Determinants of Households' Default Probability in Uruguay

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Abstract

This paper estimates models on the default probability of households in Uruguay considering sociodemographic and financial characteristics using data obtained from the second edition of the Household Financial Survey and the Continuous Household Survey. It studies the differences between the nonmortgage credit and credit card segments. Household income, the relation between income and expenditure, and the age of the household head are significant for explaining default probability in all the segments, while the education of the household head is only relevant for the nonmortgage credit segment. Furthermore, we apply the results of the model to assess the impact on household debt default by the obligation to pay salaries through electronic media introduced by the Financial Inclusion Law. According to the results, having a bank account increases the number of households with nonmortgage and credit card debt. However, in the former segment the group of households that take out nonmortgage credit is riskier and the debt default rate remains at the same level.

Keywords: financial stability, Uruguay, financial survey, indebtedness.
JEL classification: G19, G01, C5.

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1. INTRODUCTION

Determining the individual and financial characteristics of households that make a statistically significant contribution to the probability of debt default is important for monitoring credit risks and their impact on financial stability. The aim of this study is to estimate models that explain households' debt default based on their demographic and financial characteristics and considering different credit segments. For this purpose, it employs data for Uruguay taken from the second edition of the Household Financial Survey (EFHU2) conducted in 2013 by the Economics Department, Social Sciences Faculty, Universidad de la República, and the Continuous Household Survey (ECH) conducted by the Instituto Nacional de Estadística, de Uruguay (INE) during 2012. This information was used to create a nationally representative database of 3,490 households. The results obtained show that factors determining debt default differ according to the credit segment studied. For instance, education is only significant when considering the nonmortgage credit segment, and income ceases to be significant when considering delinquency on credit card payments. Meanwhile, the relevant sociodemographic variables are those referring to individuals with most knowledge of a household's financial matters, the reference person[1] according to the EFHU2, and not the individual that makes the significant contribution in terms of income.

Models on the default probability of households in Uruguay allow for forecasting their behavior and vulnerability to macroeconomic conditions, as well as assessing the policies that affect debt default probability. The Financial Inclusion Law (No. 19210) of April 29, 2014, imposes the payment of salaries through electronic media. As one application of the models estimated, a forecast was made for the impact of the said measure on debt delinquency and therefore on the default rate of the financial system as a whole.

According to the results, having a bank account increases the number of households with nonmortgage credit and credit cards. However, in the former segment the household group using nonmortgage

1 The reference person (RP) is the person in a household who is most familiar with the economy of all its members. It is the individual who is in charge of financial matters and is familiar with expenses, income, assets, and investments, among others.

credit is riskier and the credit default rate increases, while in the credit card segment the default rate remains unchanged, given that the group using them has the same average risk as that for credit cards before the reform.

The paper is organized as follows. Section 2 presents a review of the literature on the determinants of household debt default. Section 3 briefly describes the data and variables used in the models. Section 4 describes the methodology employed for estimating the debt default probability models. Section 5 presents the results of the model estimations. Section 6 performs an assessment, based on the models developed in the previous sections, of the impact of the obligation to pay salaries via electronic media established in the Financial Inclusion Law on debt default rates among households. Finally, Section 7 presents some final remarks.

2. LITERATURE REVIEW

The literature on the determinants of household debt default includes a set of empirical works that study the relation between the sociodemographic and financial characteristics of households and their debt default using data from household financial surveys. The aforementioned studies include that presented by Costa (2012) that estimates, employing logit models, a probability of default for households which depends on their economic and sociodemographic characteristics, as well as taking into account the existence of shocks that adversely affected their financial situation. To do this, the study uses data from Portugal's household finance and consumption survey and finds a higher probability of debt default for households with lower levels of income and wealth and higher levels of expenditure. The probability of default is also higher for households with children and whose reference person is unemployed or has a lower than tertiary education. Recent adverse changes in the financial situation of households also have a positive and significant correlation with debt default probability. We identify the same outcomes for Uruguay in terms of income and the relation between income and expenditure. The probability of debt default is lower if the household head is in formal employment or retired than if they are unemployed or in informal employment.

Meanwhile, Alfaro et al. (2010) use the Household Financial Survey of Chile to estimate probit models in pursuit of personal and financial characteristics that have an impact on the average probability of household debt default. They study mortgage and consumer default separately given that, as mortgage debt is guaranteed by the real estate as collateral, it can be assumed that households' behavior differs for these two types of debt. According to the results, the variables of income and access to the banking system are significant for both types of loan, while the sex and marital status of the household head are not significant. On the other hand, although education, the number of individuals within the household that contribute to the total family income, age, and financial burden are not significant for mortgage credit, they are for consumer credit. They do not find any evidence that the loan-to-value ratio is significant for mortgage debt. It is not possible to perform an analysis of the mortgage market in this paper, given the few defaults observed in that segment. Furthermore, unlike the estimation for Chile, the sex of the household head and whether they live with their partner are significant. Meanwhile, the financial burden is significant for the credit card segment, but not for the nonmortgage credit segment, although only in the conditional probability models.

For the unconditional probability estimation, Alfaro et al. (2010) use a first stage equation for the probability of a household having debt and a second stage to estimate the unconditional probability, adding the logistic transformation of the probability of debt default estimated in the first stage as a dependent variable. To analyze default probability in Uruguay, we estimate the bias-corrected (heckprobit) models proposed by Van de Ven and Vann Praag (1981). The unconditional probability model is corrected by the fact that debt default is only observed for households with debt. This methodology is proposed for analyzing the probability of debt default by Baum (2006), considering a selection model with a binary variable that takes the value of one if the individual has a loan and zero if not. This is also used by Valdés (2016) to analyze the determinants that influence the ownership and usage of debit and credit cards. Larrañaga and Olivari (2005) employ a heckprobit estimation to study the determinants of whether an individual has a debt considering a binary selection variable that indicates when an individual has a university degree.

Fuenzalida and Ruiz-Tagle (2009) adopt another approach to analyze households' financial vulnerability. They measure the risks of indebtedness among households under different unemployment scenarios, defining debt at risk as that of households with financial burden to income ratios of between 50% and 70% and a negative financial margin, that is, total expenditure is more than 20% higher than the household's income. They find that the main source of fragility among households is the loss of income, particularly employment income. The authors use panel data survival analysis for different aggregate unemployment levels to estimate the probability of employment at the individual level, taking into account sociodemographic characteristics and calculating the impact on aggregate debt at risk among households.

Iregui et al. (2016) study the determinants of the probability of a household being delinquent on at least one of its loans in Colombia based on data obtained from the Colombian Longitudinal Survey of the Universidad de los Andes. The paper presents logit estimations for a sample of households with loans and for a sample of households with loans whose head is also in employment. According to the results, if the head is male, the probability of a household being delinquent on at least one loan increases for urban areas. Meanwhile, this probability decreases for households with higher levels of income or whose head lives with their partner. They find that the higher the number of household members, the greater the probability of a household being delinquent on its debt. In the estimations performed for Uruguay, we find evidence to support the fact a larger number of household members increases the probability of default and that households whose head is male have a greater debt default probability in the nonmortgage credit segment in the conditional probability model.

One of the most important studies on Uruguay is that of Mello and Ponce (2014) who study the determinants of households' indebtedness using data from the Uruguayan Household Survey and the Continuous Household Survey of 2012. They analyze households' borrowing decisions using probit and logit estimations and conclude that variables related to having access to financial services, particularly those that take into account a prior relation with the bank and the use of credit and debit cards as payment media, have the largest impact on a family's borrowing decisions. Other variables related to income distribution, the household head's employment status and having bank savings also have a significant influence on the probability of taking out a loan. In the same paper, the authors study the characteristics that best explain levels of indebtedness among households and the determinants of their financial burden.

Finally, also for the case of Uruguay, Borraz and González (2015) analyze financial risk in the country, simulating a negative income shock similar to the one in 2002, and using data from the Uruguayan financial survey. They find the risk is modest because, although a shock with such characteristics increases the number of households with a financial burden above 0.75 by 175%, this group only represents 10% of the population.

3. DATA AND VARIABLES

3.1 Data

Two databases were used in this paper: the 2012 Continuous Household Survey (ECH) conducted by the National Statistics Institute of Uruguay (INE), and the second edition of the Financial Survey of Uruguayan Households (EFHU2) conducted by the Department of Economics, Faculty of Social Sciences, Universidad de la República in 2013. The EFHU gathers information that describes the composition of households' asset and liability portfolios and includes data on real assets and related debts, nonmortgage loans, businesses owned by the household, income and employment history, financial assets, payment media, insurance policies and personal income plans, and consumption and saving. Given the type of data they collect, there is usually a high proportion of nonresponses in economic and financial surveys. The pattern of missing data is generally not random, meaning that making estimations only using households for which data is available tends to generate bias in the estimation. One of the features of the second edition of the EFHU is its treatment of nonresponses. For the missing data, it uses a stochastic multiple imputation approach with ten imputations and 100 iterations, whose aim is to recreate the distribution of variables with missing data. A detailed description of the method employed is presented in the document "Methodology of the 2014 Financial Survey of Uruguayan Households (EFHU2) and User Guide" (Decon, 2016).

The EFHU is used to analyze the probability of default among households with data available on a total of 3,490 households. Nonmortgage loans and credit cards are considered separately. Nonmortgage debt includes debt a household has with banks, financial companies and commercial establishments, family, friends, moneylenders, and automotive companies, etc. This category includes personal loans the household took out for their business and excludes credit card debt, debts to the state and debts from real estate purchases. Credit card debt includes credit from credit cards issued by commercial banks, cooperatives, and consumer loans companies. It does not consider the mortgage credit segment given the reduced level of delinquency observed in that type of debt.[2]

3.2 Variables

The variables used for specifying the models and the expected relation, according to the literature, between them and debt default probability are presented below.

3.2.1 Dependent Variables

Nonmortgage debt default: A household is considered to be in nonmortgage debt default if it is paying some nonmortgage loan and declares itself delinquent in its payments. Nonmortgage debt encompasses all loans the household has except credit card debt, loans from the state, and debt from purchasing, constructing, or remodeling real estate.

Credit card debt is considered separately from nonmortgage credit given that 38% of the population has credit cards, but do not have nonmortgage credit. Moreover, the importance of nonbank card operators in the Uruguayan market should also be pointed out. 45% of cards are issued by nonbank operators (Banco Central del Uruguay, 2016).

We consider two default situations for the credit card segment:

1) *Credit card default in the broad sense:* A household has defaulted on a credit card in the broad sense if any member of the household has fallen into to delinquency with credit card payments during the last year.

[2] A total of 11 mortgages in arrears were observed, representing 10% of the all households with this type of debt.

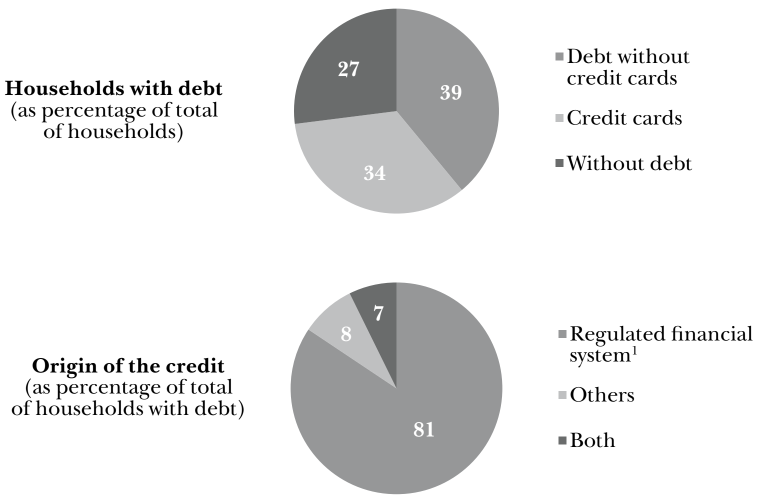
2) *Credit card default in the strict sense:* A household has defaulted on a credit card in the strict sense if any member of the household has fallen into delinquency with credit card payments during the last year and said delinquency was for more than three months.

Separation into these categories is possible using information from the EFHU, while default in the broad sense is a transitory delay in payment, default in the strict sense responds to more permanent delinquency.

In the sample, 73% of households has some type of debt. When credit card debt is excluded, this figure falls to 39%[3]. The 81% of the debt (excluding credit cards) is granted by institutions regulated by the central bank, while 8% of the households obtain credit from institutions not regulated by the central bank, as well as from friends, private individuals, or family members (Figure 1).

Figure 1

URUGUAYAN HOUSEHOLD DEBT



[1] Regulated financial system: banks, financial entities, savings and credit unions.
Source: own elaboration using the EFHU database.

[3] The Annex shows the breakdown by credit segment (Table 1).

The 18% of the households which have some debt are delinquent on their payments. If we consider credit card default in the strict sense, this figure decreases to 7%. Out of the households with mortgage debt, 4% are delinquent in their payments. In the nonmortgage credit segment delinquency is 10%, while in credit cards it is 17%, and 3% when considering default in the broad sense and strict sense, respectively.

3.2.2 Independent Variables

Households' sociodemographic and financial characteristics were employed to specify the models. The characteristics included in the models are those which according to the literature and other previous empirical studies influence the probability of default among households.[4]

Sociodemographic variables refer to the household head. Two definitions are used for household head which are tested alternatively. First, the head is considered as the individual who is most familiar with the economy of all members of the household, that is, the person in charge of financial matters with knowledge of expenditures, income, assets, investments and is the reference person according to the EFHU. Second, the household head is considered as the individual who makes the greatest contribution to household income. In this case, the sociodemographic characteristics are obtained from the ECH. For financial variables, such as income, information is included for all household members.

3.2.3 Sociodemographic Variables

Sociodemographic variables include sex, whether the household head lives with their partner, their age, education, and whether they are in formal employment or are retired, the proportion of workers among all the household members, the number of household members, and whether there are children in the household.

Sex: Incorporated through a binary variable that takes the value of one if the household head is a man, or zero if is a woman.

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[4] Characteristics linked to the loans were not included because 20% of households in the sample have more than one loan with different features as regards term, interest rate and denomination currency, among others.

The relation between sex and debt repayment is not conclusive in the literature. D'Espallier et al. (2009) identify three causes that explain why women are less likely to default on their debt. First, women are more conservative and cautious in their investment strategies which translates into better debt repayment. Second, women are more restricted in their access to different credit channels and they therefore have a stronger incentive to repay and ensure continued access to financing. Finally, women are more responsive to coercive enforcement methods applied by institutions. Lower geographical and employment mobility among women also increases the effectiveness of institutions' collection efforts. The empirical results are not conclusive. Marrez and Schmit (2009), and Ormazabal (2014) find evidence to support that women are less likely to fall into delinquency. Meanwhile, Alfaro et al. (2010) do not find sex to be statistically significant as a determinant of the default probability for consumer and mortgage credit.

Cohabitation: A binary variable is included that is equal to one if the household head lives with their partner, and zero otherwise.

According to the literature, if the marital status of the household head is married or living with their partner the probability of debt default is lower. The reason behind this effect is that such households are less sensitive to income shocks given that they tend to have two incomes. Alfaro et al. (2010) do not find evidence to support this relation. Özdemir and Boran (2004) find a statistically significant and negative relation between debt default and the debtor being married.

Age: Age (in years) of the household head.[5]

Age is a demographic variable that is usually included as a determinant of debt default. The literature states that default probability is possibly higher when the household head is younger, becoming lower as age increases. Individuals make more investments in their youth, they also have greater expenses and lower incomes (Alfaro et al., 2010). To analyze the impact of age on the probability of default a variable representing the age of the household head is included.

[5] The relationship between default probability and age is linear. Models are estimated that include age squared, but the relationship is not statistically significant and for that reason only age is represented in the models. Meanwhile, the relation between indebtedness and age is quadratic.

Level of education: A binary variable is used that is equal to one if the individual has completed a bachelor's or higher university degree, and zero otherwise.[6]

According to the literature, the level of education of the reference person in the household has a significant and negative effect on debt default probability because more educated individuals have a greater ability to make decisions on their financial situation. Moreover, education is positively correlated with income, which reduces the probability of debt default. Costa (2010) finds evidence to support this relation. Alfaro et al. (2010) find that education is only a significant determinant of mortgage debt default and is not significant for nonmortgage debt.

Proportion of household members in employment: The proportion of household members with paying jobs is used as an explicative variable.

The larger the proportion of family members with paying jobs, the less sensitive the household is to income shocks, meaning their probability of debt default should be lower. Alfaro et al. (2010) find a significant relation between the proportion of household members with paying jobs and debt default probability, but with an opposite sign. They explain this relation based on job security and the motivation behind the number of people working in a household. On the one hand, households belonging to the lowest income quintiles are those with less education and therefore access to less qualified jobs and more vulnerable to changes in macroeconomic conditions. People belonging to higher income quintiles tend to be better educated and have access to more qualified and stable jobs. These results are demonstrated by Fuenzalinda and Ruiz-Tagle (2009). Lower income households with more vulnerable job sources might have greater incentives for more members of the household to work than richer households. Furthermore, the fact that a larger number of members work does not imply that a household has a higher income. This is true if the income earned by households with more members

[6] No information is available on the number of years in education as a continuous variable given that data contained in the EFHU is an ordinal variable for different levels of education. Different levels of education are tested and that of bachelor's or higher degree is reported because it is statistically significant.

in paying jobs are on average lower than the income generated by households with less members in employment.

Household members: Number of household members.

A variable used to characterize the structure of a household. The literature generally finds a positive and significant relation between the number of household members and debt default.

Children: A binary variable that takes the value of one if the household head's children live at home, and zero otherwise.

Costa (2010) finds evidence that households with children living in them have a higher probability of debt default than those whose members are all adults. The study we elaborate for Uruguay only considers whether any of the household head's children are living at home regardless of their age.

Formal employment: A binary variable that takes the value of one if the household head is an employee and makes pension contributions.

Formality is associated with a more stable employment situation. It should be expected that being formal reduces a household's debt default probability.

Retired: A binary variable that takes the value of one if the household head is retired or receives a pension.

Just as with formal employees who have a stable monthly income, it should be expected that being retired or a pensioner reduces a household's debt default probability.

The omitted group is composed of households in which the head is unemployed or in formal employment.

3.2.4 Household Financial Variables

Financial variables include income, the financial burden of the household, the relation between expenditures and income earned by the household, and the type of institution or individual that grants them credit.

Income: To analyze the impact of income on default probability, the log of monthly household income obtained from the ECH is included.

Most empirical works find a significant and negative relation between income and the probability of debt default among households, Costa (2010), Alfaro et al. (2010), Ormazabal (2014).

Financial burden: A binary variable is included that takes the value of one if a household declares it spends more than 75% of its income on loan repayments, and zero otherwise.

According to Alfaro et al. (2010), borrowers will avoid defaulting on their debt as long as they have sufficient income to cover the repayments. They test different thresholds of the financial burden declared by households, finally selecting one at 75% because it is statistically significant. This threshold is also used by Fuenzalinda and Ruiz-Tagle (2009), who define households with a financial burden of more than 75% of their income as those with a high financial burden. It is to be expected that households with a high financial burden have a greater probability of defaulting on their debt.

Relation between household expenditure and income: A binary variable that adopts the value of one if a household's expenditures are higher than its income, and zero otherwise.

A household might find it difficult to repay their debt because the expenses it incurs are higher than the income it earns. Households with expenditures higher than their income are expected to have a greater probability of defaulting on their debt.

Number of credit cards: The number of credit cards a household has. Used for the credit card segment.

Considers all the credit cards a household has. If a relation exists between the number of credit cards and default probability it should be positive. A larger number of credit cards implies more debt or contingent debt for the household.

Regulated sector: A binary variable that is equal to one if at least one of the loans is granted by an institution regulated by the central bank, and zero otherwise.

This variable is included in the model estimated for each credit segment in order to determine whether the probability of debt default is higher or lower for loans granted by the financial system regulated by the central bank as compared to loans from other sources.

Banking sector: A binary variable that is equal to one if all the loans are granted by the banking sector, and zero otherwise.

This variable is included in the model estimated for the regulated sector in order to determine whether there are any differences between the banking sector and other financial institutions regulated by the central bank.

Table 1 shows the descriptive statistics used in the estimations.

Table 1

DESCRIPTIVE STATISTICS

Variable	*Observations*	*Mean*	*Standard deviation*	*Min*	*Max*
Nonmortgage debt	3,490	0.341	0.474	0	1
Nonmortgage debt default	1,191	0.102	0.303	0	1
Credit card	3,490	0.615	0.487	0	1
Card default	2,146	0.169	0.375	0	1
Card default (strict sense)	2,146	0.025	0.157	0	1
Male	3,490	0.360	0.480	0	1
Cohabits	3,490	0.573	0.495	0	1
Age	3,489	51.578	16.470	17	100
University	3,490	0.210	0.407	0	1
Log (income)	3,489	10.408	0.743	7.31	13.64
Proportion of workers	3,490	0.566	0.339	0	1
Members	3,490	3.003	1.663	1	15
Children in the household	3,490	0.551	0.497	0	1
Expenditures higher than income	3,483	0.148	0.355	0	1
High financial burden	3,442	0.035	0.185	0	1
Formal employment	3,490	0.458	0.498	0	1
Retired	3,490	0.229	0.420	0	1
Unemployed or informal employment	3,490	0.313	0.464	0	1
Regulated sector	3,490	0.301	0.459	0	1
Banking sector	1,051	0.532	0.499	0	1
Number of credit cards	3,490	1.405	1.713	0	20

Source: EFHU2 and ECH.

4. METHODOLOGY

We propose two models to explain household debt default, one conditional on having debt and another unconditional on having debt. The conditional model explains the determinants of default for households that have debt, while the unconditional model allows for obtaining the determinants of default for all households in the sample when it is considered there might be selection bias. In this case, selection bias can be determined because the decision of the household to have debt and not pay it is not independent. We test for this in the nonmortgage credit segment and that of credit card default in the broad sense.

All the estimations use household weights, so the results are nationally representative. These weights can be found in the EFHU database.

4.1 Conditional Estimation

A probit model is estimated for the credit card and nonmortgage debt segments. The aim is to be able to determine which financial and demographic characteristics are significant for each segment, as well as analyze whether there are differences in the variables explaining default among said segments.

Two models are specified for each segment. The first model refers to all the households that have at least one loan in that segment, adding the regulated sector as an independent variable in order to determine whether the debt default probability is different according to the type of institution or individual granting a loan. The second model only considers households in which at least one loan is granted by the regulated financial system.

$$\text{Model } \Pr\left(y_i \middle| x_i = 1\right) = F\left(Z_i \beta\right),$$

where, y_i is a binary variable that takes the value of one if household i is not up to date on its debt payments and zero if it is;[7] x_i is a binary

[7] For the credit card segment two definitions of default are considered and two models are estimated. The first of them defines household default in the broad sense as when any member of the household has fallen into delinquency on credit card payments during the last year. In the second we define that a household is delinquent in the strict sense if such payments are more than three months overdue.

variable that is equal to one if household i has a debt in the credit segment being analyzed; Z_i is a vector of independent sociodemographic and financial variables including the regulated sector variable. The number of credit cards is included as an explicative variable in the models for the credit card segment. And F is the standard cumulative distribution function.

4.2 Unconditional Estimation

To estimate the probability of default by unconditional credit segment the information from all the households in the sample is used to estimate a heckprobit model.

This estimation is important given the selection bias that might exist in the conditional models towards households with debt if their decision to have debt and default on it are related. In this case we can say that selection bias exists and the estimation used to determine the effects of model variables should be the unconditional one, or the estimations will be biased.

In light of the above, we estimate three models: a model for the nonmortgage credit segment, another for credit card default in the strict sense, and a model for credit default in the broad sense.

To estimate the unconditional probability, we define y_{1i} as a dichotomous variable that takes the value of one if the household is delinquent in its debt repayments, and zero if not. We also define y_{2i} as a dichotomous variable that takes the value of one if the household has debt in the credit segment being analyzed and zero if it does not.

$$y_{1i} = \begin{cases} 1 \text{ if } \ y_{1i}^{*} > 0 \ \text{ and } \ y_{2i} = 1 \\ 0 \text{ if } \ y_{1i}^{*} \leq 0 \ \text{ and } \ y_{2i} = 1 \\ \text{there are no observations if } y_{2i} = 0 \end{cases} .$$

where y_{1i}^{*} is a latent variable for the debt payment decision of the household. Selection takes place in this model and we observe y_{1i} if y_{2i}=1. The selection equation is written as follows:

$$y_{2i} = \begin{cases} 1 \text{ if } \ y_{2i}^{*} \geq 0 \\ 0 \text{ if } \ y_{2i}^{*} \leq 0 \end{cases}$$

where y_{2i}^{*} is a latent variable on the decision to acquire a loan or have a credit card for the credit segment. Following Mello and Ponce (2014) the decision for requesting a loan is theoretically derived from the maximization of some utility function which depends on credit. A household contracts debt if the utility of consumption financed with debt exceeds the cost of such financing.

The equations for the latent variables in this model are:

$$y_{1i}^{*} = x_i \beta + v_{1i} \, ,$$

$$y_{2i}^{*} = z_i \beta + v_{2i} \, .$$

It assumed that the vector (v_{1i}, v_{2i}) has bivariate normal distribution with mean (0, 0)variance (1, 1) and correlation ρ.

The selection equation determines the probability of a household contracting nonmortgage or credit card debt and is estimated based on some of the variables suggested by the model presented in Mello and Ponce (2014). To correctly identify the model there should be at least one variable in the selection equation that is not present in the original equation. In the models presented, this binary variable takes the value of one if the household has a bank account, and zero otherwise. The exclusion variable, having a bank account, is a variable of access to the financial system and is positively and significantly correlated with a household having debt (Mello and Ponce, 2014). However, there is no relation between having a bank account and a household's decision to pay its debt.

$$\text{Selection equation} \quad \Pr\left(y_{2i}\right) = F\left(C_i \beta\right),$$

where F(·) is the standard cumulative distribution function; y_{2i} is a binary variable that is equal to one if household i has a debt in segment i, and zero otherwise; and C_i is a vector of regressors that includes a group of binary variables that indicate whether a household has a bank account, if there are children in the household, if the head has a bachelor's or higher degree, and if the head is in formal employment or retired. Moreover, age, age squared, the number of members, and the log of household income are added as regressors.

We test with all the independent variables used for the probability of debt default and only those that are significant for explaining the probability that a household has nonmortgage or credit card debt, using a backward selection approach [8] that eliminates the regressors with a p-value higher than 0.1, are left in the selection equation. Furthermore, a binary variable is added that identifies households with a bank account.

Given that the aim is to assess the effects of default probability on credit granted by the regulated financial system in the nonmortgage credit segment, only households with loans from regulated institutions are considered.

Because the assumption of normality is strong and the effects of the parameters in the decision to acquire debt might be non-linear with the decision not to pay it, Alfaro et al. (2010) propose an alternative method. They define the effect of the first stage (decision to have debt) on the second stage (debt default decision) of household i as the logistic transformation of the probability of an individual having a debt $G_i=g(PX_i)$, where g is the logistic transformation and PX_i is the probability that $y_{2i}=1$. Furthermore, the standard errors are adjusted by a bootstrapping procedure with 2,000 replications.

The same estimation proposed by Alfaro et al. (2010) is carried out to compare the results with the heckprobit estimation. The results, which are presented in the Table A.3, show that the logistic transformation and its second-degree polynomial are not significant in the models estimated.

5. RESULTS

5.1 Conditional Probability of Default Model for the Nonmortgage Credit Segment

Two conditional probability models are estimated. The first considers total nonmortgage credit and the regulated sector variable is added as a control. A second model is then estimated that only considers households with at least one loan granted by a regulated

[8] Backward selection of variables estimates a model with all the regressors of interest and then eliminates those that are least significant, starting with the one with the highest p value. This method uses the *stepwise [, options]* Stata command to select variables and the level of significance established for the estimations is 0.10. In this way, the method eliminates all the variables with a p above 0.10.

financial institution and the probability of default on nonmortgage debt is estimated. The banking sector variable is added to the second model as a control. The results are shown in Table 2.

The sociodemographic variables that are significant in the conditional probability model include age, sex, type of employment of the household head, whether they live with their partner, and the number of household members. The probability of mortgage credit default is less for households where the household head lives with their partner and where the household head is older. Meanwhile, if the household head is male or the household has more members the probability of debt default is greater. If the household head is in formal employment or retired the probability of default is less than for households where the head is unemployed or in informal employment.

Among the financial variables, income and the relation between current expenditures and income are significant. In households where current expenses are higher than the income the probability of debt default is larger. The higher the income of a household the less likely it is to default on its debt. If the household has at least one loan granted by the regulated sector, the probability of debt default is also higher. The latter result is related to the fact that besides banks the regulated sector also encompasses financial companies and savings and credit cooperatives, which have a higher default rate than banking institutions.

This is supported by the model estimated for default on nonmortgage credit granted by the regulated sector where a binary variable is added (banking sector) that takes the value of one if all a household's loans are from the banking sector, and zero otherwise. The variable is significant with a negative sign, meaning that if the credit is granted by the banking system the probability of default is lower than if it is granted by other types of regulated institutions. The estimated average probability of default in the conditional nonmortgage credit segment is 9.5%, while the estimated average default for loans granted by the banking system is 3.4 percent.

When the household head is considered as the member making the largest contribution to household income, variables such as living with a partner, and variables linked to employment status and sex cease to be significant. This result provides evidence to support the fact that the important sociodemographic characteristics are those that refer to who actually makes the household's financial decisions

Table 2

MODELS CONDITIONAL ON HAVING NONMORTGAGE DEBT

Dependent variable	*Credit default*		*Regulated sector credit default*	
	(a)	*(b)*	*(a)*	*(b)*
Male	0.363[b]	0.373[a]	0.323[b]	0.326[b]
	(0.146)	(0.142)	(0.154)	(0.150)
Cohabits	−0.259[b]	−0.269[b]	−0.170	
	(0.133)	(0.133)	(0.139)	
Age	−0.024[a]	−0.023[a]	−0.021	−0.021[a]
	(0.005)	(0.005)	(0.006)	(0.005)
University	−0.282		−0.297	
	(0.223)		(0.246)	
Log(income)	−0.2134[b]	−0.202[b]	−0.180	−0.183[b]
	(0.108)	(0.093)	(0.116)	(0.098)
Proportion of workers	0.255		0.132	
	(0.270)		(0.287)	
Members	0.096[b]	0.070[b]	0.075	
	(0.047)	(0.039)	(0.051)	
Children	−0.069		−0.153	
	(0.168)		(0.183)	

Expenditure > income	0.539[a]	0.563[a]	0.509[a]	0.536[a]
	(0.132)	(0.131)	(0.140)	(0.141)
Financial burden > 75%	0.195			
	(0.201)			
Formal employee	−0.552[a]	−0.577[a]	−0.506[a]	−0.549[a]
	(0.146)	(0.147)	(0.150)	(0.151)
Retired	−0.524[b]	−0.576[b]	−0.527[b]	−0.548[b]
	(0.225)	(0.237)	(0.245)	(0.256)
Regulated sector	0.640[a]	0.663[a]		
	(0.223)	(0.222)		
Banking sector			−0.649[a]	−0.678[a]
			(0.154)	(0.152)
Constant	1.193	1.194	1.734	1.896[a]
	(1.009)	(0.998)	(1.103)	(1.047)
Observations	1,125	1,125	1,006	1,006
Pseudo R^2	0.1836	0.1762	0.1727	0.1992
Log pseudo-likelihood	−96,784.21	−97,657.14	−91,883.32	−88,944.707

Notes: standard errors in parenthesis. [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.10$ // (a) model with all variables of interest (b) model with a backward selection of independent variables for a *p*-value of less than 0.10.

Table 3

CONDITIONAL MODELS FOR CREDIT CARDS

Dependent variable	*Credit card default, broad sense*		*Credit card default, strict sense*	
	(a)	*(b)*	*(a)*	*(b)*
Male	−0.0005		0.143	
	(0.083)		(0.142)	
Cohabits	−0.076		−0.054	
	(0.087)		(0.153)	
Age	−0.014[a]	−0.015[a]	−0.0213[a]	−0.021[a]
	(0.003)	(0.003)	(0.005)	(0.004)
University	−0.013		−0.280	
	(0.093)		(0.185)	
Log(income)	−0.123[c]	−0.125[b]	−0.192[c]	−0.298[a]
	(0.067)	(0.063)	(0.114)	(0.109)
Proportion of workers	0.0268		−0.252	
	(0.147)		(0.272)	
Members	0.114[a]	0.086[a]	0.045	
	(0.035)	(0.027)	(0.053)	
Children	−0.105		−0.215	
	(0.100)		(0.158)	

Expenditure>income	0.632[a]	0.637[a]	0.793[a]	0.831[a]
	(0.103)	(0.103)	(0.160)	(0.15)
Financial burden > 75%	0.354[b]	0.347[c]	0.1758703	
	(0.180)	(0.180)	(0.263)	
Formal employee	−0.024		−0.146	
	(0.097)		(0.295)	
Retired	−0.069		−0.025	
	(0.160)		(0.158)	
Number of credit cards	0.067[a]	0.068[a]	−0.040	
	(0.0234)	(0.023)	(0.055)	
Constant	0.45	0.523	1.12	1.93
	(0.67)	(0.657)	(1.158)	(1.188)
Observations	2,072	2,072	2,072	2,072
Pseudo R^2	0.0849	0.0833	0.1541	0.1377
Log pseudo likelihood	−274,496.33	−274,987.29	−74,174.24	−75,610.25

Notes: standard errors in parenthesis. [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.10$. (a) denotes a model with all variables of interest and (b) a model with a backward selection of independent variables for a p-value of less than 0.10.

and not to who participates most in income generation. The results of the models estimated for this definition of household head are presented in Table A.2 in the Annex.

5.2 Conditional Probability of Default Model for the Credit Card Segment

In the credit card segment, household default probability models are estimated for two types of delinquency. The dependent variable in the first model is a binary variable that takes the value of one if a household declares that any of its members fell into delinquency with a credit card during the last year. In the second model, we define that a household is in default in the strict sense if said delinquency is longer than three months. The number of credit cards a household has is added as an independent variable. The results are presented in Table 3.

We find a negative and statistically significant relation between the age of the household head and the probability of falling into delinquency with a credit card. Sex, or whether the household head has a university education or lives with their partner, are not significant for this credit segment. Moreover, the higher a household's income, the lower the probability of it being delinquent with a credit card. Households with a larger number of members have a higher probability of being overdue with credit card payments. Households with higher expenditures than income or with a financial burden greater than 75% of its income are also more likely to default on credit card payments. The number of credit cards a household has is significant and positively correlated to the probability of default on repayments of at least one credit card.

When we consider the probability of being delinquent in credit card payments for more than three months, the age of the household head is statistically significant. The older the household head, the lower the probability of being delinquent for more than three months in credit card payments. The higher the household income, the lower the probability of being delinquent for more than three months in credit card payments. The number of members, number of credit cards, and financial burden are not significant variables for explaining delinquency of longer than three months. Once again, the relation between current expenditures and income is significant. Households with current expenditures above their income are more likely to fall into delinquency with credit card payments for three months or more than households with expenditures lower than or equal to their income.

5.3 Comparison between Segments

The characteristics that determine household debt default therefore differ by credit segment. In the nonmortgage credit segment, some sociodemographic variables referring to the individual who administers the household's finances, whether they live with their partner, their age, sex, and if they are in formal employment or retired, as well as other household linked variables, such as number of members, are significant. Meanwhile, in the credit card segment, only the age of the household head and number of members are significant sociodemographic variables.

Differences are also observed among the financial variables. The relation between households' current expenditures and income is significant for all credit segments. This result is evidence in favor of the *ability-to-pay* theory on debt default in which households will avoid not paying their debt as long as their income is sufficient to cover the payments.

The financial burden is only significant for the credit card segment and for delinquency in payments in the broad sense. Variables associated with the employment status of the household head are only significant in the nonmortgage credit segment. Income, on the other hand, is significant in all the credit segments and for all default definitions.

5.4 Unconditional Probability Models

5.4.1 Nonmortgage Credit

The results of the unconditional default probability model for the segment of nonmortgage credit granted by the regulated financial are presented in Table 4.

The results obtained from the selection equation of the nonmortgage credit default model indicate that having a bank account increases the probability of having a nonmortgage loan granted by the regulated financial sector. Meanwhile, households with more members or with children of the household head living in them are more likely to have this type of debt. If the head has a bachelor's or higher degree the probability of the household having nonmortgage debt is lower.

With respect to the age of the household head, there is a life-cycle effect through which as age increases the probability of having nonmortgage debt grows, but at a decreasing rate. Higher income households are more likely to have nonmortgage debt. If the household head is retired or in formal employment, the probability that the household has nonmortgage debt is greater than for those where the head is in informal employment or unemployed.[9]

The Wald test shows that there is a significant correlation between the error terms and it is therefore appropriate to use a heckprobit model to obtain the unconditional probability of nonmortgage debt default.

In this specification, the probability of the household defaulting on its mortgage debt is higher if the head is male. The older the household head the less likely it is not to pay its debt. The cohabitation variable ceases to be significant in the unconditional model. However, the *university* variable is significant and negative in that model. The higher the income of the household, the less likely it is to default on its debt. Households with a larger number of members or with expenditures above their income have a higher probability of debt default. Finally, being retired is not significant in the unconditional model, while the household head being in formal employment reduces the probability of debt default.

5.4.1 Credit Cards

An unconditional probability model is estimated for the credit card segment in the broad sense and in the strict sense. The results are presented in Table 4. Besides the variables considered previously, these models also include the number of credit cards a household has as an independent variable in the main equation.

According to the selection equation, having a bank account,[10] and the household head having children, being in formal employment,

[9] These results are similar to those obtained by Mello and Ponce (2014) in their study on the determinants of debt default among Uruguayan households. However, they use a survey (prior) different from the EFHU.

[10] It is not necessary to have a bank account in Uruguay in order to have a credit card. In the sample, the 36% of households that own a credit card does not have a bank account.

and having a bachelor's or higher degree increase the probability of owning a credit card. The probability is also higher in older age, although it then declines. Higher income households are also more likely to have a credit card.

In the unconditional probability model for credit card default in the strict sense, the Wald test does not reject the null hypothesis that the probability of credit card debt default and that of having a credit card are independent. Hence, the estimation for credit card default in the strict sense is used without considering selection bias.

When we consider credit card default in the broad sense, we cannot reject the hypothesis that they are independent and we therefore use the unconditional probability model.

According to the results obtained, the older the household head, the more likely they are to fall into delinquency with their credit cards. Households with more members have a greater probability of credit card default. If the household head is in formal employment the probability of credit card default decreases. If household expenditures are higher than income the probability of falling into delinquency with credit card payments is greater. Finally, households with a larger number of credit cards are more likely to be overdue in their payments of at least one of them.

5.5 Household Risk

The household default probability estimated can be used as a measure of household risk. We perform a test for difference of means in the estimated probability of nonmortgage debt default considering, on the one hand, households that have at least one loan granted by the regulated financial sector and, on the other, those who do not have nonmortgage debt in the regulated sector.[11] The results are shown in Table 5. According to the test for difference of means, households with a nonmortgage debt in the regulated system have a different and slightly higher mean than households that do not have a nonmortgage debt in the regulated system.

If, on the other hand, we consider households with nonmortgage credit in the banking sector and nonmortgage credit in other institutions from the regulated sector, we observe that the former have

[11] In other words, those that have all their debt in the unregulated sector or those without debt.

Table 4

UNCONDITIONAL PROBABILITY MODELS

Dependent variable	*Regulated nonmortgage credit default*	*Credit card default, broad sense*	*Credit card default, strict sense*
Male	0.292[b]	0.007	0.157
	(0.116)	(0.077)	(0.148)
Cohabit	−0.163	−0.069	−0.039
	(0.101)	(0.079)	(0.209)
Age	−0.016[a]	−0.013[a]	−0.021[a]
	(0.004)	(0.003)	(0.01)
University	−0.35[b]	0.049	−0.268
	(0.181)	(0.089)	(1.489)
Log (income)	−0.221[b]	0.043	−0.152
	(0.089)	(0.068)	(3.387)
Proportion of workers	0.212	−0.001	−0.252
	(0.204)	(0.134)	(0.549)
Members	0.104[a]	0.0799[b]	0.039
	(0.040)	(0.034)	(0.402)
Children	0.085	−0.038	−0.219
	(0.126)	(0.093)	(1.127)

Expenditure>income	0.464 [a]	0.584 [a]	0.806 [a]
	(0.098)	(0.099)	(0.291)
Financial burden > 75%	0.097	0.329	0.251
	(0.15)	(0.161)	(0.461)
Formal employee	−0.213 [c]	−0.200 [b]	− 0.015
	(0.121)	(0.089)	(3.853)
Retired	−0.2515	−0.030	−0.122
	(0.187)	(0.142)	(1.064)
Number of credit cards		0.069 [a]	−0.035
		(0.022)	(0.12)
Constant	0.6215452	−1.613002	0.587
	(0.828)	(0.7)	(42.94)
Selection equation			
	Nonmortgage debt in the regulated sector	*Credit card, broad sense*	*Credit card, strict sense*
Bank account	0.216[a]	0.533[a]	0.517[a]
	(0.057)	(0.059)	(0.094)
Members	0.05[b]	−0.03	−0.031
	(0.021)	(0.022)	(0.023)
University	−0.232[a]	0.275[a]	0.285[b]
	(0.075)	(0.083)	(0.125)

	Nonmortgage debt in the regulated sector	*Credit card, broad sense*	*Credit card, strict sense*
Age	0.0292[a]	0.0261[a]	0.03
	(0.009)	(0.01)	(0.033)
Age^2	−0.0003[a]	−0.0003[a]	−0.0003
	(0.0001)	(0.0001)	(0.0003)
Formal employee	0.273[a]	0.52[a]	0.514[a]
	(0.067)	(0.067)	(0.092)
Retired	0.409[a]	0.154[c]	0.158
	(0.095)	(0.093)	(0.113)
Children	0.173[b]	0.127[c]	0.126
	(0.071)	(0.073)	(0.100)
Log income	−0.078[b]	0.423[a]	0.428[a]
	(0.041)	(0.043)	(0.0652)
Constant	−0.911[c]	−5.14[a]	−5.262
	(0.445)	(0.477)	(0.515)[a]
ρ	4.834[b]	0.788[a]	0.135
	(2.092)	(0.302916)	(12.826)
Wald test $(\rho=0)$ $\chi^2(1)=$	5.34	6.76	0
Prob > $\chi^2=$	0.0209	0.0093	0.9916
Observations	3,464	3,452	3,452
Censored observations	2,438	1,343	1,343
Uncensored observations	1,026	2,109	2,109

Notes: standard errors in parenthesis. [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.10$.

Table 5

TEST FOR DIFFERENCE OF MEANS BETWEEN HOUSEHOLDS THAT HAVE CREDIT IN THE REGULATED SECTOR AND THOSE THAT DO NOT

Group	*Observations*	*Mean*	*Standard error*	*Standard deviation*	*[95% confidence*	*interval]*
Without nonmortgage debt in the regulated sector	2,407	0.030	0.0007	0.0358	0.03	0.0315
With nonmortgage debt in the regulated sector	1,026	0.033	0.0012	0.0342	0.03	0.0352

Difference = mean (without debt) − mean (with debt)

H_0: difference=0

H_1: difference<0 p value=0.0088

H_1: difference≠0 p value=0.0175

H_1: difference>0 p value= 0.9912

an estimated average probability that is statistically significant and lower than the latter (Table 6).

Finally, we consider the probability of credit card default estimated as a measure of household risk. A difference of means test is performed for the probability of credit card default in the broad sense, considering on one side households that have credit cards and on the other those who do not. The results are presented in Table 7.

According to the difference of means test, households with at least one credit card have an estimated mean probability of debt default different from and higher than those that do not have a credit card.

Table 6

TEST FOR DIFFERENCE OF MEANS BETWEEN HOUSEHOLDS WITH CREDIT IN THE BANKING SECTOR AND THOSE THAT HAVE IT WITH OTHER INSTITUTIONS FROM THE REGULATED SECTOR

Group	*Observations*	*Mean*	*Standard error*	*Standard deviation*	*[95% confidence*	*interval]*
Nonmortgage debt in other institutions from the regulated sector	479	0.0405	0.0018	0.0386	0.0371	0.04
Nonmortgage debt in the banking sector	547	0.0266	0.0012	0.0283	0.0242	0.03

Difference = mean (without debt) − mean (with debt)

H_0: difference=0

H_1: difference<0 *p* value=1

H_1: difference≠0 *p* value=0.000

H_1: difference>0 *p* value= 0.000

Table 7

TEST FOR DIFFERENCE OF MEANS BETWEEN HOUSEHOLDS WITH CREDIT CARDS AND THOSE WITHOUT THEM

Grupo	*Observations*	*Mean*	*Standard error*	*Standard deviation*	*[95% confidence*	*interval]*
Households without credit card	1,324	0.0815	0.002	0.0736	0.0775	0.09
Households with credit card	2,109	0.124	0.0019	0.0879	0.1203	0.13

Difference = mean (without debt) −mean (with debt)

H_0: difference=0

H_1: difference<0 *p* value=0.000

H_1: difference≠0 *p* value=0.00

H_1: difference>0 *p* value= 1

6. APPLICATION: IMPACT OF THE FINANCIAL INCLUSION LAW ON HOUSEHOLD DEFAULT

The purpose of this section is to project the possible impact of the Financial Inclusion Law on household debt default by applying the models estimated. In particular, the study focuses on the impact of the measure enforced by the Law that establishes the obligation to pay dependent employees' wages through electronic payment media. Article 10 of the Financial Inclusion Law (19.210) stipulates that "payment of salaries and all other money items dependent employees are entitled to receive, whoever their employer might be, must be credited to an account at financial intermediation institutions or in an electronic money instrument at institutions offering such services." As of October 2016, all workers must collect their earnings through electronic media. However, they may agree with the paying party to continue receiving their earnings through different media than that set out by the Law, including cash, until April 30, 2017.

To perform the projection for the models estimated, we first identify the households with at least one dependent worker and without a bank account. We then assume that those workers open a bank account once the Financial Inclusion Law comes into force. Finally, using the models estimated in Section 5, a prediction is made for the probability of those households requesting credit and falling into delinquency on their debt according to their sociodemographic and financial characteristics. The projection is made for the nonmortgage credit and credit cards segment.

From the EFHU, 50% of the households do not have bank accounts, and out of those households 57% have at least one member who is a dependent worker. Once the Financial Inclusion Law comes into effect, the households that have at least one member who is a dependent worker should be expected to open a bank account.

According to the unconditional probability estimations performed for the cards and nonmortgage credit segment, in the selection equation, having a bank account increases the probability of having a debt or a credit card. The existence of a prior link to the bank, such as a bank account, makes the individual, who was previously unknown to the bank, a potential credit customer. Mello and Ponce (2014) find a positive and statistically significant relation between having a bank account and having a loan with the financial sector in Uruguay.

We proceed as follows. For households that have at least one member with a paying job, a value of 1 is imputed for the binary variable that represents having a bank account. Next, the probability of this household having a nonmortgage loan or access to a credit card is estimated with the model presented for unconditional probability.

To be able to determine the threshold probability based on which it is considered that a household does decide to have a loan or a credit card we select the value that maximizes the Youden index. This index is used as a summary measure of the ROC[12] curve and defines criteria for selecting an optimal threshold probability of debt or credit card (Fluss et al., 2005).

$$IY = \max_c \left\{ Se(c) + Sp(c) - 1 \right\}$$

where *Se(c)* is the ratio of true positives or sensitivity and *Sp(c)* is the ratio of true negatives. In this case, *Se(c)* is the percentage of households classified as having nonmortgage or credit card debt if the household in the sample has a debt or a credit card and *Sp(c)* is the percentage of households classified as not having nonmortgage debt or credit card if the household in the sample does not have debt or credit card. The index can go from 0 to 1, where a value close to 1 means the selected threshold is very effective for separating both populations and a value of 0 means it is not.

Based on the unconditional probability models, threshold *c* is established as the value that maximizes the joint probability of true positive and true negative ratios. Next, the probability that a household has debt or not is estimated using unconditional models. Finally, if the probability of the household having debt is greater than the established threshold, 1 is imputed to the debt variable[13] for that household, and the probability of the household defaulting on that debt is estimated. The thresholds obtained are shown in Table 8.

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[12] The signal detection theory uses ROC (Receiver Operating Characteristics) curves to make a graphic representation of sensitivity versus specificity for a binary classifier system according to variations in the discrimination threshold.

[13] To perform the exercise, it is assumed that households above the threshold will have access to credit and the loan is granted to them.

Table 8

THRESHOLDS

Classification (Pr > c)	*Threshold c*
Nonmortgage debt	0.288936
Nonmortgage debt default	0.028952
Credit card	0.647420
Credit card default	0.155079

6.1 Nonmortgage Debt

The average probability of having nonmortgage debt increases from 30% to 33%when considering salaried employees' obligation to have a bank account.

Out of the households that have at least one salaried employee and do not have a bank account before the reform, 34% had nonmortgage debt. After the reform, and considering the imputed threshold, this percentage increases to 86%. To determine whether this group of households (with a least one member who is a salaried employee, and who did not have a bank account or loan prior to the reform, and then when they have a bank account decide to request a loan) has a probability of debt default significantly different from the group of individuals that had a bank account before the reform or who did not have a bank account but do not decide to take out a loan, we perform a test for difference of means. As can be seen in Table 9, the difference is statistically significant and higher for those new households that obtain credit after opening a bank account. The average probability of default for them is equal to 4%, a figure slightly above the average unconditional probability for the sample as a whole.

Table 9

DIFFERENCE OF MEANS TEST ON THE DEFAULT PROBABILITY FOR THE NEW GROUP ACCESSING CREDIT

Group	*Observations*	*Mean*	*Standard error*	*Standard deviation*	*[95% confidence interval]*	
Other households	2,968	0.0264	0.0006	0.0346	0.025	0.028
With nonmortgage debt due to Financial Inclusion Law	2,109	0.124	0.0019	0.0879	0.12	0.128

Difference = Mean (without debt) −mean (with debt)

H_0 = Difference=0

H_1 = Difference < 0 *p* value=0.000

H_1 = Difference ≠0 *p* value=0.000

H_1 = Difference > 0 *p* value=1

Table 10

DESCRIPTIVE STATISTICS BY GROUP

Variable	*With nonmortgage credit due to the financial inclusion law*	*Other households*
Age	49	52
Income	30,626.5	33,514.7
Members	3.77	2.88
Expenditures higher than income	0.1663158	0.1449468
University	0.210084	0.2398806
Formal employee	0.4054622	0.4661579

Table 10 shows some descriptive statistics for variables that are statistically significant in the nonmortgage debt default probability model for the group of households without a bank account, with at least one salaried employee among their members and that incur debt once they have a bank account, and for the remaining households.

As can be seen, households without a bank account, with at least one salaried employee among their members and that incur debt once they have opened a bank account after the Financial Inclusion Law, on average have a younger household head. The average income of these households in Colombian pesos is lower, and they have a higher average number of members. Moreover, the proportion of households whose expenditures surpass their income is larger among this group, while the proportion of households whose head holds a bachelor's or higher degree is smaller. Finally, the proportion of households whose head is in formal employment is also lower.

For households that have a higher probability of incurring debt than the estimated threshold, the value one is imputed for the nonmortgage debt variable, and the probability of default on the nonmortgage credit granted by the formal financial sector is estimated. Households with a mortgage debt default probability above the defined threshold are considered not to pay their debt. The proportion of unpaid nonmortgage debt shifts to approximately 15%, representing an increase of around four percentage points in the default rate for this type of loan.

6.2 Credit Cards

According to data from the EFHU, 61% of households have at least one credit card. Out of the households that do not have a bank account but have at least one member with a paying job, 51% have credit cards.

Following Youden index criteria, a threshold is determined above which households have a credit card. The proportion of households without a bank account and with at least one member with a paying job that have credit cards after opening a bank account increases by up to 82 percent.

If the probability of having a credit card surpasses the threshold, the household is therefore imputed to have a credit card, and we estimate the probability of it falling into delinquency with its payments (in the broad sense). The average default probability, in the broad sense, of those that obtain a credit card is similar to the average for the sample as a whole and equal to 14.5 percent.

We perform a test for difference of means between this group of households, which we call "group with at least one member with a paying job, without a bank account before the reform and that once they have opened a bank account decide to have at least one credit card," and the rest of the sample. The group of households that obtain credit cards after the Financial Inclusion Law does not have a default probability (in the broad sense) statistically different from the rest of the sample. The results are presented in Table 11.

Table 11

DIFFERENCE OF MEANS TEST FOR THE PROBABILITY OF CREDIT CARD DEFAULT IN THE BROAD SENSE

Group	*Observations*	*Mean*	*Standard error*	*Standard deviation*	*[95% confidence*	*interval]*
Other households	3,145	0.1433	0.0019	0.106	0.14	0.147
With credit card due to the Financial Inclusion Law	288	0.1454	0.0057	0.0967	0.134	0.16

Difference = Mean (without debt) −mean (with debt)

H_0 = Difference=0

H_1 = Difference<0 *p* value=0.3475

H_1 = Difference ≠0 *p* value=0.7491

H_1 = Difference>0 *p* value= 0.6255

7. FINAL REMARKS

In this paper, we estimate models for Uruguayan households' default probability in different credit segments. The results of the variables that are statistically significant differ according to the credit segment considered. However, the age of the household head and the relation between household expenditure and income are significant in all the segments. Income is also important in explaining household default in all the segments except falling into delinquency with credit card payments (in the broad sense) when the model estimated is corrected for selection bias.

Furthermore, the sociodemographic variables of importance are those referring to the person with most knowledge of the household's financial matters, the reference person according to the EFHU and not the person who makes the greatest contribution in terms of income.

Having models on the probability of default among Uruguayan households enables different studies to be carried out on household behavior, their vulnerability to macroeconomic conditions and to assess policies that have an impact on debt default. This paper extends the use of the models by presenting an assessment of the Financial Inclusion Law and the effect of the obligation to pay salaries through electronic media on debt default, and thereby on total delinquency in the system.

The models estimated lay the foundations for future works to analyze the relation between credit constraints and the probability of household debt default as a measure of household credit risk, and study the effects of an income shock on household debt default. Furthermore, using data from the EFHU, it is possible to analyze the determinants of default on loans based on their characteristics.

ANNEX

Table A.1

BREAKDOWN BY CREDIT SEGMENT
Percentage of all households with debt

Exclusively mortgage debt	1
Exclusively nonmortgage debt	15
Exclusively credit cards	47
Mortgage debt and credit cards	6
Nonmortgage debt and credit cards	28
Mortgage and nonmortgage debt	1
Credit cards, mortgage debt, and nonmortgage debt	4

Source: Author's calculations based on data from the EFHU.

Table A.2

MODELS FOR NONMORTGAGE CREDIT
Household head as the largest contributor to household income

Dependent variable	*Nonmortgage credit default*	*Regulated nonmortgage credit default*
Male	0.054	0.091
	(0.137)	(0.144)
Cohabits	0.023	0.076
	(0.146)	(0.154)
Age	−0.015[a]	−0.013[a]
	(0.005)	(0.005)
University	−0.312	−0.196
	(0.304)	(0.336)
Log(income)	−0.258[b]	−0.257[b]
	(0.114)	(0.123)
Proportion of workers	0.353	0.258
	(0.259)	(0.277)
Members	0.138[a]	0.122[a]
	(0.043)	(0.047)
Children	−0.069	−0.128
	(0.167)	(0.179)
Expenditure>income	0.500[a]	0.453[a]
	(0.127)	(0.137)
Financial burden > 75%	0.060	−0.059
	(0.185)	(0.217)
Formal employee	−0.148	−0.137
	(0.165)	(0.171)
Banking sector		−0.701[a]
		(0.143)
Regulated sector	0.608[a]	
	(0.222)	
Constant	0.769	1.608
	(1.060)	(1.162)
Observations	1,150	1,027
Pseudo R^2	0.1158	0.1513
Log pseudo-likelihood	−105,977	−95,216.382

Notes: standard errors in parenthesis. [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.10$.

Table A.3

TWO-STAGE ESTIMATIONS FOLLOWING THE METHODOLOGY PROPOSED BY ALFARO ET AL. (2010)

Dependent variable	*Nonmortgage debt default (broad sense)*	*Card default*
Male	0.252[c]	−0.057
	(0.132)	(0.145)
Cohabits	−0.261[b]	0.053
	(0.13)	(0.149)
Age	−0.016[a]	−0.021[a]
	(0.005)	(0.006)
University	−0.494[c]	−0.332[c]
	(0.263)	(0.199)
Log(income)	−0.276[b]	−0.175
	(0.107)	(0.195)
Proportion of workers	0.421[c]	−0.317
	(0.247)	(0.29)
Members	0.133[a]	0.036
	(0.05)	(0.062)
Children	0.392[c]	−0.264
	(0.208)	(0.176)
Expenditure>income	0.605[b]	0.797[a]
	(0.121)	(0.157)
Financial burden > 75%	0.165	0.37
	(0.188)	(0.273)
Formal employment	−0.09	−0.052
	(0.239)	(0.329)
Retired	−0.117	−0.044
	(0.29)	(0.21)
Number of credit cards		−0.028
		(0.065)
G(px)	−0.455	−0.084
	(0.581)	(0.186)
$G(px)^2$	0.17	0.102
	(0.251)	(0.248)
Constant	0.899	0.938
	(1.053)	(1.935)
Observations	1,149	1,026
Simulations	2,000	2,000

Bootstrapped standard errors in parenthesis. [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.10$.

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