and together we wrote, edited, revised, and corrected previous versions of the paper.

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Appendix

Table A1
Probability of requesting consumer credit and requesting it from the credit union: probit models.

Variables	Requesting consumer credit		Requesting credit from the credit union	
	Coefficients	Marginal effects	Coefficients	Marginal effects
	(1)	(2)	(3)	(4)
Age	0.004***	0.00155***	0.004***	0.000217***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.044***	0.0163***	−0.060***	−0.00366***
	(0.003)	(0.001)	(0.009)	(0.001)
Female head of household	0.257***	0.0983***	−0.040***	−0.00240***
	(0.004)	(0.002)	(0.012)	(0.001)
Primary education	0.376***	0.139***	−0.072***	−0.00443***
	(0.003)	(0.001)	(0.009)	(0.001)
Secondary education	0.703***	0.274***	−0.133***	−0.00725***
	(0.006)	(0.002)	(0.016)	(0.001)
College/technical education	0.799***	0.310***	−0.321***	−0.0154***
	(0.006)	(0.002)	(0.017)	(0.001)
Appliances: fridge	0.186***	0.0673***	0.034*	0.00200*
	(0.005)	(0.002)	(0.019)	(0.001)
Appliances: washing machine	0.162***	0.0603***	−0.047***	−0.00289***
	(0.003)	(0.001)	(0.009)	(0.001)
Appliances: colour television	−0.079***	−0.0295***	−0.042	−0.00252
	(0.007)	(0.003)	(0.029)	(0.002)
Appliances: cable connection	−0.107***	−0.0399***	0.042***	0.00256***
	(0.003)	(0.001)	(0.009)	(0.001)
Appliances: heating	−0.087***	−0.0325***	0.055***	0.00332***

(*continued on next page*)

Table A1 (*continued*)

Variables	Requesting consumer credit		Requesting credit from the credit union	
	Coefficients	Marginal effects	Coefficients	Marginal effects
	(1)	(2)	(3)	(4)
	(0.004)	(0.001)	(0.009)	(0.001)
Appliances: oven	−0.139***	−0.0518***	0.085***	0.00518***
	(0.003)	(0.001)	(0.009)	(0.001)
Appliances: air-conditioning	−0.083***	−0.0311***	0.073*	0.00445*
	(0.014)	(0.005)	(0.039)	(0.002)
Married/cohabiting	0.250***	0.0932***	−0.091***	−0.00561***
	(0.003)	(0.001)	(0.009)	(0.001)
Working	0.818***	0.298***	0.009	0.000541
	(0.004)	(0.001)	(0.016)	(0.001)
Looking for a job	0.239***	0.0920***	0.042	0.00262
	(0.008)	(0.003)	(0.032)	(0.002)
House tasks	0.145***	0.0548***	−0.225***	−0.0117***
	(0.005)	(0.002)	(0.021)	(0.001)
Retired	0.984***	0.377***	0.377***	0.0304***
	(0.007)	(0.002)	(0.020)	(0.002)
Living from rent	0.432***	0.169***	−0.119	−0.00643
	(0.045)	(0.018)	(0.159)	(0.008)
Strata 0 and 1	−0.022	−0.00827	0.072	0.00462
	(0.110)	(0.041)	(0.327)	(0.022)
Stratum 2	0.216**	0.0804**	0.027	0.00163
	(0.110)	(0.041)	(0.327)	(0.020)
Stratum 3	0.269**	0.101**	−0.069	−0.00413
	(0.110)	(0.042)	(0.327)	(0.020)
Stratum 4	0.234**	0.0904**	−0.218	−0.0107
	(0.112)	(0.044)	(0.334)	(0.013)
Contribute to health insurance	0.505***	0.186***	0.242***	0.0132***
	(0.003)	(0.001)	(0.011)	(0.001)
Homeownership	0.132***	0.0489***	−0.040***	−0.00245***
	(0.003)	(0.001)	(0.008)	(0.000)
Number of unemployed at home	0.156***	0.0580***	−0.006	−0.000384
	(0.002)	(0.001)	(0.006)	(0.000)
Adults older than 60			0.040***	0.00241***
			(0.006)	(0.000)
Constant	−1.528***		−2.497***	
	(0.114)		(0.340)	
Observations	1,309,393		505,224	
Pseudo R^2	0.212		0.046	
LR	369,953.9		6334.1	
p-value LR	0.000		0.000	

Note: Standard errors in parentheses. For dummy variables it corresponds to changes from 0 to 1. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.
Source: SISBEN, Financial Supervisory Authority and Credit Union; authors' calculations.

Table A2
Descriptive statistics of credit applications in the credit union: 2007:01–2014:03.

Variable	All credits		Approved credits		Rejected requests		Mean difference	SD
	Mean	SD	Mean	SD	Mean	SD		
Proportion of credits with 1–24 months of maturity	0.21	0.41	0.22	0.41	0.18	0.38	−0.00***	0.000
Proportion of credits with 25–48 months of maturity	0.50	0.50	0.49	0.50	0.56	0.50	0.07***	0.004
Proportion of credits with 49 months of maturity and more	0.29	0.45	0.29	0.45	0.26	0.44	−0.03***	0.004
Log of real labour income	13.68	0.54	13.67	0.52	13.78	0.67	0.11***	0.004
Indebtedness	0.51	0.21	0.50	0.21	0.61	0.20	0.11***	0.000
Age	48.75	16.77	49.50	16.74	39.08	13.92	−10.42***	0.135
Female	0.46	0.50	0.46	0.50	0.47	0.50	0.02***	0.004
Married/cohabiting	0.51	0.50	0.52	0.50	0.32	0.46	−0.21***	0.004
Single	0.28	0.45	0.28	0.45	0.27	0.44	−0.02***	0.004
Separated/divorced	0.06	0.25	0.07	0.25	0.04	0.19	−0.03***	0.002
Widow	0.11	0.31	0.12	0.32	0.03	0.16	−0.09***	0.003
Elementary school	0.33	0.47	0.34	0.47	0.18	0.39	−0.15***	0.004
High school	0.43	0.50	0.42	0.49	0.51	0.50	0.09***	0.004
Technical	0.13	0.34	0.13	0.33	0.17	0.38	0.04***	0.003
College	0.09	0.29	0.09	0.29	0.12	0.32	0.03***	0.002
Postgraduate	0.00	0.07	0.00	0.07	0.00	0.06	−0.00	0.001
Education not reported	0.01	0.10	0.01	0.10	0.01	0.10	−0.00	0.001
Employee	0.39	0.49	0.37	0.48	0.65	0.48	0.28***	0.004

(*continued on next page*)

Table A2 (*continued*)

Variable	All credits		Approved credits		Rejected requests		Mean difference	SD
	Mean	SD	Mean	SD	Mean	SD		
Independent worker	0.04	0.20	0.03	0.18	0.14	0.35	0.11***	0.002
Retired	0.25	0.43	0.26	0.44	0.13	0.33	−0.13***	0.004
Other	0.32	0.47	0.34	0.47	0.08	0.27	−0.26***	0.004
Open-ended contract	0.27	0.44	0.26	0.44	0.45	0.50	0.20***	0.004
Fixed-term labour contract	0.09	0.29	0.09	0.29	0.14	0.35	0.05***	0.002
Learning contract	0.00	0.01	0.00	0.01	0.00	0.02	0.00***	0.000
Contract by association	0.01	0.11	0.01	0.11	0.01	0.11	0.00	0.001
Temporal contract	0.00	0.05	0.00	0.05	0.00	0.06	0.00**	0.000
For tasks	0.01	0.12	0.01	0.11	0.04	0.20	0.03***	0.001
No contract – independent	0.61	0.49	0.63	0.48	0.35	0.48	−0.28***	0.004
Stratum 1	0.19	0.39	0.18	0.39	0.20	0.40	0.01***	0.003
Stratum 2	0.28	0.45	0.28	0.45	0.26	0.44	−0.03***	0.004
Stratum 3	0.45	0.50	0.45	0.50	0.45	0.50	−0.00	0.004
Strata 4–6	0.07	0.26	0.07	0.26	0.09	0.29	0.02***	0.002
Stratum not reported	0.01	0.10	0.01	0.10	0.01	0.10	−0.00	0.001
Family house	0.17	0.38	0.18	0.38	0.12	0.33	−0.05***	0.003
Homeowner	0.50	0.50	0.52	0.50	0.24	0.43	−0.28***	0.004
Rented	0.30	0.46	0.30	0.46	0.29	0.45	−0.01**	0.004
Another type of house	0.04	0.18	0.01	0.10	0.35	0.48	0.34***	0.001
Active people at home: 1	0.35	0.48	0.36	0.48	0.30	0.46	−0.05***	0.004
Active people at home: 2	0.43	0.49	0.43	0.49	0.46	0.50	0.04***	0.004
Active people at home: 3	0.15	0.36	0.15	0.36	0.16	0.37	0.01***	0.003
Active people at home: 4	0.05	0.21	0.05	0.21	0.05	0.22	0.00	0.002
Active people at home: 5 or more	0.01	0.11	0.01	0.11	0.01	0.12	0.00**	0.001
Number of dependent people at home: 1	0.31	0.46	0.31	0.46	0.31	0.46	0.01*	0.004
Number of dependent people at home: 2	0.21	0.41	0.21	0.41	0.20	0.40	−0.01**	0.003
Number of dependent people at home: 3	0.11	0.31	0.11	0.32	0.09	0.28	−0.02***	0.003
Number of dependent people at home: 4	0.04	0.20	0.04	0.21	0.03	0.17	−0.01***	0.002
Number of dependent people at home: 5 or more	0.01	0.09	0.01	0.09	0.00	0.07	−0.00***	0.001
Payment through deductions from monthly payroll	0.69	0.46	0.74	0.44	0.14	0.34	−0.60***	0.004
Observations	222,977		206,874		16,103			

Source: Credit Union; authors' calculations.

References

Agarwal, S., Liu, C., Souleles, N.S., 2007. The reaction of consumer spending and debt to tax rebates—evidence from consumer credit data. J. Polit. Econ. 115 (6), 986–1019. https://doi.org/10.1086/528721.

Alessie, R., Hochguertel, S., Weber, G., 2005. Consumer credit: evidence from Italian micro data. J. Eur. Econ. Assoc. 3 (1), 144–178. https://doi.org/10.1162/1542476053295340.

Arango, L.E., Quevedo-Rocha, I., 2022. Credit Constraints in Colombia: Evidence from the Use of Credit Cards among Low- and Middle-Income Individuals. Mimeo, Banco de la República, Bogotá.

Arango, L.E., Cardona-Sosa, L., Pedraza-Jiménez, N., 2021. The use of credit cards among low- and middle-income individuals in Colombia and the channels of monetary policy. Econ. Model. 94, 150–169. https://doi.org/10.1016/j.econmod.2020.09.018.

Attanasio, O.P., Goldberg, P.K., Kyriazidou, E., 2008. Credit constraints in the market for consumer durables: evidence from micro data on car loans. Int. Econ. Rev. 49 (2), 401–436. https://doi.org/10.1111/j.1468-2354.2008.00485.x.

Bazzi, S., Sumarto, S., Suryahadi, A., 2015. It's all in the timing: cash transfers and consumption smoothing in a developing country. J. Econ. Behav. Organ. 119, 267–288. https://doi.org/10.1016/j.jebo.2015.08.010.

Becerra, Ó., Melo, L.F., 2009. Transmisión de tasas de interés bajo el esquema de metas de inflación: evidencia para Colombia [Transmission of interest rates under inflation targeting: evidence for Colombia]. Cuad. Econ. 46 (133), 107–134. https://doi.org/10.4067/S0717-68212009000100005.

Bertola, G., Disney, R., Grant, C., 2006. The economics of consumer credit demand and supply. In: Bertola, G., Disney, R., Grant, C. (Eds.), The Economics of Consumer Credit. MIT Press, Cambridge, MA, pp. 1–26.

Cox, D., Jappelli, T., 1993. The effect of borrowing constraints on consumer liabilities. J. Money Credit Bank. 25 (2), 197–213. https://doi.org/10.2307/2077836.

Crook, J.N., 2001. The demand for household debt in the USA: evidence from the 1995 survey of consumer finance. Appl. Financ. Econ. 11 (1), 83–91. https://doi.org/10.1080/09603100150210291.

Crook, J.N., 2006. Household debt demand and supply: a cross-country comparison. In: Bertola, G., Disney, R., Grant, C. (Eds.), The Economics of Consumer Credit. MIT Press, Cambridge, MA, pp. 1–26.

Duca, J.V., Rosenthal, S.S., 1993. Borrowing constraints, household debt, and racial discrimination in loan markets. J. Financ. Intermed. 3 (1), 77–103. https://doi.org/10.1006/jfin.1993.1003.

Durkin, T.A., Elliehausen, G., Staten, M.E., Zywicki, T.J., 2014. Consumer Credit and the American Economy. Oxford University Press, Oxford.

Einav, L., Jenkins, M., Levin, J., 2012. Contract pricing in consumer credit markets. Econometrica 80 (4), 1387–1432. https://doi.org/10.3982/ECTA7677.

Einav, L., Jenkins, M., Levi, J., 2013. The impact of credit scoring on consumer lending. RAND J. Econ. 44 (2), 249–274. https://doi.org/10.1111/1756-2171.12019.

Gan, C., Cohen, D.A., Hu, B., Tran, C., Dong, W., Wang, A., 2016. The relationship between credit card attributes and the demographic characteristics of card users in China. J. Bank. Mark. 34 (7) https://doi.org/10.1108/IJBM-09-2015-0133.

Garmaise, M.J., Natividad, G., 2017. Consumer default, credit reporting, and borrowing constraints. J. Financ. 72 (5), 2331–2368.

Grant, C., 2007. Estimating credit constraints among US households. Oxf. Econ. Pap. 59 (4), 583–605. https://doi.org/10.1093/oep/gpm024.

Gross, T., Notowidigdo, M.J., Wang, J., 2014. Liquidity constraints and consumer bankruptcy: evidence from tax rebates. Rev. Econ. Stat. 96 (3), 431–443. https://doi.org/10.1162/REST_a_00391.

Hall, R.E., Mishkin, F.S., 1982. The sensitivity of consumption to transitory income: estimates from panel data on households. Econometrica 50 (2), 461–481. https://doi.org/10.2307/1912638.
Haque, N.U., Montiel, P., 1989. Consumption in developing countries: tests for liquidity constraints and finite horizons. Rev. Econ. Stat. 71, 408–415.
Heckman, J.J., 1979. Sample selection bias as a specification error. Econometrica 47 (1), 153–161. https://doi.org/10.2307/1912352.
Herkenhoff, K.F., 2019. The impact of consumer credit access on unemployment. Rev. Econ. Stud. 86 (6), 2605–2642. https://doi.org/10.1093/restud/rdz006.
Hubbard, R.G., Judd, K., 1986. Liquidity constraints, fiscal policy, and consumption. Brook. Pap. Econ. Act. 1986 (1), 1–59. https://doi.org/10.2307/2534413.
Jappelli, T., 1990. Who is credit constrained in the US economy? Q. J. Econ. 105 (1), 219–234. https://doi.org/10.2307/2937826.
Jappelli, T., Pagano, M., 1994. Saving, growth, and liquidity constraints. Q. J. Econ. 109 (1), 83–109. https://doi.org/10.2307/2118429.
Jappelli, T., Pagano, M., 2006. The role and effects of credit information sharing. In: Bertola, G., Disney, R., Grant, C. (Eds.), The Economics of Consumer Credit. MIT Press, Cambridge, MA, pp. 347–371.
Jappelli, T., Pistaferri, L., 2017. The Economics of Consumption: Theory and Evidence. Oxford University Press, New York, NY. https://doi.org/10.1093/acprof:oso/9780199383146.001.0001.
Juster, F.T., Shay, R.P., 1964. Consumer Sensitivity to Finance Rates: An Empirical and Analytical Investigation. National Bureau of Economic Research, pp. 6–46. http://www.nber.org/books/just64-2.
Keys, B.J., Tobacman, J., Wang, J., 2018. Rainy Day Credit? Unsecured Credit and Local Employment Shocks. Working paper.
Ludvigson, S., 1999. Consumption and credit: a model of time-varying liquidity constraints. Rev. Econ. Stat. 81 (3), 434–447. https://doi.org/10.1162/003465399558364.
Maddala, G.S., 1983. Limited-Dependent and Qualitative Variables in Econometrics. In: Econometric Society Monographs 3. Cambridge University Press, Cambridge.
Maddala, G.S., 1992. Introduction to Econometrics, 2nd edn. Macmillan, New York, NY.
Magri, S., 2002. Italian Households' Debt: Determinants of Demand and Supply. Temi di Discussione, Working Paper No. 454. Taken from: https://www.bancaditalia.it/pubblicazioni/temi-discussione/2002/2002-0454/index.html?com.dotmarketing.htmlpage.language=1.
Magri, S., 2007. Italian households' debt: the participation to the debt market and the size of the loan. Empir. Econ. 33 (3), 401–426. https://doi.org/10.1007/s00181-006-0107-0.
Mariger, R.P., 1987. A life-cycle consumption model with liquidity constraints: theory and empirical results. Econometrica 55 (3), 533–557. https://doi.org/10.2307/1913599.
Mester, L.J., 1997. What's the point of credit scoring?. In: Business Review, Federal Reserve Bank of Philadelphia, September–October, pp. 3–16.
Mian, A., Sufi, A., 2018. Finance and business cycles: the credit-driven household demand channel. J. Econ. Perspect. 32 (3), 31–58.
Ponce, A., Seira, E., Zamarripa, G., 2017. Borrowing on the wrong credit card? Evidence from Mexico. Am. Econ. Rev. 107 (4), 1335–1361.
Puri, M., Rocholl, J., Steffen, S., 2011. Global retail lending in the aftermath of the US financial crisis: distinguishing between supply and demand effects. J. Financ. Econ. 100 (3), 556–578. https://doi.org/10.1016/j.jfineco.2010.12.001.
Ramcharan, R., Verani, S., Van den Heuvel, S.J., 2016. From wall street to main street: the impact of the financial crisis on consumer credit supply. J. Financ. 71 (3), 1323–1356. https://doi.org/10.1111/jofi.12209.
Ruiz-Tagle, J., Vella, F., 2016. Borrowing constraints and credit demand in developing economy. J. Appl. Econ. 31, 865–891. https://doi.org/10.1002/jae.2465.
Runkle, D.E., 1991. Liquidity constraints and the hypothesis. J. Monet. Econ. 27 (1), 73–98. https://doi.org/10.1016/0304-3932(91)90005-9.
Scholnick, B., 2013. Consumption smoothing after the final mortgage payment: testing the magnitude hypothesis. Rev. Econ. Stat. 95 (4), 1444–1449.
Shapiro, M.D., Slemrod, J., 2003. Consumer response to tax rebates. Am. Econ. Rev. 93 (1), 381–396.
Shapiro, M.D., Slemrod, J., 2009. Did the 2008 tax rebates stimulate spending? Am. Econ. Rev. 99 (2), 374–379.
Sullivan, J.X., 2008. Borrowing during unemployment: unsecured debt as a safety net. J. Hum. Resour. 43, 383–412. https://doi.org/10.1353/jhr.2008.0016.
Tobin, J., 1958. Estimation of relationships for limited dependent variables. Econometrica 26 (1), 24–36.
Zeldes, S.P., 1989. Consumption and liquidity constraints: an empirical investigation. J. Polit. Econ. 97 (2), 305–343. https://doi.org/10.1086/261605.