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Borrowing constraints and credit demand:
evidence for Uruguay

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En la memoria del tío Kevi:

por contagiarme sabiduría y cariño.

BORROWING CONSTRAINTS AND CREDIT DEMAND: EVIDENCE FOR URUGUAY

Abstract

This paper analyses the determinants of credit demand in the presence of borrowing constraints for Uruguayan economy. I model the determinants of debt level for Uruguayan households taking into account selection bias and endogeneity of household income and non-real estate assets. I found differences considering the type of debt that families face; mortgage and consumer debt. For instance, in average, income-to-debt elasticities are smaller than one for both type of debt. Additionally, consumer debt income elasticity is smaller compared to mortgage debt. Besides, in average age-to-debt semi-elasticity are negatives for any type of debt. The effect is larger in consumer debt compared to mortgage debt. However, variable age is not statistically significant in determining debt semi-elasticity. In addition, I find evidence of sample selection for any type of debt, but I do not find evidence of endogeneity for consumer debt, nor for mortgage debt.

Key words: consumer debt, mortgage debt, borrowing constraints, sample selection, income endogeneity, income-to-debt elasticities, age-to-debt elasticities.

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1. Introductions

The present investigation studies the determinants of credit demand in the presence of borrowing constraints for Uruguayan economy. In other words, I investigate socio-demographic and financial characteristics of Uruguayan households that explain debt level. Regarding market characteristics, I analyze consumer and mortgage debt separately. Moreover, the decision of holding debt and the condition of being credit constrained impose that estimation of debt level is not straightforward. In this line, first I study socio-demographic and financial characteristics that affect the probability of holding debt and the condition of being unconstrained. Second, I study households' characteristics that explain the size of the loan. Finally, I try to predict debt evolution considering income evolution and the aging process.

Studying credit market is relevant in a micro as well as in a macroeconomic level. From a microeconomic perspective it is important to identify common factors that motivate families to ask for credits. I try to answer fundamental questions of household credit decisions. Does family income affect the probability of holding debt? Are less educated families more likely to ask consumer credits? Being unemployed, affects the probability of asking credits? Middle-age families, are more likely to ask a mortgage credit? Having real estate assets affects the probability of having mortgage loans?

Additional, it is critical to identify key factors that explain the size of the loan. I estimate consumer and mortgage debt separately regarding the nature of each market. For consumer debt the amounts traded are smaller and the interest service higher, compared to mortgage credit. I try to answer the following questions, does income family affects consumer and mortgage debt? How does household age affect the size of the loan? Is wealth important in order to explain family indebtedness? How does household education affect family indebtedness?

Alternatively, credit market plays an important role from a macroeconomic perspective extending private consumption and investment, leading to economic growth. Nevertheless, credit market dynamism can lead to high economic risk as long as credit conditions are relaxed and private sector hold excessive indebtedness levels (Landaberry: 2019). An excessive credit liquidity that does not follow the long-run economic fundamentals is known as credit boom. Credit booms can generate financial and economic crisis. For this reason, it is important to detect, anticipate and monitor market credit level. Landaberry (2019) identifies different credit booms for Uruguay between 1985 and 2018. Using ex-post techniques[1], evidence suggests credit booms took place in 2002, 2009 and between 2014 and 2015. Alternatively, using ex-ante techniques, credit booms were identified between 2000 and 2003, 2008 and 2010 and 2012 and 2015.

Studying credit market is a topic of interest after the financial crises of 2002, where most of the debt was denominated in US dollar. In the 1990s currency mismatch had increased

[1] For methodological explanation see Landaberry (2019).

into the private sector sheet balances. Loans denominated in dollars raised from 58 per cent in 1995 to 87 per cent in 2002, but most of borrowers earned in local currency (Wolf: 2007). Households' debt increased considerably as a consequence of large devaluation, affecting families' capacity to pay, forcing to default. After that, credit market dynamism was recovered showing large availability of consumer credits, widespread use of credit card and mortgage credit lines. In this regard, there is a "growing non-banking credit sector (despite) the low structural indebtedness level of Uruguayan households" (Mello and Ponce: 2014). Moreover, Landerry (2018) examined impacts of income shocks on non-mortgage credits for Uruguay. She found that income shocks similar to 2002 would increase considerably the arrears credits proportion, from 8 to 15%.

Another motivation to study credit markets is due to the link with financial markets. Uruguay displays a shallow financial market compared to international standards. This is particularly true for non-banking financial market. Compared to the rest of the MERCOSUR members, Uruguay is under the average in terms of stock market dimension and the value traded (Aboal, Lanzilotta y Perera, 2007a). Banking sector relative size, deposits-to-GDP ratio, more than doubles the rest of the MERCOSUR members. Indeed, Uruguayan financial market is based on banking system where stock market plays a marginal role in the economy.

In 2005, commercial banks assets hold 67% of the financial system, whereas financial intermediaries share reached 19%. (Aboal, Lanzilotta y Perera, 2007b). Additionally, financial market development, under an effective regulatory scheme, can avoid economy fluctuation and can lead to a stable economic growth. Financial market characteristics described imply a great challenge to think the possible response of households' debt level in the process of develop financial market. Therefore, this process could have an impact on the decision of holding debt and/or the condition of being constrained, affecting households' debt level.

In order to have an insight into Uruguayan debt, I replicate Ruiz-Tagle and Vella (RTV) (2015) paper who investigates the determinants of credit demand under borrowing constraints for Chile. RTV (2015) propose a semiparametric approach to deal with selection and endogeneity, comparing it with OLS procedure and Heckman approach. Moreover, non-real estate assets and income are thought to be endogenous. Also, there are two sources of selection; the household decision of having credit and the condition of being constrained.

Credit constrained is an important issue to deal with. In line with RTV (2015), I use the most common definition, as there exist several in literature. A household is considered to be credit constrained if it was either rejected or discourage from applying for credit. I split credit constraint by type of deb. RTV (2015) use only aggregated constraint. Other theoretical frameworks accept that families are constrained if demand for credit is higher than the offer they face, or families that cannot access to low-cost credit.

I estimate consumer, mortgage and total debt separately, regarding the nature of each market. A first intuition suggests that the conditions asked for giving consumer loans are less strict, while the amounts are smaller and the interest service higher, compared to mortgage credit. I estimate separately to capture the impact of each covariables in both market. In order to analyze the impact of covariables on aggregate credit demand I consider total debt, capturing the average effect.

I study debt changes conditional to socio-economic structures and over the life cycle. Indeed, I analyze the impact of income and education on the different types of debts. Moreover, the value of real estate assets is also a variable of interest in order to analyze it´s impact on debt, as indicator of wealth. I also include area income –average income of the neighborhood where the house it is located– and a dummy indicating if the family lives in the capital department in order to analyze territorial segregation.

The last part of the investigation pretends to predict the debt evolution taking age and income semi-elasticities and elasticity of debt demand, respectively. I estimate weighted average derivative in order to estimate contemporaneous elasticities/semi-elasticities. Besides, I estimate elasticities/semi-elasticities in 5 years' time, considering income and age evolution between 2004 and 2014, while other variables remain constant. It displays a first approach to the debt evolution in the next years.

The next section revises related literature. Section 3 introduces the dataset and describes the variables related. Section 4 presents general information of the data and some descriptive. Section 5 analyzes the determinant of being constrained and holding debt (by type) using a linear probability approach. Also, it provides estimation of income and non-real estate assets in order to account for endogeneity. Section 6 presents the estimation of debt level equation, considering ordinary least square, Heckman approach and a semiparametric model. Section 7 estimates the debt evolution using age and income semi-elasticity and elasticity of debt demand. Section 8 presents methodological questions that help understandings some of the results achieved. Finally, section 9 concludes.

2. Related literature

Literature for Uruguay concerning household debt using balance sheets is relatively new and there are not many research in this area. Mello and Ponce (2014) studied the determinants of Uruguayan households' indebtedness using two complementary datasets conducted by the Statistic National Institute (INE, in Spanish). They merged the Continuous Household Survey (ECH, in Spanish) with the first edition of the Financial Uruguayan Household Survey (EFHU, in Spanish). Both surveys use the same definition of household, allowing full comparability. The paper uses Heckman approach to purge for selection. In the first stage they identify the characteristics of households that affect the probability of having debt. Using Probit and Logit approach, they found that having bank account, having credit card and the condition of being a public employee (at least one of the members of the household) increase the probability of having debt. On the other hand, the condition of being a poor household (measured by income level) and having saving in a bank account reduce the probability of having debt.

In the second stage they estimate households' indebtedness level. Indebtedness is defined as the ratio of total debt to annual income. The paper finds that loans granted by banks and household wealth have a positive impact on households' indebtedness. On the other hand, percentage of debt denominated in local currency and bank savings have a negative and significant impact on determining indebtedness level equation. Finally, they analyze the determinants of households' financial burden; defined as monthly households' income used to pay debts. They found that credits granted by banks, having a mortgage credit, percentage denominated in local currency have a positive and significant impact in explaining the financial burden.

Correa (2020) analyzes the determinants of households' credit constraint for Uruguay using the second edition of EFHU. A household is defined as credit constraint if it presents one of the following conditions: i) credit demand are rejected by financial institution; ii) families do not ask for credit considering financial institution will not grant it; or iii) credit demand is larger than credit supply. Using this definition, 18% of households present some type of credit constraint. This research founds that Age, Education, Being retired[2], Having bank account, Having credit card and Income decrease the probability of having any constraint in the credit market. On the other hand, dummy High indebtedness, Number of kids and Over-expenditure (dummy equal one if expenditure is larger than income) increase the probability of having any constraint.

In order to obtain detailed information, Correa (2020) analyzes the impact of a set of covariates on different types of credit constrained. First, credit constraint is analyzed by the origin of the restriction. Therefore, two models are estimated: rejected and discouraged credits. The first includes credits that were rejected or credits granted for less than the requested amount. The second includes families that do not ask for credit considering companies will not grant it. Second, credit constraint is analyzed by market segment. Four models are estimated: consumer constraint, mortgage constraint, quantity constraint; that is, households that credit demand exceeds credit supply. Last model considers households that present more than one constraint.

For Chile, RTV (2015) analyses the determinants of credit demand in the presence of borrowing constraint. The paper employs a semiparametric approach to account for the presence of selection and endogeneity, comparing with Heckman approach (benchmark). As a first step, they estimate the probability of holding debt (consumer debt, mortgage debt, and total debt) and the probability of being unconstrained, using a linear probability

[2] Correa (2020) takes age, years of education, dummy woman and the condition of being constraint referring to the person who answer the survey (person of reference).

model. They find that the value of real estate assets, self-employed, neighborhood average income, living in the center of the country and inhabitants over number of banks by municipality affect negatively the probability of holding consumer debt. On the other hand, spouse present (in the house), number of persons employed in the household, credit delayed payments, number of credit arrears, number of households' insurance, having pension found, use telebanking and inhabitants over number of banks by region affect positively the probability of holding consumer debt.

The probability of holding mortgage debt is affected positively by the value of real estate assets, years of education, spouse present, age, neighborhood average income, number of formal credits arrears, number of insurance, amount of pension found, having pension found, having current account, using telebanking and inhabitants over number of banks by region. On the other hand, the probability of holding mortgage debt is affected negatively by self-perception of paying high financial service and if the household head is male. Additionally, they estimate the probability of being unconstrained. Evidence for Chile suggests that the value of real estate assets, years of education, formal employ and neighborhood average income affect positively the probability of being unconstrained; whereas self-perception of paying high financial service, variables related to delay payments, having pension found and inhabitants over number of banks by municipality affect negatively.

In the second stage Ruiz-Tagle and Vella (2015) estimate the determinants of debt level, distinguished by type of debt. Moreover, in the second stage they test for endogeneity. Using the semiparametric approach, main conclusions indicates that Income, Real estate assets, Age, Self-perception of paying high financial service and Having delay payments affect positively consumer debt level. Furthermore, they find evidence of endogeneity of income and non-real estate asset and also find evidence of sample selection. For mortgage debt level Income, Age, Self-perception of paying high financial service and Number of credit arrears affect positively. Moreover, they find endogeneity of non-real estate assets and sample selection.

In the last part of the investigation, they estimate debt-to-income elasticity and debt-to-age semi-elasticity to anticipate the debt evolution in an income growth and aging process economy. For consumer debt, they found a very strong response of debt-to-income (estimated elasticity of 1.47), whereas debt-to-age semi-elasticity is estimated in - 0.9%. For mortgage debt, income elasticity is weaker, estimated in 0.88, and debt-to-age semi-elasticity is estimated in - 3.75%. Finally, for total debt, debt-to-income elasticity is estimated in 1.78, whereas debt-to-age semi-elasticity is estimated in - 1.98%.

For developed economies there are a number of studies that investigate the determinants of households' debt. For instance, for USA Wildauer (2016) studies the sustained increase in household debt-to-income ratio since the early 1990s up to 2007, using the Survey of Consumer Finances (SCF). He tested two popular explanations. First, the *expenditure cascade hypothesis* states that in an economy with an increasingly polarized income distribution, relatively poor individuals will take on debt in order to maintain level consumption compared to wealthier people. Second, *Minskyian household hypothesis* makes emphasis in the role of rising property prices and homeownership rates in order to explain household indebtedness. This hypothesis states that rising assets prices over a long period of relative stability leads to a general optimism, thus households take on mortgage debt assuming that increasing property prices is a permanent phenomenon. Wildauer (2016) finds "that is the interaction of rising asset prices and the polarization of the income distribution which explains a large part of the increase in household borrowing before the crisis in 2008".

Atif Mian and Amir Sufi have made several research about household indebtedness. For instance, Mian and Sufi (2018) studied the role of financial sector in explaining business cycle. They state that "expansion in credit supply, operating primarily through household demand, have been an important driver of business cycle". Initially, credit supply shocks boost household debt expansion, rising household consumption. Then, household spending drops substantially, affecting aggregated demand and anticipating economic recessions. Therefore, Main and Sufi (20018) state that "a rise in household debt generate a consumption boom-bust cycle" that affects the entire economy.

Magri (2002) investigates the determinants of households' debt for Italy from 1989 to 1998, using a panel data from the Bank of Italy's Survey of Household Income and Wealth (SHIW). The paper includes the estimation of the probability of demanding a loan and of being liquidity constrained. It also distinguishes consumer from mortgage debt. Main conclusions indicate that low indebtedness of Italian families may be due to credit rationing and to the judicial enforcement of loan contracts. Net wealth and education affect positively the probability of holding debt and the amount of the loan. Level of income affects positively the probability of holding debt, but it has a negative effect on desired debt. The probability of asking a credit increases with household head age until 29 years old; decreasing from this point forward. The paper also finds that an increase in the income uncertainty decreases the probability of asking a credit. However, self-employed workers desire 32 per cent more debt than employees.

3. Dataset and variables

3.1 The Dataset

The present investigation is based on the data provided by the second edition of the Uruguayan Household Financial Survey (EFHU, Spanish acronym). EFHU is the only statistical source in Uruguay providing complete information of households' balance sheets. It allows delving into the households' financial situation and gathering information to understand heterogeneities. Furthermore, it offers households ability to serve financial commitments. Developed countries and some of Latin America, such as Chile, have incorporated similar surveys for years, indicating the importance of collecting microdata to analyze households' economy (dECON: 2016). Moreover, I use Continuous Household Survey (ECH, in Spanish) to obtain specific variables. EFHU's households are included in ECH-2012; thus, it guarantees complementarity.

EFHU was promoted by Central Bank of Uruguay (BCU), Ministry of Economy and Finance (MEF), Planning and Budget Office (OPP) and Bank Saving Protection Corporation (COPAB). Data was conducted by the Economic Department (dECON) of Faculty of Social Science – UdelaR. Primary, in 2012, EFHU was annexed as a subpart of the ECH, survey conducted by the Statistic National Institute (INE, in Spanish). In 2014, EFHU was collected independently, providing more information of households' economy and finances. It is divided in 8 sections, including information of real assets and debts related, financial assets, non-mortgage debts, means of payment, household consumption and saving, insurance and personal income plans, income and labor history and household business property. Therefore, the survey provides detailed information about household´s labor market status, real state ownership, financial assets, debts, access to financial markets, saving and use of means of payment. Additionally, EFHU provide information related to households' sociodemographic characteristics.

Person of Reference is the member of the family that answers the survey. It is the person in charge of financial affairs and knows about expenses, income, assets and investments. Some of the variables are referred only to person of reference, as we will see in the following part.

3.2 The Variables

In order to compare Uruguayan and Chilean economies, I try to use same covariate set. However, I had to exclude or redefine some variables regarding differences in surveys information. I use households' debt in logarithm as the dependent variable in the structural model. I estimate separately by type of debt; consumer, mortgage and total debt. In a first stage I estimate the probability of holding debt and the condition of being unconstrained (results are reported in table IV). Therefore, dummies holding debt and being unconstrained are the dependent variables in that first stage estimation. Moreover, I estimate income and non-real estate assets to obtain the residuals in order to account for endogeneity in the structural model (results are reported in table IV).

In the structural model for the three types of debt I use a set of covariates that are related to households' sociodemographic and financial characteristics.

- Income: household annual total income in thousands of US dollars.
- Real estate assets: logarithm of total value of home plus other real estate assets in US dollars.

- Non-real estate assets: total value of mean of transports, financial assets, loans granted by the household and other assets in thousands of US dollars (jewelry, cattle and electrical appliance)
- Years of education: household's average years of education for adults.
- Spouse present: dummy equals one if the spouse is present in the household.
- Gender: dummy equals one if the person of reference is male.
- Age: household's average age for adults.
- Number of person in household: total number of person in the household.
- Number of person employed in the household: total number of person employed in the household.
- Unemployed: dummy equals one if the person of reference is unemployed (ECH)
- Formality: dummy equals one if the person of reference contributes to retirement.
- Self-employed: dummy equals one if the person of reference is self-employed. It includes entrepreneurs running large companies.
- Area Income: neighborhood average income where the household is located.
- Montevideo: dummy equals one if the household is located in Montevideo.
- Had delay payments in the past 12 months: dummy equals one if the household has delay payments in the past 12 months.

Additionally, to estimate the probability of being unconstrained and holding debt I use the aforementioned covariates plus the instrumentals variables. These are:

- Insurance: dummy equals one if the household holds the following type of insurance: life, vehicle or property insurance.
- Current account: dummy equals one if any member of the household has a current account.
- Use telebanking: dummy equals one if the any member of the household uses telebanking.
- Over-expenditure: dummy equals one if household expenditure exceeded household income in the previous 12 months.
- Number of bank over population by area and region[3]: ratio of banks over population multiplied by 10.000
- Number of retailers by area and region[4].

[3] Area is defined by departments and Montevideo by neighborhood (defined by INE). Regions are defined in terms of departments: "Metropolitan" includes Montevideo, San José and Canelones; "East" includes Maldonado, Rocha, Lavalleja, Treinta y Tres; "West" includes Colonia, Soriano, Rio Negro; "South-Central" refers to Flores, Florida, Durazno; and "North" includes Artigas, Salto, Paysandú, Rivera, Tacuarembó and Cerro Largo.

[4] Information of the banks and retailers available was consulted in the Central Bank web: https://www.bcu.gub.uy/Servicios-Financieros-SSF/Paginas/emp_admin_cred.aspx

Number of banks over population, number of retailers and over-expenditure are considered the mains exclusion restriction in the first stage estimation. Retailers is defined as credit companies that lends consumption credits.

4. Stylized facts of debt holding and borrowing constraints in Uruguay

Uruguayan mortgage market displays some peculiarities. 61.7% of households own the house, and only 9.1% of households hold mortgage credit. Compared to Chile, housing tenure is similar to Uruguay (71% in Chile), but mortgage credits reach 21% of households. Hence, I estimate mortgage credits with less data, forcing larger variance and thus larger confidence intervals. Nevertheless, mortgage credit explains around 60% of total debt. On the other hand, 41.7% of homes hold consumer debt.

Table I displays income share distribution, debt share distribution (mortgage, consumer and total debt) and whether households hold debt, by type of debt. Information is analyzed in four categories: income groups (quintile), age group, educational level and geographical regions. Level of education takes 3 categories in table I: "Primary"; adults with less than 7 years of formal education (average), "Secondary" between 7 and 12, and "Tertiary" more than 12 years. For Chile, authors use age and level of education of the household head.

It is observed, in general terms, that the distribution of each component of households' debt share (mortgage, consumer and total), is similar to income share for each category. Consumer debt share displays less variability compared to mortgage and total debt analyzing by income quintile category. Results for Chile are different. In Chile, the first quintile income holds 5.9% of consumer debt, Uruguay holds 14.31%. In the opposite tail of income distribution, the last quintile holds 45.8% of Chilean consumer debt, and Uruguay hold 24.2%.

In addition, wealthier households and middle-age group hold the vast majority of income and debt. The richest quintile holds almost the half of income share and total debt share, 47.3% and 44.67% respectively. Analyzing by type of debt, wealthier homes hold 57.3% of mortgage debt and 24.2% of consumer debt. Middle age-group, households that adult members are between 35 and 54 years old, holds 53% of total income and 65.3% of total debt (61.7% of consumer debt and 67.5% of mortgage debt). Analyzing by education, I observe a wide gap between primary and the other levels, concerning to income and total debt share. The gap between secondary and tertiary is quite narrow. However, if total debt share is disaggregated, heterogeneity emerges: middle educated families' holds 60.6% of consumer debt share, whereas high educated families' holds 62.7% of mortgage debt share. By region, there are not important differences between Montevideo and Interior for income share, mortgage debt and total debt share. However, Interior holds almost two thirds of consumer debt.

Table I. Distribution of debt and credit constraints

	Income Share (1)	Total Debt Share (2)	Mortgage Debt share (3)	Consumer Debt Share (4)	Househol d w/any debt (5)	Household w/mortgage debt (6)	Household w/consumer debt (7)	Total Constrain ed househol d (8)	Mortgage Constraine d household (9)	Consumer Constrained household (10)
Percentage points										
By income quintile										
I	5,18	6,72	2,04	14,31	46,58	2,68	45,09	25,42	13,42	18,42
II	9,93	11,26	7,88	16,73	43,44	6,96	40,73	21,72	11,28	16,46
III	15,13	13,78	10,71	18,75	52,66	7,22	49,21	19,41	11,92	11,70
IV	22,45	23,56	22,04	25,99	50,04	9,76	44,87	11,39	6,84	6,12
V	47,30	44,67	57,33	24,23	46,54	18,75	36,02	6,60	3,43	3,72
By age										
18-24	0,97	0,16	0,06	0,33	27,83	3,11	26,54	30,84	18,19	24,64
25-34	14,55	16,64	17,50	15,26	53,93	8,33	48,59	26,12	13,95	18,25
35-44	32,56	40,26	42,56	36,56	52,31	12,40	46,11	19,75	10,58	13,55
45-54	20,46	25,05	24,97	25,17	53,58	11,22	48,38	17,03	8,42	13,18
55-64	11,01	9,19	8,73	9,93	43,02	8,61	38,30	13,63	9,05	7,13
65+	20,44	8,70	6,19	12,76	38,44	4,80	36,15	8,29	5,30	4,00
By education [a]										
Primary	12,81	7,95	4,37	13,75	42,88	2,97	41,34	19,65	10,86	13,58
Secondary	46,22	43,51	32,94	60,58	51,75	8,64	47,65	19,08	10,31	13,18
Terteary	40,97	48,54	62,70	25,67	44,22	16,18	35,14	9,32	5,82	4,77
By region										
Mdeo	49,89	46,17	53,36	35,24	48,22	11,45	42,33	18,87	11,32	11,77
Interior	50,11	53,83	46,64	64,76	48,72	7,46	45,24	15,59	8,07	10,96
Total	100,0	100,0	100,0	100,0	48,5	9,1	44,1	16,9	9,4	11,3

Source: EFHU 2014

[a] Primary is 0-6 years of education; secondary is 7-12 years of education; and tertiary is 13 and more years of education (Average for adults in household)

Additionally, table I displays that 48.5% of households' hold some debt (last row of column 5); 44.1% hold consumer debt and 9.1% hold mortgage debt. It is worth noting that mortgage debt is related to high income families. First quintile holds less than one third from average, and last quintile doubles the average. Holding consumer debt is similar in all quintile groups (columns 6 and 7, first panel of Table 1). Analyzing by age group (second panel of Table I), mortgage debt holding exhibits the life cycle inverted U-shaped profile, while consumer debt profile is relatively age invariant. Analyzing by education, less educated families are less likely to have mortgage debt (3%), while high educated families are more likely to hold mortgage debt (16%). On the other hand, consumer debt holding is relatively invariant across education groups. It can be observed similar patterns in debt to income behavior. Finally, analyzing by region, Montevideo exhibits higher rates of mortgage debt (11%) compare with the rest of the country (7%), while consumer debt is barely higher compare with Interior, 42% versus 45% respectively.

The last three columns of table I is related to constraining. Column 9 displays mortgage constraining, column 10 consumer constraining and column 8 any constraining. One in four households presents some type of constraint in the first income quintile group. On the other hand, less than 7% of families are constrained in the top quintile. Some interesting patterns arise analyzing by type of constraint. Quintile I and II exhibit more limitation applying for consumer debt rather than mortgage debt. For quintile III to V there are not important differences. Analyzing by age, it can be observed that the probability of being credit constrained decreases as long as household average age increase. Younger families (households from 18 to 54 years old in average) are less likely to be constrained in the mortgage rather than in the consumer segment. On the other hand, older families are less likely to be constrained in the consumer rather than in the mortgage segment. By education level, I find no difference comparing primary and secondary (almost 20% for total constrained, less than 11% for mortgage constrained and 13% for consumer constrained). High educated families are less likely to be credit constrained. For each type of debt, the probability of being constrained is less than half compared to primary and secondary. Last, in Montevideo the probability of being constrained is higher compared to the rest of the country by any kind of restriction.

Table II. Prevalence of borrowing and credit constraints

	Constrained (N = 0)	Unconstrained (N = 1)	Total
Porcentages			
Any debt			
Non Debt Holder (B = 0)	6.90	44.58	51.48
Debt Holder (B = 1)	10.01	38.51	48.52
Total debt	16.91	83.09	100.00
Mortgage debt			
Non Debt Holder (B = 0)	9.29	81.64	90.93
Debt Holder (B = 1)	0.09	8.98	9.07
Total mortgage debt	9.38	90.62	100.00
Consumer debt			
Non Debt Holder (B = 0)	4.45	51.49	55.93
Debt Holder (B = 1)	6.84	37.23	44.07
Total consumer debt	11.29	88.71	100.00

Source : EFHU 2014

Note : B = 1 if household holds the corresponding type of debt (0 otherwise)

N = 1 if the household is credit unconstrained (0 otherweise)

Table II displays interception of debt holding with any credit constraints, by type of debt. The following analysis of debt demand takes place after selection of those who decide to hold debt and are unconstrained. In other word, I consider debt level of those household which hold debt and are not constrained. Thus, we define two binary variables: B = 1 if households hold the corresponding type of debt, and 0 otherwise; and N = 1 if households are unconstrained debt holder. Panel I in table II shows that 38% of households are unconstrained debt holder, whereas only 7% are constrained non-debt holder and 10% are constrained debt holder. Regarding households that are constrained non-debt holder (7%), it seems that relaxing borrowing constrained by active policies would affect a relatively small number of households at the extensive margin; that is, few households would shift from zero to positive debt holding. Moreover, this change would affect deeper in mortgage credit rather than consumer credit, considering that households' mortgage non debt holder that face limiting in access to credit demand doubles consumer restriction. In addition, the features described suggest that going deep in the financial system could play a limited role in increasing borrowing levels. However, the intensive margin of credit demand needs to be analyzed, that is, changes in household debt level as a response of variations in socioeconomic and demographic characteristics of families. I go into detail in the following sections.

5. The determinants of participating in the debt market and being unconstrained

The main objective of this research is analyzing the impact of specifics covariates in households' debt level. Nevertheless, estimates are not straightforward. Estimating by ordinary least square implies omitting specification errors. Indeed, Heckman two-steps and the semiparametric models need a source of identification. A set of exclusion restrictions and a control function approach are needed to overcome the inherent selection and endogeneity due to unobserved heterogeneity. In first place, I model whether the household is borrowing constrained, by type of constraint; mortgage, consumer or any constraint. The model has the form:

$$N_{\mathbf{i}} = I\,(\mathrm{X}_{\mathrm{Ni}}\,\beta_{\mathrm{N}} + u_{\mathrm{Ni}} > 0) \qquad (1)$$

where $N_{\mathbf{i}}$ is a dummy that takes value 1 if the household is borrowing unconstrained and value 0 otherwise; X_{Ni} are covariates, β_{N} is an unknown parameters vector and u_{Ni} are zero mean error term. I estimate equation (1) by linear probability model (LPM method). The control function approach requires the imposition of exclusion restriction for identification. In other words, vector X_{Ni} must include variables that affect the probability of being unconstrained but do not affect the debt-level equation. Thus, the exclusion restriction must be related to credit accessibility. Following RTV (2015) I use five main exclusion variables: number of banks per number of inhabitants and number of retailers' stores, both by Area and Region. "Area" is considered Montevideo by neighborhood and the rest of the country by department, while "Region" is divided in 5 categories: Metropolitan, East, West, South-Central and North[5]. These variables are proxies for financial depth. Location decision of banks and retailers are motivated by local aggregate variables, such as urban density, demographic, socioeconomic and commercial variables. Local aggregate variables capture the supply side and I assume that they do not affect any aspect of individual household-level demand. Additionally, I included 'over-expenditure'[6]; dummy equals 1 if expenditures exceed household income, as a main exclusion variables. Therefore, it is expected that over-expenditure increases the probability of asking for credit but do not affect the credit amount.

Variables variability must be large enough to be used as instruments. Table III displays variables summary statistics, mean and standard deviation. In order to account for the variability I use the coefficient of variation[7]. For column 1 of table III, the coefficient of variation of the ratio of banks over population is 1.18, whereas the coefficient of variation of the number of retailers is 1.14, both by area. Therefore, variables show large variability. By region, the dispersion is shorter. The coefficient of banks is 0.22 and 0.47 for retailers. However, dispersion is large enough. Coefficient of variation for over-expenditure is 2.3. For the rest of the columns the coefficients of variability are similar. In addition, other exclusion variables are incorporated: using telebanking, using current account and having insurance, by type.

Vector X_N includes additional covariates that determine the probability of being unconstrained. Large majority of covariates are included following RTV (2015) to maintain consistency. Nevertheless, some covariates were not included in this investigation regarding countries' specific characteristics, such as 'Pension fund'. Besides, I did not include 'checks rejected', information not included in EFHU. 'Formality', dummy equals 1 if the person of reference contributes to a retirement found, is defined differently. For Chile, they use 'Signed job contract'.

Vector X_N includes real estate assets (in logarithm), years of education and age for household's adults (both variables expressed in averages), dummies variables for gender (male equals 1), spouse (spouse present in household equals 1) and place where household is located (Montevideo equals 1 if household is located in the capital city, 0 otherwise), number of persons in household, had delayed payment in past 12 months and annual income, among others.

[5] Montevideo's neighborhood are defined in INE and Regions are defined in terms of departments: "Metropolitan" includes Montevideo, San José and Canelones; "East" includes Maldonado, Rocha, Lavalleja, Treinta y Tres; "West" includes Colonia, Soriano, Rio Negro; "South-Central" refers to Flores, Florida, Durazno; and "North" includes Artigas, Salto, Paysandú, Rivera, Tacuarembó and Cerro Largo.

[6] This variable is not available for Chile, but I decided to include it due to the pertinence and significance in the control functions used in the followings chapters.

[7] Coefficient of variation is defined as the standard deviation divided into the mean of the variable. Both statistics are expressed in same units, so coefficient of variation shows the extent of variability in relation to the mean.

Table III. Summary statistics of variables (mean)

Variables	All	Any Constraint	Un-constrained	Mortgage Constrained	Mortgage un-conconstrained	Consumer Constrained	Consumer Unconstrained	Any debt holder	Mortgage debt holder	Consumer debt holder	Non-debt Holder
N° of observations	3490	541	2949	293	3197	361	3129	1662	349	1495	1828
Any debt holder = 1	0.485	0.592	0.463	0.549	0.478	0.634	0.466	1	1	1	0
	(0.500)	(0.492)	(0.499)	(0.498)	(0.50)	(0.482)	(0.499)	(0.00)	(0.00)	(0.00)	(0.00)
Mortgage debt holder	0.091	0.0571	0.098	0.0092	0.100	0.081	0.092	0.188	1	0.107	0
= 1	(0.288)	(0.232)	(0.298)	(0.096)	(0.30)	(0.273)	(0.29)	(0.391)	(0.00)	(0.31)	(0.00)
Consumer debt holder	0.441	0.571	0.414	0.542	0.430	0.606	0.42	0.909	0.518	1	0
= 1	(0.497)	(0.495)	(0.493)	(0.499)	(0.495)	(0.489)	(0.494)	(0.287)	(0.50)	(0.00)	(0.00)
Total debt	4420	3571	4593	2127	4657	4226	4445	9123	30802	6732	0
	(18943)	(13885)	(19813)	(6498)	(19774)	(16044)	(192.84)	(26419)	(52120)	(17862)	(0.00)
Mortgage debt	2570	820	2926	426	2791	952	2776	5304	28185	2533	0
	(17560)	(5389)	(19091)	(5467)	(18346)	(4553)	(18563)	(24941)	(51636)	(14625)	(0.00)
Consumer debt	1850	2750	1667	1701	1865	3273	1669	3819	2618	4199	0
	(6681)	(12849)	(4470)	(3584)	(6923)	(15459)	(4439)	(9200)	(5368)	(9564)	(0.00)
Unconstrained = 1	0.831	0	1	0	0.917	0	0.937	0.794	0.894	0.781	0.866
	(0.375)	(0.00)	(0.00)	(0.00)	(0.276)	(0.00)	(0.244)	(0.405)	(0.308)	(0.414)	(0.341)
Mortgage	0.906	0.446	1	0	1	0.668	0.937	0.894	0.991	0.885	0.918
Unconstrained = 1	(0.291)	(0.498)	(0.00)	(0.00)	(0.00)	(0.471)	(0.244)	(0.308)	(0.097)	(0.319)	(0.274)
Consumer	0.887	0.333	1	0.60	0.917	0	1	0.852	0.900	0.845	0.920
Unconstrained = 1	(0.316)	(0.472)	(0.00)	(0.491)	(0.276)	(0.00)	(0.00)	(0.355)	(0.301)	(0.362)	(0.272)
Annual income	18678	12921	19850	13220	19243	11951	19534	18558	27591	17324	18791
	(19275)	(10158)	(20447)	(10489)	(19880)	(9383)	(20029)	(19121)	(22367)	(17772)	(19423)
Total assets	84308	28034	95760	18339	91126	32542	90894	66931	141082	58828	100643
	(259043)	(61239)	(281469)	(49271)	(270728)	(63419)	(273400)	(249112)	(537814)	(254765)	(267082)
Real estate assets	73338	24203	83337	14613	79408	29117	78964	58735	125416	51829	87066
	(240652)	(57802)	(261595)	(46740)	(251558)	(59799)	(254064)	(238044)	(517351)	(244525)	(242342)

Table III. Continued

Variables	All	Any Constraint	Un-constrained	Mortgage Constrained	Mortgage un-conconstrained	Consumer Constrained	Consumer Unconstrained	Any debt holder	Mortgage debt holder	Consumer debt holder	Non-debt Holder
Non-real estate assets	10970	3832	12423	3726	11719	3425	11930	8197	15667	7000	13577
	(35633)	(9170)	(38712)	(8946)	(37239)	(8468)	(37603)	(20678)	(33520)	(17684)	(45254)
Age (average adults)	50	44	51.5	44.9	50.8	42.5	51.2	48.0	46.9	48.2	52.3
	(17)	(14.3)	(16.9)	(15.0)	(16.8)	(13.42)	(16.8)	(15.3)	(13.5)	(15.4)	(17.6)
Years of educations	9.82	8.87	10.02	8.95	9.9	8.67	9.97	9.80	11.7	9.5	9.85
(average adults)	(3.76)	(3.14)	(3.85)	(3.23)	(3.8)	(2.9)	(3.83)	(3.52)	(3.67)	(3.41)	(3.98)
Gender (male = 1)	0.344	0.310	0.350	0.27	0.351	0.336	0.345	0.345	0.369	0.335	0.342
	(0.475)	(0.463)	(0.477)	(0.445)	(0.477)	(0.473)	(0.475)	(0.475)	(0.483)	(0.472)	(0.475)
N° of persons in	2.917	3.35	2.83	3.12	2.90	3.55	2.84	3.20	3.18	3.22	2.66
household	(1.66)	(1.84)	(1.614)	(1.73)	(1.66)	(1.92)	(1.614)	(1.76)	(1.64)	(1.77)	(1.53)
Credit card holding = 1	0.595	0.453	0.624	0.511	0.604	0.378	0.623	0.669	0.844	0.653	0.525
	(0.49)	(0.50)	(0.48)	(0.50)	(0.49)	(0.48)	(0.48)	(0.47)	(0.36)	(0.48)	(0.50)
Spouse present = 1	0.547	0.525	0.551	0.507	0.551	0.533	0.549	0.574	0.641	0.564	0.521
	(0.50)	(0.50)	(0.50)	(0.501)	(0.50)	(0.50)	(0.50)	(0.50)	(0.481)	(0.502)	(0.50)
Unemployed	0.0176	0.030	0.015	0.036	0.016	0.028	0.016	0.014	0.013	0.014	0.021
	(0.132)	(0.17)	(0.122)	(0.187)	(0.124)	(0.165)	(0.12)	(0.119)	(0.112)	(0.116)	(0.143)
Employed	0.674	0.731	0.663	0.706	0.671	0.739	0.666	0.704	0.776	0.697	0.646
	(0.469)	(0.444)	(0.473)	(0.456)	(0.470)	(0.44)	(0.472)	(0.456)	(0.417)	(0.46)	(0.478)
Formality	0.457	0.442	0.460	0.429	0.460	0.43	0.46	0.504	0.698	0.478	0.413
	(0.498)	(0.497)	(0.498)	(0.496)	(0.498)	(0.496)	(0.50)	(0.50)	(0.46)	(0.50)	(0.493)
Wage	636	506	662	545	645	449	659	653	1121	589	619
	(1310)	(755)	(1395)	(881)	(1346)	(651)	(1370)	(994)	(1501)	(849)	(1550)
Self-employed	0.199	0.185	0.202	0.208	0.198	0.169	0.203	0.197	0.200	0.193	0.202
	(0.40)	(0.389)	(0.402)	(0.407)	(0.399)	(0.375)	(0.403)	(0.398)	(0.40)	(0.395)	(0.401)
Area income	24141	22811	24411	23310	24227	22141	24395	23325	25237	23052	24907
	(7418)	(5093)	(7780)	(5629)	(7574)	(3994)	(7709)	(6076)	(6961)	(5791)	(8418)
Montevideo	0.403	0.450	0.393	0.485	0.394	0.420	0.401	0.401	0.509	0.387	0.405
	(0.491)	(0.498)	(0.489)	(0.501)	(0.489)	(0.494)	(0.49)	(0.49)	(0.50)	(0.487)	(0.491)

Table III. Continued

Variables	All	Any Constraint	Un-constrained	Mortgage Constrained	Mortgage un-conconstrained	Consumer Constrained	Consumer Unconstrained	Any debt holder	Mortgage debt holder	Consumer debt holder	Non-debt Holder
Interior	0.597	0.550	0.607	0.515	0.606	0.580	0.599	0.599	0.491	0.613	0.595
	(0.491)	(0.498)	(0.489)	(0.501)	(0.489)	(0.494)	(0.49)	(0.49)	(0.50)	(0.487)	(0.491)
N° of banks over	0.889	0.806	0.906	0.917	0.886	0.693	0.914	0.795	0.907	0.772	0.977
population by area	(1.051)	(1.13)	(1.035)	(1.37)	(1.01)	(0.902)	(1.07)	(0.917)	(1.28)	(0.820)	(1.16)
N° of banks over	0.840	0.821	0.844	0.823	0.842	0.820	0.843	0.839	0.812	0.843	0.842
population by region	(0.181)	(0.170)	(0.183)	(0.175)	(0.181)	(0.171)	(0.182)	(0.184)	(0.165)	(0.187)	(0.178)
N° of retailers by area	41.46	39.9	41.78	37.6	41.9	43.0	41.3	43.1	43.4	43.1	39.9
	(47.23)	(48.5)	(47.0)	(46.9)	(47.26)	(51.3)	(46.7)	(50.0)	(55.3)	(49.4)	(44.4)
N° of retailers by	344	360.6	340.7	365	341.9	360.0	342.1	348.7	388.6	343.5	339.8
region	(163)	(158)	(163.9)	(158.3)	(163.4)	(157)	(163.7)	(162)	(153.82)	(162.4)	(164.03)
Over-expenditure	0.158	0.255	0.138	0.192	0.154	0.301	0.139	0.228	0.168	0.242	0.091
	(0.364)	(0.436)	(0.345)	(0.394)	(0.361)	(0.459)	(0.346)	(0.42)	(0.374)	(0.428)	(0.288)
Had delay payments in	0.199	0.356	0.167	0.309	0.188	0.419	0.171	0.369	0.267	0.394	0.039
the past 12 month	(0.40)	(0.479)	(0.373)	(0.463)	(0.391)	(0.494)	(0.377)	(0.483)	(0.443)	(0.489)	(0.195)
Life insurance = 1	0.149	0.127	0.154	0.129	0.151	0.116	0.153	0.184	0.293	0.179	0.116
	(0.356)	(0.333)	(0.361)	(0.336)	(0.358)	(0.320)	(0.360)	(0.388)	(0.456)	(0.383)	(0.321)
Vehicle insurance = 1	0.331	0.211	0.355	0.205	0.344	0.194	0.348	0.332	0.550	0.304	0.329
	(0.47)	(0.408)	(0.479)	(0.404)	(0.478)	(0.396)	(0.476)	(0.471)	(0.498)	(0.460)	(0.47)
Property insurance = 1	0.0562	0.0075	0.0662	0.0094	0.061	0.0075	0.062	0.043	0.110	0.033	0.069
	(0.230)	(0.086)	(0.249)	(0.097)	(0.24)	(0.086)	(0.242)	(0.202)	(0.314)	(0.179)	(0.254)
Current account owner	0.0815	0.0371	0.090	0.041	0.086	0.022	0.089	0.065	0.134	0.055	0.097
= 1	(0.274)	(0.189)	(0.287)	(0.199)	(0.28)	(0.146)	(0.285)	(0.247)	(0.341)	(0.228)	(0.295)
Use telebanking = 1	0.100	0.0559	0.109	0.067	0.103	0.044	0.107	0.094	0.203	0.078	0.106
	(0.30)	(0.230)	(0.311)	(0.250)	(0.304)	(0.205)	(0.309)	(0.291)	(0.403)	(0.269)	(0.307)

Note: Standard deviations in parentheses

Source : EFHU 2014

All monetary variables are expressed in US dollars

Furthermore, table III shows summary statistics of variables of interest. In average, consumer debt is low (USD 1.850) but the dispersion is high, considering all household. Restricting to consumer debt holder, the figure rises to USD 4.199, and the dispersion is high too. Mortgage debt average is higher (USD 2.570) taking all households. Considering households that hold mortgage debt, in average they owe USD 28.185. Table III also shed light on how Uruguayan household keep their assets. On average, 87% of total assets are real estate assets. Only 13% are kept as non-real assets and other real assets like cars, jewelry, etc. Finally, the proportion of person of reference equal male is 34.4%.

Estimation of equation 1 is presented in columns 1 to 3 of table IV. First column shows consumer unconstraint, second column mortgage unconstraint and third any type of unconstraint. ‘Real estate assets’ (in logarithm) is statistically significant at 1% and it affects positively for the three models considered. The impact of real estate assets in increasing the probability of being unconstrained is stronger for mortgage than consumer constraint, *ceteris paribus*. Years of education and Formality are statistically significant in the three models, increasing the probability of being unconstrained. Self-employed reduces the probability of being unconstrained in the mortgage segment, but it increases in the consumer segment. However, it is only statistically significant for mortgage restrictions. Having delay payment reduced the probability of being unconstrained in the three models considered. Living in Montevideo reduce the probability of being unconstrained, for all models. Area income does not affect equation 1 for mortgage unconstraint, but it affects positively the probability of being unconstraint for consumer debt. Gender (male equals 1) is statistically significant at 10% only for mortgage constraint, affecting positively.

Analyzing main exclusion restrictions, I observe that ratio of banks over population by region and over-expenditure are statistically significant at 5% and 1% respectively (for consumer debt.). For mortgage constraint three ratios of financial depth are significant, except ratio of banks by area. Over-expenditure does not affect the probability of applying for a mortgage credit. Besides, life insurance affects the probability of being unconstrained for mortgage and any debt, whereas any insurance affects the probability of being unconstrained only for mortgage debt. Current account is statistically significant at 10% for consumer constrained. Using telebanking is not statistically significant for any of the three models.

In second place, I model whether the household hold debt, by type. The model has the form:

$$B_{\mathbf{i}} = \mathrm{I}\,(\mathrm{X}_{\mathrm{Bi}}\,\beta_{\mathrm{B}} + u_{\mathrm{Bi}} > 0) \qquad (2)$$

where $B_{\mathbf{i}}$ is a binary variable indicating if the household has positive debt, vector X_{Bi} includes the same covariates considered in equation 1, β_{B} is an unknown parameter vector to estimate and the u_{Bi} are zero mean error term. Columns 4, 5 and 6 of table IV present the estimation of having consumer debt, mortgage debt and any type of debt, respectively.

Table IV. Estimates for selection and endogenous variables models

	Consumer Unconstrain-ed = 1	Mortgage Unconstrain-ed = 1	Any Unconstrain-ed = 1	Positive Consumer Debt = 1	Positive Mortgage Debt = 1	Positive Total Debt = 1	Annual Total Income	Non-real Estate Assets
Real Estate Assets	0.00587***	0.0142***	0.0154***	-0.00235	0.0131***	0.00366**		
	(0.00102)	(0.000934)	(0.00119)	(0.00154)	(0.00101)	(0.00158)		
Year of education	0.00821***	0.00474***	0.00961***	-0.00169	0.00632***	0.000727	0.946***	1.006***
	(0.00168)	(0.00153)	(0.00195)	(0.00252)	(0.00165)	(0.00259)	(0.103)	(0.294)
Spouse present = 1	0.0151	-0.00368	0.0132	-0.0141	0.00299	-0.00512	2.080***	3.144
	(0.0113)	(0.0103)	(0.0131)	(0.0169)	(0.0111)	(0.0174)	(0.675)	(1.988)
Gender (male = 1)	-0.0131	0.0173*	0.00393	0.00172	-0.00852	0.00703	1.866***	3.140*
	(0.0104)	(0.00952)	(0.0122)	(0.0157)	(0.0103)	(0.0161)	(0.625)	(1.839)
Age	0.00348	-0.00103	0.000871	0.0115***	0.000854	0.00968***	-0.0521	0.0792
	(0.00212)	(0.00193)	(0.00247)	(0.00318)	(0.00208)	(0.00327)	(0.126)	(0.370)
Age^2	-7,68E-06	1.58E-05	1.44E-05	-1.02E-04**	-1.30E-05	-9.11E-05***	0.00164	0.00155
	(0.0000197)	(0.0000180)	(0.0000230)	(0.0000296)	(0.0000194)	(0.0000304)	(0.00118)	(0.00346)
No. of persons in household	-0.00204	0.00309	-0.00225	0.0201***	0.00615	0.0206***	1.181***	1.037
	(0.00382)	(0.00348)	(0.00445)	(0.00573)	(0.00375)	(0.00589)	(0.230)	(0.671)
No.of persons employed household	0.00380	0.00578	0.00936	0.00381	0.00580	0.00472	-0.406	1.551
	(0.00589)	(0.00537)	(0.00686)	(0.00884)	(0.00579)	(0.00908)	(0.362)	(1.037)
Unemployed = 1	-0.0170	-0.0337	-0.0386	-0.144**	-0.0148	-0.135**	0.242	-1.099
	(0.0438)	(0.0400)	(0.0511)	(0.0658)	(0.0431)	(0.0677)	(2.626)	(7.731)
Formality	0.0303***	0.0234**	0.0364***	0.0188	0.0535***	0.0508***	2.948***	2.321
	(0.0116)	(0.0106)	(0.0135)	(0.0174)	(0.0114)	(0.0179)	(0.695)	(2.042)
Self-employed	0.0173	-0.0257**	-0.00862	-0.0415**	-0.0177	-0.0414**	1.299*	7.626***
	(0.0113)	(0.0103)	(0.0132)	(0.0170)	(0.0111)	(0.0175)	(0.679)	(1.997)
Area income	0.00146*	0.000759	0.00167*	-0.0050***	-0.0029***	-0.00629***	0.153***	0.844***
	(0.000797)	(0.000727)	(0.000929)	(0.00120)	(0.000784)	(0.00123)	(0.0485)	(0.140)
Montevideo	-0.0745**	-0.116***	-0.145***	0.0326	0.0306	0.0502	-2.269	-10.298*
	(0.0334)	(0.0305)	(0.0390)	(0.0502)	(0.0329)	(0.0516)	(2.003)	(5892.0)
Had delay payments in the past 12 month	-0.102***	-0.0322***	-0.102***	0.495***	0.0400***	0.461***	-1.360*	-2.478
	(0.0131)	(0.0119)	(0.0153)	(0.0196)	(0.0129)	(0.0202)	(0.782)	(2.304)
Life insurance = 1	-0.00933	-0.0336**	-0.0342*	0.0898***	0.0445***	0.0929***	3.590***	-0.957
	(0.0172)	(0.0157)	(0.0200)	(0.0258)	(0.0169)	(0.0265)	(1.030)	(3.024)
Vehicle insurance = 1	0.0235	-0.0237	-0.00506	-0.0449	0.00608	-0.0236	5.020***	12.217***
	(0.0239)	(0.0218)	(0.0278)	(0.0359)	(0.0235)	(0.0369)	(1.435)	(4.208)
Property insurance = 1	-0.00630	-0.00622	0.00649	-0.0480	0.0189	-0.0308	6.522***	16.904***
	(0.0209)	(0.0191)	(0.0244)	(0.0314)	(0.0206)	(0.0323)	(1.259)	(3.676)

Table IV. Continued

	Consumer Unconstrain-ed = 1	Mortgage Unconstrain-ed = 1	Any Unconstrain-ed = 1	Positive Consumer Debt = 1	Positive Mortgage Debt = 1	Positive Total Debt = 1	Annual Total Income	Non-real Estate Assets
Any insurance = 1	-0.00349	0.0399*	0.0305	0.0209	0.0167	0.0162	-2.587*	-1.901
	(0.0258)	(0.0236)	(0.0301)	(0.0388)	(0.0254)	(0.0399)	(1.547)	(4.551)
Current account owner = 1	0.0315*	0.0166	0.0308	-0.0387	0.00525	-0.0273	3.645***	18.980***
	(0.0182)	(0.0166)	(0.0212)	(0.0273)	(0.0179)	(0.0281)	(1.096)	(3.207)
Use telebanking = 1	-0.0121	-0.0203	-0.0230	0.00887	0.00472	0.0250	5.301***	9.462***
	(0.0173)	(0.0158)	(0.0202)	(0.0260)	(0.0170)	(0.0267)	(1.041)	(3.050)
Over-expenditure	-0.0626***	-0.00543	-0.0633***	0.126***	0.0221	0.125***	-2.384***	-2.076
	(0.0144)	(0.0131)	(0.0168)	(0.0216)	(0.0142)	(0.0222)	(0.861)	(2.532)
N° of banks over population by area	0.00688	-0.00505	0.000867	-0.0167**	0.00371	-0.0131*	-0.535*	0.187
	(0.00515)	(0.00470)	(0.00601)	(0.00773)	(0.00507)	(0.00795)	(0.308)	(0.908)
N° of banks over population by region	0.0948**	0.0832**	0.131**	0.0441	0.0288	0.0300	-0.790	-9.722
	(0.0455)	(0.0416)	(0.0531)	(0.0684)	(0.0448)	(0.0703)	(2.726)	(8.026)
N° of retailers by area	-0.000310	-0.000513**	-0.000563**	0.000156	0.000244	0.000306	-0.0156	-0.0683*
	(0.000228)	(0.000208)	(0.000266)	(0.000342)	(0.000224)	(0.000352)	(0.137)	(0.040)
N° of retailers by region	0.000150	0.000227**	0.000286**	-0.0000543	0.0000907	-0.0000146	0.00589	0.00441
	(0.0000968)	(0.0000883)	(0.000113)	(0.000145)	(0.0000952)	(0.000149)	(0.00580)	(0.0171)
Annual total income (ECH)							0.383***	
							(0.0155)	
Constant	0.483***	0.651***	0.366***	0.0971	-0.160**	0.120	-13.457***	-29.735**
	(0.0804)	(0.0734)	(0.0938)	(0.121)	(0.0791)	(0.124)	(4.832)	(14.114)
Observations	3490	3490	3490	3490	3490	3490	3490	3490
R^2	0.1072	0.1037	0.1405	0.2378	0.1099	0.2091	0.4559	0.1282

Note: Standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; $p < 0.1$. Interior region excluded

Real estate assets (in logarithm) affects positively the probability of having mortgage debt but negatively (and non-significant effect) on consumer debt holding. Years of education and Formality yield a positive effect on mortgage debt holding, but they are not statistically significant for consumer debt holding. This result suggest it is relatively easy to obtain consumer credits regardless the borrower level of education and the formality condition. However, mortgage market is more restrictive. Age presents aconcave profile for all type of debts, but it is not statistically significant for mortgage debt, contrary to what is expected. Area income yields a negative effect on having debt for all types. This finding it is surprisingly for mortgage debt. As expected, Had delay payments affects the probability of having debt in the three models. Spouse, gender and number of persons employed yield no effect on having debt. Unemployed affects negatively holding consumer and any debt at 5% level.

Now, focus on the impact of the main exclusion restrictions. Financial depth variables do not affect the probability of having mortgage debt, contrary to what RTV (2018) found for Chile. This result could be explained considering the size of the country. Uruguay is a small country and distances may not be a restriction for asking mortgage loans. Also, over-expenditure yields no effect on the probability of holding mortgage debt. This result seems reasonable. Thus, the main exclusion variables are not statistically significant to determine the probability of holding debt. This finding questions the properly identification of two-step procedure for mortgage debt, discussed in the next session. Therefore, results for mortgage credit must be taken cautiously.

For consumer debt holding, ratio banks per inhabitant by area and over-expenditure are statistically significant at 5% and 1%, respectively. Last, it is important to highlight that the differences found in consumer and mortgage debt models suggest estimating separately, regarding the nature of each of them. So, in the following chapters, I keep them separate to analyze the impact of the covariates on the debt level demand.

6. Estimating the determinants of household debt

6.1 The model

In this chapter I estimate the determinants of household debt level. D_i, logarithm of debt in US dollars, is the dependent variable. As aforementioned, 48.5% of households hold any debt: 44.1% hold consumer debt, while 9.1% hold mortgage debt. Moreover, a fraction of indebtedness households are credit constrained, affecting debt level. Therefore, estimating by OLS considering the subsample $\{B_i = 1 \ \& \ N_i = 1\}$ leads to biased estimators (sample selection).

I need to estimate the following equation:

$$D_{\mathbf{i}} = X_{Di}\, \beta_D + g_1(I_i) + g_2(A_i) + u_{Di} \qquad (3)$$

Where X_{Di} are exogenous variables, β_D is an unknown parameter vector, $g_1(I_i)$ and $g_2(A_i)$ are unknown functions, and u_{Di} are zero mean error term. I_i and A_i are household´s annual income and the value of non-real estate assets, respectively. Taking the conditional mean of equation 3, considering the subsample $\{B_i = 1 \ \& \ N_i = 1\}$ I have:

$$E\,[D_{\mathbf{i}} \mid N_i = 1 \ \& \ B_i = 1] = X_{Di}\, \beta_D + g_1(I_i) + g_2(A_i) + E\,[u_{Di} \mid N_i = 1 \ \& \ B_i = 1] \qquad (4)$$

As RTV (2015) explain, it is necessary to “account for the misspecification of the conditional mean captured by the term $E\,[u_{Di} \mid N_i = 1 \ \& \ B_i = 1]$” in order to have consistent estimation. One option is assuming that error terms u_{Di}, u_{Bi} and u_{Ni} are jointly normal. Two-step procedure proposed by Heckman (1979) is available to overcome sample selection, under the error term hypothesis assumed.

Moreover, it can be assumed that u_{Ni}'s and u_{Bi}'s are uncorrelated and estimate equation (1) and (2) separately. Then, calculate inverse Mills ratio from each equation, adding as additional regressors in equation (3). Contrary, if u_{Ni}'s and u_{Bi}'s are assumed correlated it is necessary to estimate error terms correlation and then estimate holding debt and having constraint jointly with a biprobit, instead of two univariate probit.

The semiparametric approach presents two advantages. First, it allows the correlation between the error terms u_{Ni} 's and u_{Bi} 's. Second, it relaxes normality assumption. Das *et al.* (2003) proposed a semiparametric methodology that considers the following approximation:

$$E\,[u_{Di} \mid N_i = 1 \;\&\; B_i = 1] \approx f\,[\Pr(N_i = 1|X_{Ni}), \Pr(B_i = 1|X_{Bi})]$$

Where f (.) is an unknown function, Pr (.) are probabilities defined as the propensity score estimated in equation (1) and (2) and X are exogenous variables in the model. The specification of f (.) will be driven by a series of polynomials which is determined by cross-validation procedure. It consists of minimizing the sum of squares of forecast error. In this point Ruiz-Tagle and Vella follow Das et al (2003) methodology, *leave one out cross validation*, "where all the other observations are used to predict each single observation". By contrast, I consider k-fold cross-validation, where the original sample is randomly partitioned into *k* equal sized subsample. Thus, observations included in *k-1* folders are used as training data to fix the model and then use it to predict observations included in the rest subsample (validation data). The procedure is done *k* times, taking an average. In this paper I use $k = 10$.

Debt level equations consider annual total income (*I*) and non-real estate (*A*) as regressors, both expressed in thousands of US dollars. However, *I* and *A* are likely to be endogenous in equation 3. Following Das *et al.* (2003), a possible solution to control for endogeneity is using a control function including the residuals, r_{Ii} and r_{Ai}, as additional regressors. Both are estimated from the reduced-form equation for I and A. Additionally, in debt level equations I allow for non-linearity adding second and third polynomials term for annual income and non-real estate assets. Residuals and propensity score are considered in their second and third order. Finally, interaction between residuals and propensity score are also allowed until second order.

OLS estimations for annual income and non-real estate assets are displayed in columns 7 and 8 of table IV, respectively. I include the same covariates used in the selection equations to maintain consistency. Nevertheless, real estate asset, capturing families' wealth position, is excluded due to its possible simultaneity with I and A. ECH Income is included as an additional instrument for annual income, in order to control for measure error. Annual Income is referred to total household income in the previous month of the survey, times 12. Unfortunately, EFHU does not collect average income that would be more appropriate.

Table V. Polynomial sets for cross-validation (number of polynomial terms)

Set	Base polynomial (always included)	I	I^2	I^3	A	A^2	A^3	r_I	r_I^2	r_I^3	r_A	r_A^2	r_A^3	p_N	p_N^2	p_N^3	p_B	p_B^2	p_B^3	Int1	Int2	No. of variables to combine
1	—	1	1	1	1	1	1	1			1			1			1					10
2	—	1			1			1			1			1			1			6		12
3	I, A			1		1	1	1			1			1			1			6		13
4	I, I^2, A			1		1	1	1			1			1			1			6		13
5	I, I^2, A, A^2, Int1			1			1	1			1			1			1				6	12
6	I, r_I, A, r_A					1			1			1		1	1		1	1		6		13
7	I, I^2, r_I, A, r_A					1			1			1		1	1		1	1		6		13
8	I, r_I, A, r_A			1		1	1		1	1		1	1	1	1	1	1	1	1			13
9	I, I^2, r_I, A, r_A			1		1	1		1	1		1	1	1	1	1	1	1	1			13
10	$I, I^2, r_I, r_I^2, A, A^2, r_A, r_A^2$						1			1			1	1	1		1	1		6		13
11	$I, I^2, I^3, r_I, r_I^2, A, A^2, r_A, r_A^2$						1			1			1	1	1		1	1		6		13
12	$I, I^2, I^3, r_I, r_I^2, r_I^3, A, A^2, A^3, r_A, r_A^2, r_A^3$, Int1														1	1		1	1		6	10

I = income; A = non-real estate assets; $p_N = X_N \widehat{\beta}_N$ = p-score, unconstrained; $p_B = X_B \widehat{\beta}_B$ = p-score, positive debt; r_I = residual from income; r_A = residual from non-real estate assets. Int1 = first-order interaction terms set; Int2 = second- order interaction terms set.

To implement Das *et al*. (2003) estimator, the predicted propensities scores are added in debt level equations, denoted by $\hat{p}_{Ni} = X_{Ni}\,\hat{\beta}_N$ and $\hat{p}_{Bi} = X_{Bi}\,\hat{\beta}_B$, and estimated from equation (1) and (2) respectively. Thus, we need to estimate the following equation:

$$D_i = X_{Di}\,\beta_D + \sum_{j=1}^{J} \alpha 1^j\, Ii^j + \sum_{k=1}^{K} \alpha 2^k\, Ai^k + h(\hat{p}_{Ni}, \hat{p}_{Bi}, \hat{r}_{Ii}, \hat{r}_{Ai}) + u_i \qquad (5)$$

Where $h(.)$ is a function that includes the propensities score of equation (1) and (2), and residuals from reduced form of annual income and non-real estate assets. The preferredmodel is the one that minimizes the adopted CV criterion. Thus, it is necessary to estimate a large number of models. Table V shows how to combine the different variables involved. For instance, set 1 includes the base polynomial ($X_{Di}\beta_D$) and combines I and A up to the third order; residuals and propensities score only linearly. So far, there are 10 variables to combine, all the ways possible. Thus, set 1 includes 1023 possible models; set 2, 4095 combinations (12 variables to combine); set 3, 8190 combinations (13 variables to combine), and so on. Sets 3 to 12 include other variables as “fixed” beyond the base polynomial. All in all, for each type of debt there are 75.756 models to estimate.

For consumer debt, the preferred model according to the cross validation criterion does not include income, square income and non-real estate assets. However, these variables are statistically significant; thus, I decided to include them. For total debt model, I decided to include square income to the model proposed by cross validation. Moreover, I found that cross validation is “sensitive” to the variables included. For instance, initially I included Having property in the vector of covariate, dummy that equals 1 if household have any real estate assets. By doing so, the model yield includes income and square income, and also p-value of income residuals was 0.004, suggesting income endogeneity. Finally, I had to exclude Having property due to collinearity in mortgage structural model, obtaining a different model where income is not included and it suggests no income endogeneity. Therefore, a deeper analysis of automatic criterion accuracy and reliability is needed.

I also decided to exclude variable ‘Self-perception of financial service high’, dummy equals 1 if households report self-perception of paying financial service is high (interest and principal). In Chilean paper this variable was included, but I had to take it off due to problems in estimating Heckman approach. In the first stage, estimating the probability of having any debt, ‘Self-perception of financial service high’ is omitted because values that take 1 predict success perfectly. To maintain consistency and comparability I decided not to include it in any model.

6.2 The results

6.2.1 Results of sample selection and endogeneity

Results are presented in tables VI to VIII. Table VI displays consumer debt estimates, table VII mortgage debt estimates and table VII total debt estimates. Evidence of sample selection is given by the propensity scores (p_N and p_B) significance in the semiparametric model. In Heckman approach sample selection is given by the significance of the Inverse Mills Ratio (IMR). Furthermore, two sources of endogeneity are test, annual income and non-real estate assets. In the semiparametric model income and non-real estate assert endogeneity is given by the terms r_I and $r_{A,}$, respectively. Heckman approach does not include endogeneity test.

For consumer debt, I do not find evidence of endogeneity for income and non-real estate assets (semiparametric model). Moreover, I find evidence of sample selection for holding debt and being constrained, captured by the interaction of propensities scores of holding debt and being unconstrained. Alternatively, Heckman models find sample selection in both approaches.

For mortgage debt I do not find evidence of endogeneity for *I* and *A*, nor do I find evidence of selection. I also estimate joint significance of variables, regarding that single parameters might be not significant but they might be jointly significant. Results are presented in the bottom of table VII. However, variables are not statistically significant. It is worth noting that with the model yield by cross validation if variable 'Self-perception of financial service high' were included, propensity score of holding debt and its square are jointly significant, detecting sample selection. This finding reinforces the idea of how "sensitive" cross validation approach is. Alternatively, using Heckman approach I find evidence of sample selection for the first model captured by the term IMR_N, at the 10% level.

The preferred model for total debt finds endogeneity and sample selection. Results are captured by the interaction term of the non-real estate assets residuals and the propensity score of holding debt. However, evidence supporting endogeneity and sample selection is weak, as long as ra*pb is only significant at 10% level. For sample selection, propensity scores are not individually significant. I estimate joint significance trying to find stronger evidence of sample selection but interaction of propensities score are not significant. This is shown in the bottom of table VIII. Alternatively, Heckman approach indicates no sample selection in both models.

Results are quite surprisingly, considering what RTV (2015) found for Chile. For consumer debt they found strong endogeneity for income and non-real estate assets and the presence of selection bias. For mortgage debt they found endogeneity only for non-real estate assets and weak sample selection for mortgage constraint. For total debt, the also find endogeneity for income and non-real estate assets and sample selection. In section 8 I analyze possible answers to the unexpected results.

Table VI. Estimation results of borrowing demand: consumer debt

Depvar: ln(consumer debt)	No correction	Parametric Correction I	Parametric Correction II	Semiparametric correction
Income	0.0307***	0.0263***	0.0224***	0.0299***
	(0.00434)	(0.00711)	(0.00743)	(0.00756)
Income^2	-5.58e-05***	-4.72e-05	-3.92e-05	-4.26e-05***
	(1.12e-05)	(6.22e-05)	(5.90e-05)	(1.24e-05)
Non-real estate assets	-0.00236	-0.000409	-0.000409	0.0102*
	(0.00168)	(0.00233)	(0.00235)	(0.00000574)
Real Estate Assets	-0.0127	-0.0227**	-0.0330***	-0.0209**
	(0.00826)	(0.0104)	(0.0121)	(0.00975)
Year of education	0.0300**	0.0173	0.00266	-0.00263
	(0.0150)	(0.0170)	(0.0187)	(0.0187)
Spouse present = 1	0.0577	0.0565	0.0447	0.00372
	(0.0903)	(0.104)	(0.112)	(0.0931)
Gender (male = 1)	-0.0709	-0.0461	-0.0176	-0.0914
	(0.0871)	(0.0866)	(0.0920)	(0.0895)
Age	0.0620***	0.0382*	0.0271	0.0186
	(0.0196)	(0.0210)	(0.0227)	(0.0230)
Age^2	-0.000588***	-0.000424**	-0.000390*	-0.000265
	(0.000186)	(0.000193)	(0.000204)	(0.000209)
No. of persons in household	-0.0129	-0.0330	-0.0505	-0.0652*
	(0.0302)	(0.0336)	(0.0361)	(0.0347)
No. of persons employedin household	0.00848	-0.00649	-0.0155	-0.0379
	(0.0477)	(0.0527)	(0.0563)	(0.0495)
Unemployed = 1	-0.172	0.0609	0.267	0.187
	(0.461)	(0.397)	(0.462)	(0.471)
Formality	0.110	0.0305	-0.0377	-0.0587
	(0.0963)	(0.105)	(0.115)	(0.107)
Self-employed	-0.0317	-0.0105	-0.0208	-0.0463
	(0.0936)	(0.103)	(0.109)	(0.105)
Area income	-0.0148**	-0.00864	-0.00788	-0.0122
	(0.00748)	(0.00969)	(0.0101)	(0.00894)
Montevideo	-0.0983	-0.00865	0.0717	-0.00688
	(0.0934)	(0.115)	(0.129)	(0.102)
Had delay payments in the past 12 month	-0.175**	-0.607**	-0.876**	-1.263***
	(0.0884)	(0.309)	(0.351)	(0.353)
IMR_B		-0.776**	-0.877**	
		(0.365)	(0.378)	
IMR_N		-1.199*	-1.273**	
		(0.634)	(0.621)	
IMR_B * IMR_N			-1.952**	
			(0.928)	

Table VI. Continued

Depvar: ln(consumer debt)	No correction	Parametric Correction I	Parametric Correction II	Semiparametric correction
r_I				0.0000326 (0.0000390)
r_A				-0.00000766 (0.0000181)
p_B				-0.121 (1.187)
r_I*p_N				-0.0000401 (0.0000428)
r_A*p_N				-0.00000489 (0.0000189)
p_B*p_N				3.284** (1.588)
Constant	5.648*** (0.538)	7.604*** (0.936)	8.832*** (1.102)	6.429*** (0.610)
N	1275	1275	1275	1275
R2	0.105			0.118
Age & *Age*^{2}	Prob > F = 0.0066	Prob > F = 0.0381	Prob > F = 0.0099	Prob > F = 0.0391

Note: Standard errors in parentheses (Bootstrap s.e. for Heckmans' models). *** $p < 0.01$; ** $p < 0.05$; $p < 0.1$. Interior region excluded. pN = XN$\hat{\beta}$N = p-score, unconstrained; pB = XB$\hat{\beta}$B = p-score, positive debt; rI = residuals from income; rA = residuals from non-real estate assets; IMRB = inverse Mill ratio of positive consumer debt; IMRN = inverse Mill ratio of consumer unconstrained.

6.2.2 Results of the determinants of debt level

Tables VI, VII and VIII report estimation for consumer, mortgage and total debt, respectively. Each of them presents in column 1 the ordinary least square estimation, first benchmark to compare with the preferred specification, the semiparametric approach. Following RTV (2015), column 2 "provides the parametric selection bias adjusted estimates based on Cox and Jappelli (1993), in which equation (1) and (2) are each independently estimated by a probit model and their respective inverse Mills ratio are included as additional regressors". Standard errors of parameters are estimated by bootstrap. Column 3 includes interactions between inverse mill ratios. Last column displays the semiparametric models, selected by cross validation procedure.

Table VII. Estimation results of borrowing demand: mortgage debt

Depvar: ln(mortgage debt)	No correction	Parametric Correction I	Parametric Correction II	Semiparametric
Income	0.0277**	0.0220	0,021	0.0338*
	(0.0134)	(0.0204)	(0.0206)	(0.0180)
Income^2	-2.45e-04	-1.64e-04	-1.46e-04	-2.55e-04
	(1.66e-04)	(3.42e-04)	(3.5e-04)	(1.76e-04)
Income^3	5.52e-07	3.70e-07	3.30e-07	5.44e-07
	(3.72e-07)	(1.84e-06)	(1.89e-06)	(3.89e-07)
Non-real estate assets	-0.000873	-0.00184	-0.00232	0.00486
	(0.00224)	(0.00300)	(0.00302)	(0.00861)
Real Estate Assets	0.116	0.0677	0,086976	0.0664
	(0.104)	(0.149)	(0.1501445)	(0.130)
Year of education	0.0864***	0.0652*	0.0635471*	0.0656
	(0.0261)	(0.0345)	(0.0344904)	(0.0413)
Spouse present = 1	-0.145	-0.109	-0,1101882	-0.184
	(0.165)	(0.171)	(0.1698614)	(0.173)
Gender (male = 1)	0.0192	-0.0542	-0,0552217	-0.0772
	(0.148)	(0.147)	(0.1483133)	(0.165)
Age	0.000827	0.0110	0,0169054	0.00763
	(0.0372)	(0.0363)	(0.038017)	(0.0379)
Age^2	-0.000101	-0.000230	-0,0002947	-0.000215
	(0.000364)	(0.000365)	(0.0003858)	(0.000375)
No. of persons in household	-0.170***	-0.192***	-0.194421***	-0.188***
	(0.0539)	(0.0583)	(0.0594364)	(0.0611)
No. of persons employedin household	0.0344	0.0169	0,0188551	0.0120
	(0.0882)	(0.105)	(0.1059928)	(0.0954)
Unemployed = 1	0.354	0.507	0,4288178	0.602
	(0.742)	(0.726)	(0.7311725)	(0.776)
Formality	0.468***	0.399	0,403291	0.405
	(0.178)	(0.283)	(0.2844306)	(0.262)
Self-employed	0.0847	0.194	0,181483	0.0729
	(0.157)	(0.215)	(0.2163845)	(0.216)
Area income	-0.0162	-0.0208	-0.0217	-0.0294*
	(0.0131)	(0.0169)	(0.0169)	(0.0168)
Montevideo	0.0830	0.288	0,2896697	0.283
	(0.169)	(0.237)	(0.2368518)	(0.230)
Had delay payments in the past 12 month	-0.327**	-0.202	-0,2010866	-0.105
	(0.161)	(0.223)	(0.2190086)	(0.215)
IMR_B		-0.00666	0,3357207	
		(0.544)	(0.6238927)	
IMR_N		-5.353*	1,178168	
		(3.118)	(7.006081)	
$IMR_B * IMR_N$			-4,556146	
			(4.31623)	

Table VII. Continued

Depvar: ln(mortgage debt)	No correction	Parametric Correction I	Parametric Correction II	Semiparametric
ri				-0.00000658
				(0.0000122)
ri2				4.39e-11
				(2.19e-10)
ra				-0.00000381
				(0.00000726)
ra2				-2.58e-11
				(4.59e-11)
ra3				4.07e-17
				(7.49e-17)
pnh				81.21
				(65.00)
pnh2				-40.10
				(33.33)
pbh2				-6.651
				(24.81)
pbh3				8.430
				(66.78)
Constant	7.481***	8.649***	7.891008***	-32.43
	(1.327)	(2.609)	(2.709999)	(31.74)
N	344	344	344	344
R-sq	0.276			0.286
Age & Age^2	Prob > F = 0.386	Prob > F = 0.258	Prob > F = 0.239	Prob > F = 0.185
r_I & r_I^2	-	-	-	Prob > F = 0.591
r_A & r_A^2	-	-	-	Prob > F = 0.600
r_A & r_A^3	-	-	-	Prob > F = 0.600
r_A^2 & r_A^3	-	-	-	Constrained dropped
pnh & pnh^2	-	-	-	Prob > F = 0.351
pbh^2 & pbh^3	-	-	-	Prob > F = 0.835

Note: Standard errors in parentheses (Bootstrap s.e. for Heckmans' models). *** $p < 0.01$; ** $p < 0.05$; $p < 0.1$.

Interior region excluded. $p_N = X_N\hat{\beta}_N$ = p-score, unconstrained; $p_B = X_B\hat{\beta}_B$ = p-score, positive debt; r_I = residuals from income; r_A = residuals from non-real estate assets; IMR_B = inverse Mill ratio of positive mortgage debt; IMR_N = inverse Mill ratio of mortgage unconstrained.

In first place, focus on the outcome for consumer debt demand (table VI). For the four models considered income is statistically significant, affecting positively. Income OLS estimates is higher compared to other models. However, OLS estimates are biased, as it does not include sample selection. Semiparametric approach indicates nonlinearity of income, including square income. The value of real estate assets (in logarithm) is statistically significant on consumer debt demand for all models, except for OLS. As debt and real estate assets are expressed in logarithm, the coefficient represent the elasticity. The semiparametric correction yields an elasticity of -0.0209, whereas in first parametric correction elasticity is estimates in -0.0227 and in the second parametric correction elasticity is estimated in -0.033.

Age displays no effect on consumer debt (semiparametric approach), whereas it affects positively in Heckman models, accepting non-linearity. However, Age and Age^2 are jointly significant, as it can be seen in bottom of table VI, and it presents a concave profile. Therefore, Age affects positively in the first sections and then negatively.

The value of Age that maximizes consumer debt is estimated in 45 years old in the first parametric correction, whereas it is estimated in 35 years old in the second parametric and in the semiparametric correction.

Having delayed payments displays a negative and significant impact on consumer debt (Heckman and semiparametric approach), and Non-real estate assets affects positively (semiparametric correction). Education, area income, living in Montevideo and Formality plays no role in consumer debt level.

In second place, focus on the outcome for mortgage debt demand (table VII). Annual income has no effect on Heckman model, but it displays a positive effect in the semiparametric correction. Moreover, income affects linearly on mortgage debt. Increments of one thousand dollars in annual household income rise mortgage debt in 3.38%. Years of education of households (average) present a positive and significant effect at 10% level for Heckman models, contrary to the semiparametric approach. Area income displays a negative and significant impact on mortgage debt in the semiparametric model at 10% level (unexpected). In addition, living in Montevideo, Non-real estate assets, Real estate assets, Having delay payments and Formality display no effect on mortgage debt.

Age is not statistically significant on mortgage debt in all specifications. Joint significance is not significant either. This is, somehow, an unexpected finding. Age plays a central role in Chilean economy to determine mortgage debt. Ruiz-Tagle and Vella found that mortgage credit level increase with age at a certain point (nearly fifty years old) and then it decreases. A possible explanation is that I have few observations for mortgage credits, impacting on the precision of the estimates. In section 8 I go into details about methodological difficulties found in order to give an explanation about the results achieved.

Table VIII. Estimation results of borrowing demand: total debt

Depvar: ln(total debt)	No correction	Parametric Correction I	Parametric Correction II	Semiparametric correction
Income	0.0315***	0.0334***	0.0283***	0.0364***
	(0.00429)	(0.0111)	(0.00612)	(0.00657)
Income^2	-5.77e-05***	-4.85e-05	-5.11e-05	-3.84e-05***
	(1.13e-05)	(8.74e-05)	(3.74e-05)	(1.33e-05)
Non-real estate assets	-0.00293*	-0.00389*	-0.00237	0.00348
	(0.00165)	(0.00227)	(0.00203)	(0.00552)
Real Estate Assets	0.0443***	0.0320	0.0142	-0.0361
	(0.00935)	(0.0259)	(0.0241)	(0.0369)
Year of education	0.0753***	0.0716***	0.0624***	0.00637
	(0.0156)	(0.0241)	(0.0201)	(0.0259)
Spouse present = 1	0.0372	0.0259	0.0311	-0.0748
	(0.0960)	(0.133)	(0.104)	(0.100)
Gender (male = 1)	-0.0438	0.00266	-0.0530	-0.113
	(0.0914)	(0.116)	(0.0918)	(0.0937)
Age	0.0440**	0.0270	0.0392*	0.0159
	(0.0207)	(0.0291)	(0.0223)	(0.0240)
Age^2	-0.000447**	-0.000337	-0.000438**	-0.000311
	(0.000197)	(0.000273)	(0.000208)	(0.000217)
No. of persons in household	-0.00834	0.0201	-0.0182	-0.0683*
	(0.0320)	(0.0484)	(0.0333)	(0.0369)
No. of persons employedin household	-0.00124	0.0306	-0.0203	-0.0894
	(0.0511)	(0.0691)	(0.0567)	(0.0573)
Unemployed = 1	-0.358	-0.212	-0.228	0.0652
	(0.501)	(0.499)	(0.458)	(0.533)
Formality	0.367***	0.403**	0.286**	0.0192
	(0.103)	(0.159)	(0.132)	(0.159)
Self-employed	0.0184	0.0314	0.0603	0.0731
	(0.0984)	(0.142)	(0.118)	(0.124)
Area income	-0.0203***	-0.0317**	-0.0183*	-0.0194*
	(0.00777)	(0.0131)	(0.00985)	(0.0102)
Montevideo	0.0969	0.264*	0.198	0.318**
	(0.0999)	(0.158)	(0.128)	(0.156)
Had delay payments in the past 12 month	-0.345***	0.145	-0.512	-1.061***
	(0.0961)	(0.594)	(0.338)	(0.375)
IMR_B		0.692	-0.259	
		(0.756)	(0.444)	
IMR_N		-1.091	-0.697	
		(0.747)	(0.638)	
$IMR_B * IMR_N$			-0.620	
			(0.700)	
r_I				0.0000252
				(0.0000389)

Table VIII. Continued

Depvar: ln(total debt)	No correction	Parametric Correction I	Parametric Correction II	Semiparametric correction
r_A				0.0000194
				(0.0000213)
p_N				7.104
				(7.560)
p_N^2				-1.737
				(3.629)
p_B				1.393
				(2.980)
p_B^2				1.059
				(1.016)
r_I*p_N				-0.0000369
				(0.0000377)
r_I*p_B				-0.0000122
				(0.0000192)
r_A*p_N				-0.0000186
				(0.0000181)
r_A*p_B				-0.0000171*
				(0.0000102)
p_B*p_N				-0.312
				(2.555)
Constant	5.624***	5.586***	6.819***	2.783
	(0.567)	(1.652)	(1.158)	(3.867)
N	1341	3490	3490	1341
R-sq	0.223			0.237
Age **&** *Age* ^{2}	Prob > F = 0.0660	Prob > F = 0.0271	Prob > F = 0.0558	Prob > F = 0.00690
pn **&** *pn* ^{2}	-	-	-	Prob > F = 0.228
pb **&** *pb* ^{2}	-	-	-	Prob > F = 0.147

Note: Standard errors in parentheses (Bootstrap s.e. for Heckmans' models). *** $p < 0.01$; ** $p < 0.05$; $p < 0.1$
Interior region excluded. pN = XN$\hat{\beta}$N = p-score, unconstrained; pB = XB $\hat{\beta}$B = p-score, positive debt;
rI = residuals from income; rA = residuals from non-real estate assets; IMRB = inverse Mill ratio of positive total debt; IMRN = inverse Mill ratio of total unconstrained.

In third place, focus on the outcome for total debt demand (table VIII). Annual income and area income are statistically significant for the four models considered. Age displays a significant impact for the second parametric correction. However, Age and Age^2 are jointly significant in all models. Non-real estate assets is significant for the first parametric correction. Years of education and 'Formality' are significant, except in semiparametric approach. Real estate assets, Gender and Spouse presence are not statistically significant in parametric and semiparametric models. Having delay payments impacts negatively in the semiparametric model, whereas it has no effect on Heckman approach.

7. Estimating the debt evolution

A complementary analysis consists of anticipating credit demand changes as a result of income growth and aging population. I estimate implicit elasticities and semi-elasticity of debt demand considering income and age evolution, respectively. In first place, I consider the profile of debt to income (figure 2) and debt to age (figura 3), and the corresponding derivatives. Estimations include consumer, mortgage and total debt. The figures include estimations of the non-corrected model, parametric correction and semiparametric correction.

Figures 2 and 3 exhibit a concave profile. Semiparametric and parametric models present a similar response, especially in consumer and total debt. Nevertheless, the semiparametric model presents a stronger response of debt to income compared to the parametric correction. Alternatively, the parametric model presents a stronger response of debt to age compared to the semiparametric model.

In second place, I consider weighted average derivative. It incorporates income and age distribution of the sample. I calculate income to debt elasticity and age to debt semi-elasticity. It is important to highlight that evidence suggest that Age plays a weak effect in debt level (semiparametric models). In Chilean investigation, Age is statistically significant for the three models. On the other hand, debt share exhibits inverted U-shaped profile (table I), and middle age households (from 35 to 54 years old) hold more than 60% of debt. Therefore, it is not clear the role of Age in debt holding. For sake of comparison, I extend the analysis taking into account the impact of age on debt semi-elasticities.

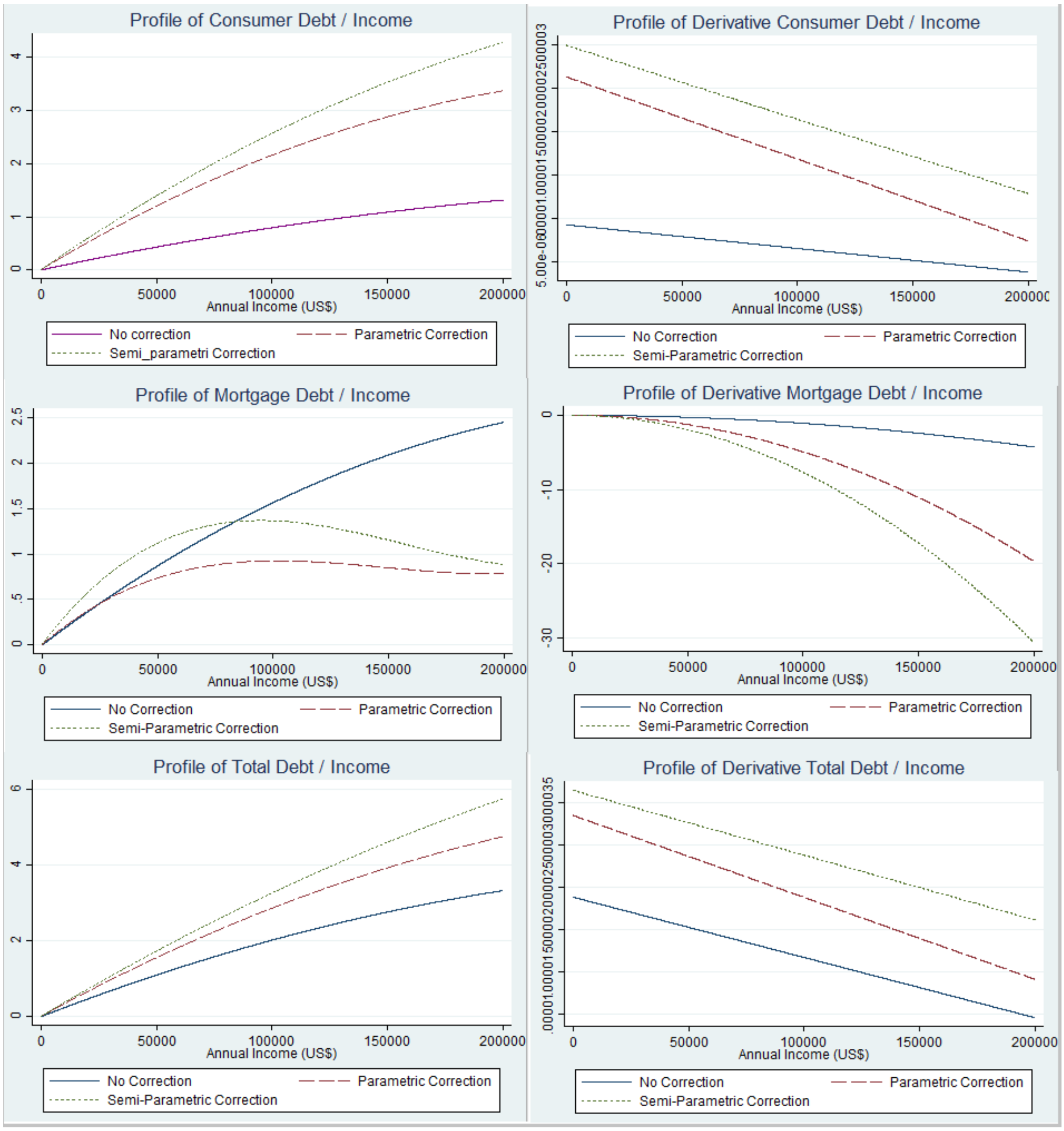

Figure 2. Estimated profile debt/income. Debt/income profile are (left) relatrionship = $\alpha_1^1 I_i + \alpha_1^2 I_i^2 + \alpha_1^3 I_i^3$, *(right) derivative =* $\alpha_1^1 + 2\alpha_1^2 I_i + 3\alpha_1^3 I_i^2$

Table IX exhibits weighted average derivatives estimates for each type of debt, considering OLS, Heckman approach and the semiparametric correction. In OLS, consumer debt-to-income estimation is 0.882% with a standard error of 0.481%. The coefficient is the semi-elasticity, regarding debt is in logarithms and income in thousands of dollars. US$ 1.000 annual income growth increases 0.882% consumer debt. Income elasticity is obtained by multiplying semi-elasticity by average income (US$ 18.066 in the corresponding subsample). Thus, debt-to-income elasticity in the uncorrected model is 0.15. In the corrected model the elasticity is larger (0.51) whereas for Heckman approach is 0.44.

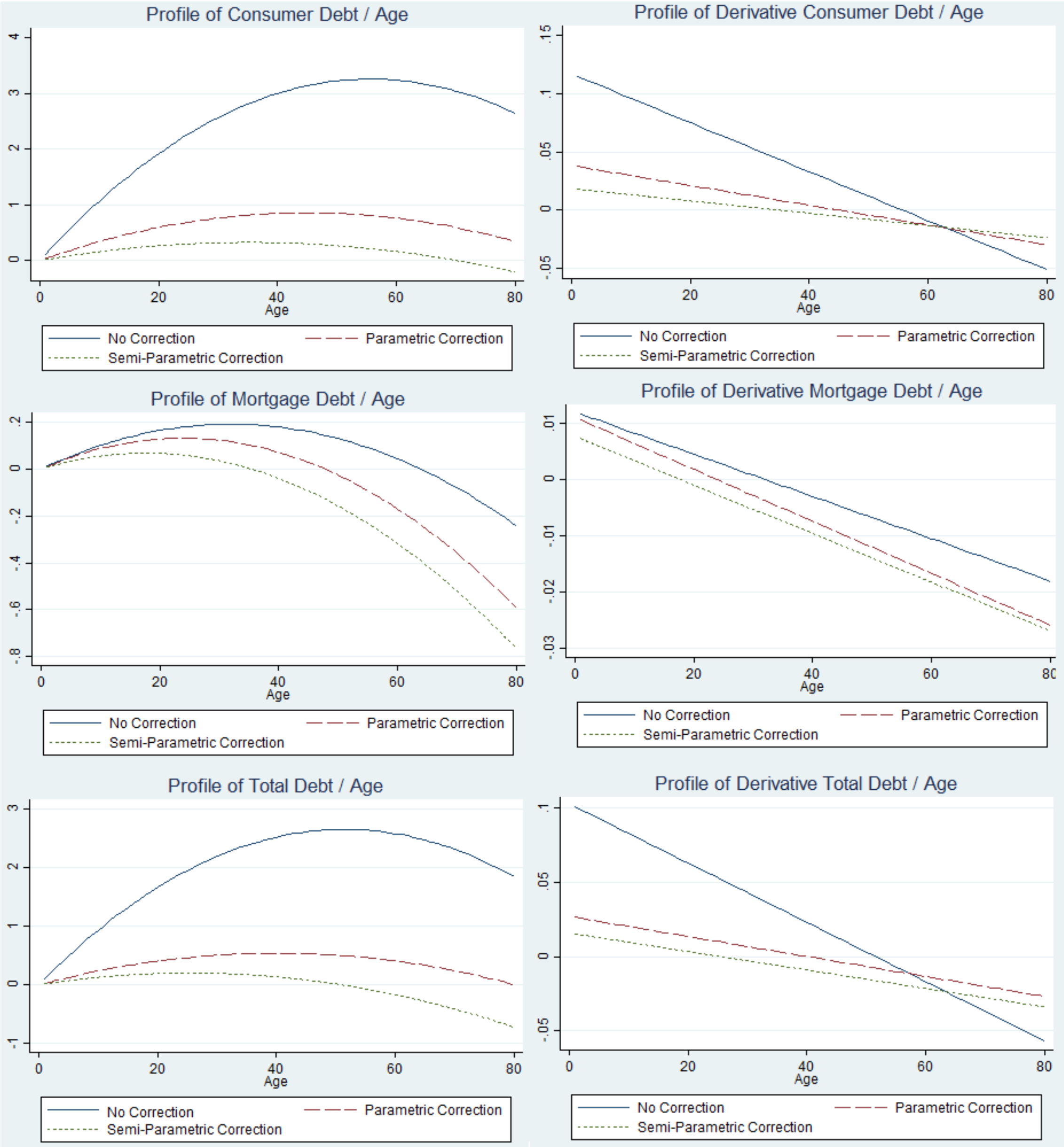

Figure 3. Estimated profile debt/age. Debt/age profile are (left) relatrionship = $\alpha_1^1 A_i + \alpha_1^2 A_i^2 + \alpha_1^3 A_i^3$, *(right) derivative* = $\alpha_1^1 + 2\alpha_1^2 A_i + 3\alpha_1^3 A_i^2$

The mortgage debt-to-income weighted average derivative is estimated in 1.72% with a standard error of 0.424% in OLS estimation. In Heckman approach is 1.41% (S.E.: 0.714%) and in the semiparametric model is 2.09% (S.E.: 0.127). As annual average household income is US$ 27.555 in the corresponding subsample, it generates an elasticity of 0.58 in the semiparametric model, 0.39 in Heckman model and 0.47 in OLS.

Total debt-to-income weighted average derivative is estimated in 3.56% (S.E.: 0.638%) in the semiparametric model. As annual average household income is US$ 19.737 in the corresponding subsample, income elasticity of total debt is estimated 0.70. This is larger compared with Heckman model (0.53) and with the OLS model (0.44). It is worth noting that using semiparametric models, elasticities are larger for any type of debt.

For Chile, estimation of elasticities of credit demand with respect to income are even larger. In the preferred model they found that income elasticity is 1.47 for consumer debt, 0.88 for mortgage debt and 1.78 for total debt. Nevertheless, they stress that results contrasts with much of the existing evidence for other economies, and also, there is even a dispute respect to the sign of the effect.

Table IX also provide information about life cycle behavior of credit demand. Results are important in an economy with an aging process. Third and fourth columns of table IX show that the consumer debt-to-age weighted average derivative is estimated in -0.76% with a 0.49% S.E. in the preferred model, compared to -0.37% with a 0.483% S.E. in Heckman model. Average age is 49.4 years old in the corresponding subsample. The mortgage debt-to-age weighted average derivative is -1.26% with a 0.803% S.E. in the semiparametric approach, larger than -1.06% in the parametric correction model. Average age is 47 in the corresponding subsample. Last, total debt-to-age weighted average derivative is -1.49% (0.644% SE) in the semiparametric model, compared to -0.25% (0.46% S.E.) in Heckman model. Debt-to-age weighted average derivatives are representing age semi-elasticity of debt demand. For Heckman and Semiparametric specifications an increase of 1 year of household average age decreases household debt level.

Table IX. Weighted average derivatives

	Income (mean)		Age (mean)		Age (25)		Age (35)		Average Income	Average Age
	Weighted average derivative	Delta standard error	Weighted average derivative	Delta standard error	Weighted average derivative	Delta standar d error	Weighted average derivative	Delta standard error		
Consumer debt										
No correction	0,00882	0,00481	0,0132	0,00525	0,0644	0,0138	0,04341	0,00965		
Parametric correct	0,0246	0,00434	-0,0037	0,00483	0,0170	0,0121	0,00848	0,00854	18,066	49,4
Semipara correct	0,0284	0,00747	-0,0076	0,00490	0,0054	0,0129	6,7E-05	0,00912		
Mortgage debt										
No correction	0,0172	0,00424	-0,0057	0,00452	0,0026	0,0110	-0,00116	0,00768		
Parametric correct	0,0141	0,00714	-0,0106	0,00774	-0,0004	0,0197	-0,00504	0,01307	27,555	47
Semipara correct	0,0209	0,0127	-0,0126	0,00803	-0,0031	0,0200	-0,00745	0,01338		
Total debt										
No correction	0,0224	0,00523	0,0044	0,00576	0,0530	0,0151	0,03296	0,01056		
Parametric correct	0,0271	0,00446	-0,0025	0,00460	0,0181	0,0121	0,00965	0,00836	19,737	49,3
Semipara correct	0,0356	0,00641	-0,0149	0,00644	0,000135	0,0138	-0,00607	0,01011		

Negative results of weighted average derivatives can be explained because age is valued in the average point. Therefore, it seems reasonable that age semi-elasticities of debt demand are negative. Families older than 47 years old are less likely to take mortgage debt. Moreover, the effect of Age on consumer debt for families older than 45 years old are negative, as indicated in section 6. Additionally, figure 3 indicates that the curve slope is negative for Heckman and Semiparametric approach. For Chile, negatives values for all type of debt were found. Columns 5 and 7 of table IX calculate age semi-elasticities of debt for different age points; 25 and 35 respectively. In consumer and total debt weighted average derivatives are positive. It indicates that an increase of one year in average age of families would increase debt level, except for semi-elasticities in the semiparametric correction when Age is set in 35 years old.

A controversial finding is observed in mortgage debt. Weighted average derivatives are negative for household if average age is set in 35 and 25 years old. Moreover, for the corrected specification semi-elasticity is still negative for 18 years old, and for Heckman approach semi-elasticity is still negative for 25 years old. For this reason, results are not in line with mortgage debt distribution showed in table I. Additionally, significance test yields that variable age is statistically non-significant for Heckman and semiparametric approach in the three age-points evaluated for the three type of debts considered. This finding re-enforce the controversial role of age seen previously.

Finally, the previous results allow forecasting and anticipating changes in debt level for the Uruguayan economy if income and age follow the recent path and credit system remains unchanged. Considering data from the ECH, from 2004 until 2014 household real income has increased 32.7%; 2.6% per year. In the same period, the aging process has implied an increase of household age average of 0.42% in eleven years, jumping from 49.58 to 49.79 years old. Using these results, in 5 years' time debt to income elasticities would increase from 0.49 to 0.56 in the case of consumer debt, from 0.57 to 0.65 in the case of mortgage debt, and from 0.67 to 0.76 in the case of total debt.

An important difference compared to Chile is that income elasticities are smaller than 1. It indicates a moderate debt growth comparing to income. Domestic credit to private sector evolution is shown in Figure 4. The feature of Uruguayan debt market suggests a relatively households' financial stability. On the other hand, for Chile, domestic credit to private sector has been increasing from 1990 in terms of the GPD. This dynamism has implied that in the middle of the last decade domestic credit is approximately three times bigger compared to 1990. Chilean credit market performance goes in line with income elasticity of debt demand (larger than 1). In addition, if income elasticity of debt demand is larger than 1, ratio debt to income increases and thus credit risk rises. It introduces more uncertainty in financial markets. In this context, economy is more vulnerable to financial shocks.

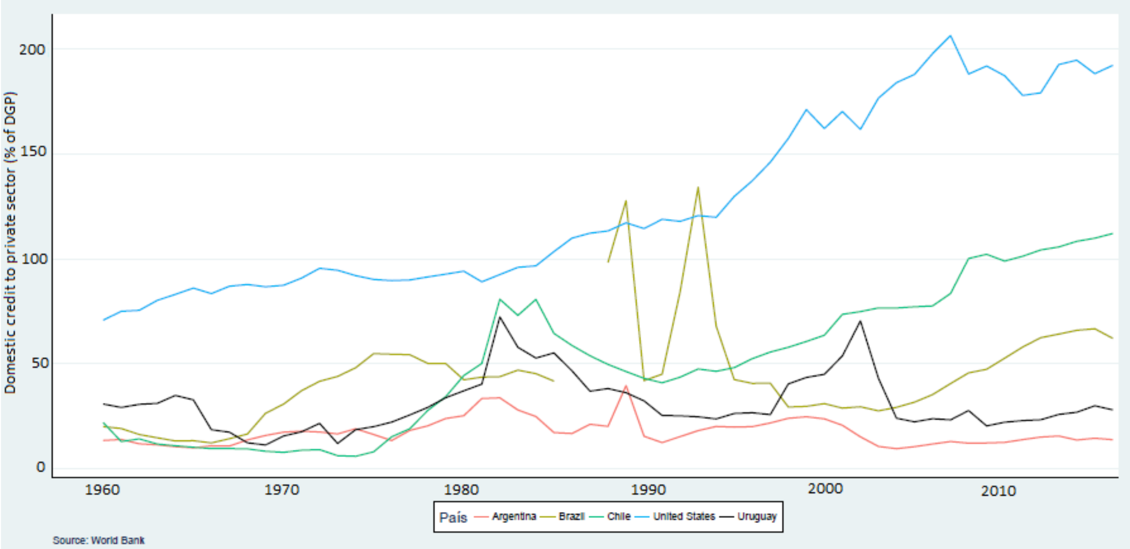

Figure 4. Domestic credit to private sector (% of GDP).
Source: World Bank

Debt-to-age elasticities would change too, as long as aging process move forward. Keeping the last decade age path, households' age average would increase 0.2% in the next five year. The aging process would change elasticity of consumer debt to age from - 0.3411 to – 0.3418, while mortgage debt to age would change from – 0.5768 to – 0.5779 and total debt to age from – 0.6885 to – 0.6899. These results indicate that an increase in age average would reduce debt holding, but changes in elasticities are hardly noted. Thus, as annual income growth rate is larger than annual age growth rate, it seems that total debt will keep growing, as long as economy follows the actual path.

8. Weak instruments

In this chapter I summarize methodological issues mentioned before and I try to explain differences respect to what RTV (2015) found for Chile. I also introduce an alternative explanation that goes in line with unexpected results. First, regarding to variable age and square age I find contrasting differences. For Chile, they found that both are statistically significant at 1% level in the semiparametric approach for the three type of debt. In contrast, I found that age and square age are not individually significant for any type of debt. Nevertheless, I found joint significance for consumer and total debt. For mortgage debt, evidence suggests age does not impact on mortgage credit level. Additionally, age does not impact on the probability of holding mortgage credit, as noted in table IV.

A possible explanation is that I have little data for mortgage debt holding. In Chile, 21% of households hold mortgage debt, but Uruguay only 9.1% does. I have 344 observations with mortgage credits that are not constrained. Thus, variance estimator is high, resulting in non-significant of age. Non-significant of Age persists in all mortgage credit models, thus results must be taken cautiously.

Second, in order to obtain the preferred model by cross validation, I had to exclude and incorporate variables. For instance, Having property[8] and Self-perception of financial service high[9]. It implied running cross validation with different set of variables obtaining different structural models. Hence, sample selection and endogeneity outcomes changed. For consumer debt, adding Having property, the semiparametric model included income and square income. Also, income residuals p-value was 0.004, suggesting income endogeneity. However, I had to exclude Having property due to collinearity in mortgage structural model, obtaining a different model where income is not included and it suggests no income endogeneity.

Alternatively, including Self-perception of financial service high in mortgage debt, the semiparametric model finds propensity score of holding debt and its square are jointly significant, detecting sample selection. Nevertheless, in the semiparametric mortgage model displayed in table VII, evidence suggest no sample selection. For these reasons, I state cross validation is "sensitive" to little changes in the specification. It wonders what is the best way is to proceed in semiparametric approach.

Third, instruments chosen present problems. Heckman and semiparametric approaches require the imposition of exclusion restriction for identification; that is, variables that affects the probability of being unconstrained or/and holding debt, but do not affect debt level equation. The main exclusion variables selected are related to credit accessibility (financial depth) and over-expenditure. A first problem is related to the variability of the instruments. Financial depth by region presents a narrow variability, and this fact could be introducing noises in the estimations. Additionally, table IV shows that financial depth variables are not statistically significant for mortgage debt holding. A possible explanation could be related to the year where financial depth variables were collected. Information of number of banks and retailers is from 2018, while data from EFHU was collected in 2014. Thus, variables related to financial depth might have measurement error.

The measurement error is defined as: $e = x_{\mathrm{K}} - x^*_{\mathrm{K}}$, where x_{K} is the observed variable (financial depth measured in 2018), and x^*_{K} is the unobserved variable (financial depth in 2014). If x_{K} and e are assumed to be correlated OLS estimations produce inconsistent estimators of all the β_j[10], forcing estimations to zero. (Wooldridge 2002: 73). The previous analysis is regarding to level equation. In this paper, measurement error is affecting the control function. So, evidence would suggest that instruments measurement error affects identification and therefore it affects level equation estimation.

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[8] Having property: dummy equals 1 if household owns any real estate assets

[9] Self-perception of financial service high: dummy equals one if household perception of paying financial service is high

[10] In literature it is known as attenuation bias due to classical errors in variables.

A complementary explanation might be related to geographical differences between both countries. Chile is four times bigger than Uruguay and it presents a heterogenic weather and geographical conditions. Distance from houses to banks might be relevant to decide asking mortgage credits. On the other hand, Uruguay is a small country, and in average distances from houses to banks might be shorter. Thus, distance may not be a restriction for asking mortgage credits for Uruguayan families. For Chile, variable "inhabitants over number of banks by region" is statistically significant at 1% in the probability of holding mortgage debt. Thus, geographical differences between Uruguay and Chile could explain exclusion restrictions relevance.

Non-significant effect of instruments violates que condition needed to run Heckman and semiparametric models properly. If instruments are not affecting the probability of holding mortgage debt, the transformed predicted values in the first stage are strongly correlated with the predictors in the second stage. The consequence of high collinearity is inconsistent estimations (Certo et al., 2006). Therefore, results related to mortgage debt must be taken cautiously.

Finally, endogeneity results should be taken cautiously. In parametric models, one way to overcome endogeneity is using instrumental variables (IV). Instruments must hold two conditions to be used properly. First, it cannot be correlated with the error term, and second it needs to be correlated with the endogenous variable. Problems emerge if endogenous and instrument variables are poorly correlated. Thus, the consequence is that "(…) the instrumental variable estimator can have a large asymptotic bias even if z (instrumental variable) and u (error term) are only moderately correlated" (Wooldridge 2002: 475). This problem is known as weak instrument.

In this part I follow Cameron and Trivedi (2009). They summarize several tests to identify weak instruments, based on analysis of the firs-stage reduced-form equation. The first test consists of calculating the correlation matrix between an endogenous regressor and instruments. It displays a first glance of the problem, but it does not conclude due to there is not a critical value to take a decision. Second, having more than one instrument, it is possible to consider the joint correlation of the endogenous variable and the instruments. Endogenous variable is regress on the instruments available and calculate the R^2 or the F statistic to evaluate the overall fit. Weak instruments are denoted by low values of R^2 or F statistic. However, there is not a critical value to take a decision. Third, Shea's partial R^2 consist of calculating the coefficient of determination (R^2) from the regression of the endogenous variable on the instruments and the exogenous variables of the structural model. This statistic coincides with standard partial R^2 if there is only one instrument. On the other hand, with more than endogenous regressors in the structural model these statistics diverge, and Shea's partial R^2 must be used. Again, there is not a critical value to take a decision.

Stock and Yogo (2005) proposed two tests to detect weak instrument. I detail and use one of the two. Having one endogenous regressor in the structural model, F is the statistic test for joint significance of instruments in the first stage regression. Having

"(…) more than one endogenous regressor in the structural model (…) the test statistic used is he minimum eigenvalue of a matrix analog of the F statistic that is defined in Stock and Yogo (2005, 84)" (Cameron and Trivedi 2009: 190). Low values of the statistic indicate the presence of weak instruments. Thus, null hypothesis implies weak instruments, whereas the alternative states that instruments are strong. Moreover, the critical value to reject the null hypothesis depends on three factors: the number of endogenous variables in the structural model, the number of instruments and the relative bias toleration of IV estimator respect to the bias of MCO estimator. Stock and Yogo (2005) generated a table with the corresponding critical values.

Table X. Estimations for weak instruments

First stage regression summary statistics

Variable	R^2	Adjusted R^2	Partial R^2	Robust F(5, 3470)	Prob > F
Income	0,3090	0,3052	0,0059	9,59316	0,0000
$Income^2$	0,0345	0,0292	0,0015	2,58019	0,0245
Non-real estate assets	0,1006	0,0956	0,0022	3,96849	0,0014

Shea's partial R^2

Variable	Shea's partial R^2	Shea's adjusted partial R^2
Income	0,0100	0,0049
$Income^2$	0,0019	-0,0033
Non-real estate assets	0,0017	-0,0034

Minimum eigenvalue statistic = 0.64365

Critical Values Ho: Instruments are weak	# of endogenous regressors: 3 # of excluded instruments: 5			
2SLS relative bias	5%	10%	20%	30%
	9,53	6,61	4,99	4,30
	10%	15%	20%	25%
2SLS size of nominal 5% Wald test	(not available)			
LIML size of nominal 5% Wald test	(not available)			

I use five main exclusion restriction. Following Das *et al*. (2003), the strategy to control for endogeneity is including, as additional explanatory variables, functions of the residuals from the reduced-form equation for income and non-real estate assets. The identification of the model requires exclusion variables. The first stage consists of regressing the variables that might be endogenous on the exogenous variables, including the exclusion restrictions. This is presented in columns 7 and 8 of table IV. Also, the first stage is the same strategy compared to 2SLS estimator. Therefore, I am in conditions to test for weak instrument the instruments used. Table X presents estimations for weak instruments.

The first panel gives the fist-stage regression summary statistics. It gives a first intuition of the problem addressed. Partial R^2 and F statistic are relative low, suggesting weak instrument problem. In fact, according to the rule of thumb suggested by Staiger and Stock (1997), F statistic value smaller 10 indicates weak instrument (Cameron and Trivedi 2009: 190). The second panel gives the Shea's Partial R^2, more appropriate than Partial R^2 in the presence of more than one endogenous regressor in the structural model. These values are considerable low suggesting weak instrument problem. Finally, the last part implements the test of Stock and Yogo. The minimum eigenvalue statistic is 0.64365. This value is smaller than any critical value presented in the last panel of table X. Additionally, adding the remaining instruments, situation does not change. Therefore, evidence suggests the presence of weak instruments.

9. <u>Finals conclusions</u>

This paper investigates que determinants of households' credit demand for Uruguay, exploring the relationship of borrowing constraints and debt holding, taking into account and comparing with Chilean economy.

Using Uruguayan household financial survey (EFHU) I find that there is an underlying selection process, based on unobservable, that it is affecting consumer debt level. However, it does not seem to fit for mortgage debt; that is, in the selection process I do not find evidence of selection based on unobservable.

These results go in line with Chilean finding. In contrast, I do not find evidence of endogeneity of Income and non-real estate assets for consumer and mortgage debt, whereas for Chile they find endogeneity of both variable for consumer debt and only endogeneity of non-real estate assets for mortgage debt. However, the presence of weak instruments incorporates noises in estimating the significance of parameters, forcing to take results cautiously.

Additionally, I estimate elasticities for debt to income, measures regarding weighted average derivatives estimations. Contrary to Chilean economy, income elasticities for Uruguay are smaller than 1; 0.49 for consumer debt, 0.57 for mortgage debt and 0.67 for total debt. In average, as households constrained income is lower, this suggests that relaxing borrowing constraints will probably increase borrowing of low-income households, changing the debt-to-income relationship. Income elasticities (smaller than 1) also suggest that will not be a credit boom destabilizing households' economy if economy keep growing.

In addition, I calculate semi-elasticities for debt to age, regarding that age is not statistically significant mortgage debt in the semiparametric models, but are jointly significant taking age and square age. Debt-to-age semi-elasticities are -0.707% for consumer debt, -1.22 for mortgage debt and -1.43 for total debt. These results show that debt decreases as long as aging process keep the actual path, ceteris paribus. Nevertheless, aging process will have a moderate effect on debt demand, regarding the relatively low age growth rate in Uruguayan households. Summarizing, I expect that debt demand grows considering that income effect on debt is larger than age effect.

Finally, in further investigations would be interesting to explore other instruments to overcome week instrument problems of variables related to financial depth. It would allow concluding the presence of income and non-real estate assets endogeneity more precisely. Additionally, it would be interesting to go deeper in the role of age for mortgage credits. Age has no impact on mortgage debt in all specifications. Joint significance is not significant either. This is, somehow, an unexpected finding.

In this line, some idiosyncratic characteristics would help to answer this question. For instance, the role of the Uruguay mortgage bank (BHU, in Spanish) in the credit market might be mitigating the role of age in determining mortgage credits. A possible explanation is that I have few observations for mortgage credits, impacting on the precision of the estimates. Additionally, the presence of weak instruments might be affecting the significance of age in the mortgage debt level equation.

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